Trade, Input Output Linkages, and Productivity

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To Paola and Oscar

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Abstract

This thesis investigates various aspects of international trade. In the first chapter, I study the effect of exporting on firms productivity. Specifically, I examine the extent to which export shocks are transmitted along the production chain through input-output linkages. I find that when firms expand into foreign markets, the increase in the derived demand for intermediates boosts the productivity of domestic input suppliers. In the second chapter, I focus on the determinants of markups at firm-product level. I find that when firms start to export new products, the effect on markups depends on the product characteristics. While, on average, markup adjustments do not appear to play a role, for more differentiated products I find evidence of an increase in markups. In the third chapter, I study the relation between exports and patent innovation. Results show that export shocks have a positive effect on firms' innovation. Firms invest the extra profits from the export market to finance the sunk costs of innovation.

Resum

Aquesta tesi investiga diversos aspectes del comerç internacional. En el primer capítol analitzo els efectes de l'exportaciò sobre la productivitat de les empreses. En particular, estudio en quina mesura els xocs d'exportaciò es transmeten al llarg de la cadena de producciò a travès d'enllaços input-output. Trobo que quan les empreses s'expandeixen en els mercats estrangers, l'augment de la demanda derivada d'inputs intermedis impulsa la productivitat dels proveïdors d'aquests inputs. En el segon capítol em centro en quins sòn els determinants dels mark-ups a nivell dels productes de cada empresa. Trobo que quan les empreses comencen a exportar nous productes, els efectes sobre els mark-ups depenen de les caracterìstiques dels productes. Mentre que en mitjana els ajustaments dels mark-ups no semblen exercir cap rol, si que ho fan per als productes mès diferenciats. En el tercer capítol estudio la relaciò entre l'exportaciò i l'innovaciò de patents. Els resultats mostren que els xocs d'exportaciò tenen un efecte positiu en les empreses d'innovaciò. Les empreses inverteixen els beneficis addicionals del mercat d'exportaciò per finançar els costos enfonsats de la innovaciò.

Foreword

My doctoral thesis is a collection of three self-contained essays that study various aspects of international trade.

In the first chapter, I examine the effect of trade liberalization on the productivity of domestic suppliers of exporting firms. Using a panel of Chilean firms during a period of trade liberalization with the European Union, the United States, and Korea, I show that when downstream firms expand into foreign markets, the increase in derived demand for intermediate inputs leads to productivity gains along the production chain. Export shocks increase market size for upstream firms through input-output linkages. This finding confirms the importance of demand in explaining firms' productivity dynamics.

In the second chapter, co-authored with Andrea Lamorgese and Frederic Warzynski, we use detailed information about firms' product portfolios to study how trade liberalization affects prices, markups, and productivity. We document these effects using firm-product level data in Chilean manufacturing. The dataset provides information about the value and quantity of each good produced by the firm as well as the amount of exports. One additional and unique characteristic of our dataset is that it provides a firm-product level measure of the average cost per unit. We use this information to compute a firm-product level measure of the profit margin that a firm can generate. We find that new products begin to be sold on foreign markets as export tariffs fall. Moreover, for those products, we observe a drop in both prices and average cost per unit. Those effects are mainly driven by an increase in productivity at the firm-product level. On average, adjustments to the profit margin does not appear to play a role. However, for more differentiated products, we find some evidence of an increase in markups, suggesting that firms do not fully pass-through increases in productivity on prices when they have adequate bargaining power.

The third chapter, co-authored with Antonio Accetturo, Matteo Bugamelli, and Andrea Lamorgese, focuses on the relation between exports and innovation. Firms exposed to higher foreign demand would have larger incentives to innovate if market size matters for innovation. We test this hypothesis using Italian data from a representative sample of manufacturing firms. Our measure of innovation is the firm-level number of patent applications to the European Patent Office. Using the dynamics of world imports as an exogenous shock to exports, we build an instrument for firm-level exports and find that moving from the 25th to the 75th percentile of the export distribution increases the probability of applying for a patent by one half of a standard deviation. This effect is driven by larger firms.

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Chapter 1

Trade Liberalization and Domestic Suppliers: Evidence From Chile

1.1 Introduction

Trade liberalization boosts productivity growth. Foreign firms increase the competitive pressure in domestic markets and force the least productive firms to exit (Pavcnik, 2002; Melitz, 2003). International trade provides incentives to improve firm productivity by fostering technological upgrades (Bustos, 2011) and allowing importing firms to access a large variety of cheap and high-quality inputs (Halpern et al., 2011).

At least as far back as Mosak (1938), we knew that equilibrium in the output and input market depends on the interrelations between production, price, and factor-derived demand. Any change in demand for a final good alters the equilibrium prices and quantities of all input products that are needed to produce that final good. Existing models of international trade with heterogeneous firms neglect these complementarities. If a firm's incentive to invest in productivity-enhancing activities depends on market size, this simplification comes at a cost: it does not account for the fact that when firms expand into foreign markets, they increase the derived demand for intermediate goods at home, leading them to underestimate the productivity gains from trade.

This paper examines the effect of international trade on the productivity of domestic input suppliers. Using Chilean firm-level data, I show that firms that supply intermediate inputs to exporting firms improve their productivity following trade liberalization. Chile is an interesting case to study.

Between 2003 and 2004, Chile signed free trade agreements (FTAs) with the European Union, the United States, and Korea. During this period, international trade increased along the intensive and extensive margin. Aggregate exports tripled, and the number of exporting firms increased substantially.

I estimate the impact of the export shock on domestic input suppliers using an input-output table and tariff data. I propose a measure of exposure of non-trading firms to the export shock, the *indirect export tariff*, which I define as the average export tariff faced by all downstream industries in the production chain that use a certain product as an intermediate input. I measure the export tariff using the weighted average import tariff applied by the E.U., the U.S., and Korea. These tariffs apply to all countries not only Chile. The identification assumption is that changes in these tariffs are exogenous to Chilean firms.

One of the main limitations of previous empirical studies has been to estimate firm productivity using proxies that blended technical efficiency with firm markups and prices (Foster et al., 2008; De Loecker, 2011). The richness of my dataset, that includes plant-level data, allows me to get precise measures of firms' productivity. For each plant I observe final products and intermediates goods prices, which I use to calculate a productivity measure that is not affected by output and input price heterogeneity.

My main finding is that the average observed decrease in the indirect export tariff increases firms' productivity on average by 1.5 percent. The gains are heterogeneous across the firm productivity distribution: the productivity of the ex-ante least productive firms increases more than the other firms in my sample. Finally, I show that the export shock increases the productivity of trading firms as well.

This is, to my knowledge, the first attempt to estimate the impact of the increase in derived demand on firm productivity. Other papers stress how international trade increases industry productivity through *selection* (Melitz, 2003; Pavcnik, 2002; Trefler, 2004). The most productive firms export; the least productive firms are forced to exit; and market shares are reallocated toward incumbent firms. These forces lead to an increase in the average industry productivity and a more efficient allocation of resources.

Several papers investigate how international trade increases the productivity of exporting firms. Lileeva and Trefler (2010) document a rise in the labor productivity of Canadian firms after an FTA with the United States went into force. Bustos (2011), finds that Argentinean firms that start to export in response to the MERCOSUR agreement invest in technology upgrades, which allows them to lower their marginal costs and become more competitive both in the domestic and foreign market. Another channel that enhances productivity of exporting firms is *learning-by-exporting*. The idea is that exporting firms acquire new knowledge and expertise from their trading partners. Among others, De Loecker (2007) provides empirical evidence supporting this mechanism using Slovenian data. Finally, another line of research investigates how international trade increases the productivity of importing firms. Using Indonesian data, Amiti and Konings (2007) show that a decrease in input tariffs increases the imports of intermediate inputs and the productivity of importing firms. Halpern et al. (2011) go one step further, showing that the increase in productivity of importing firms is mainly due to the imperfect substitution of intermediate inputs. Thus, the use of foreign inputs increases the productivity of importing firms.

The remainder of the paper is organized as follows. In section 1.2, I present the conceptual framework that guides the empirical analysis. Section 1.3 describes the FTAs. In section 1.4, I describe measurement issue and the identification strategy. Section 1.5 and 1.6 describe the data and discuss the results.

1.2 Conceptual Framework

This section discusses the conceptual background that guides my empirical analysis. I first introduce the derived demand for intermediate inputs and show how a fall in the export tariff for downstream firms can affect firms' derived demand. Second, I allow firms to invest and improve their productivity, and discuss the implications for the distribution of productivity gains across ex-ante heterogeneous firms. To simplify the analysis, I focus on one intermediate input industry that uses labor to produce a differentiated good under a technology with increasing return to scale. The output of this industry can be used as either a final consumable good or as an intermediate input in the production of other goods.[1]

I use a simplified version of Melitz's (2003) model, as discussed in Helpman (2006). Firms face an isoelastic demand function $q(i) = p(i)^{-\sigma} A$, where $p(i)$ is the price charged by firms; $\sigma > 1$ is the elasticity of substitution between any two varieties sold in the market; and A is a measure of market size. Demand faced by firms depends on three different components ($A \equiv A^h + A^m + A^x$): final domestic consumption A^h, domestic intermediate input demand A^m, and demand in a foreign market for both final and intermediate consumption A^x (see fig. 1.1). Following existing trade models, I assume that foreign demand is decreasing in the export tariffs $A^x(\tau_i^{exp})$. Firms must pay τ_i^{exp} in order to deliver a unit of goods in the destination

[1] Flour, for example, is an intermediate good that bakeries purchase to produce bread, but it is also consumed by households for producing baked goods at home.

market. Lower tariffs allow firms to reach a larger share of foreign consumers. Intermediate input demand comes from all firms in all other sectors that use output $q(i)$ as an intermediate inputs. Intermediate demands for good i from industry j can be expressed as a share α_{ij} of its total output $A^m = \sum_j \alpha_{ij} y_j$. Notice that the output of any industry j can also be expressed as a function of the export tariff faced by each firm in industry $y_j(\tau_j^{exp})$. This notation, although uncommon, clearly shows that the derived demand for intermediate inputs also depends on the export tariff faced by downstream firms in the production chain (see fig. 1.1). Existing trade models ignore the existence of the demand for intermediate inputs in the domestic market but instead focus on domestic demand for the final consumable good and foreign demand ($A \equiv A^h + A^x$).

The market structure is monopolistic competition. Firms differ in productivity. The total cost function is given by $\frac{c}{\varphi_0'} q(i)$, where φ_0' indicates productivity. Firms set the optimal price equal to a constant mark up ($\frac{\sigma}{\sigma-1}$) over the marginal cost. I set the cost of a input bundle to unity $c = 1$. Profits can be written as $\pi(0) = \varphi_0 A$ (where $\varphi_0 = \frac{\sigma^{-\sigma}}{(\sigma-1)^{1-\sigma}} \varphi_0'$).

Firms can invest and increase their productivity. I follow the literature and assume that upon paying a fixed cost (F^I), firms can increase their productivity to φ_1 and earn profits equal to $\pi(1) = \varphi_1 A - F^I$. In equilibrium, a firm is indifferent between investing or not if

$$\pi(0) = \pi(1) \quad \Rightarrow \quad \varphi_1 - \varphi_0 = \frac{F^I}{A},$$

which is represented by the horizontal solid line in fig. 1.2, panels (a) and (b). If the gains exceed the costs (above the solid line), firms find it profitable to invest. If, instead, the productivity gains are small relative to the cost (below the $\frac{F^I}{A}$ curve), then no firms find it appealing to invest. When the gains are independent of the initial productivity level φ_0, either all firms invest or none do. Equilibrium outcomes in which only some firms invest in productivity arise if the gains depend on the initial productivity level ($\varphi_1 - \varphi_0 = f(\varphi_0)$).

Productivity gains can be increasing or decreasing in the initial level of productivity. In panel (a), I plot an increasing gain function following Bustos (2011), which arises when firms invest and improve upon their productivity. For example, they might reorganize their processes or invest in R&D in order to introduce process innovations, as is likely the case when firms expand their technological frontier. The intersection of the two curves is the productivity ($\overline{\varphi_0}$) of the marginal firm, which is indifferent between investing or not. To the right of the cutoff, firms invest, while to the left, costs exceed gains and no firms invest in productivity. When productivity gains are increasing in the initial level of productivity, only the most productive firms invest. In panel (b), I plot a decreasing gain function following Lileeva and Trefler (2010). This assumption is reasonable when investment in productivity is thought of as the acquisition of new machinery at the forefront of technological innovation. In this case, the least productive firms can gain more by investing in productivity; thus firms to the left of the cutoff invest while firms to the right, because costs exceed gains, do not invest.

Consider now the effect of an increase in market size $A' > A$. When market size increases, investment becomes profitable for smaller productivity gains (the horizontal line shifts down). This happens because while gains are proportional to revenues, the cost is fixed. I get a new productivity cutoff for investment ($\overline{\varphi_0'}$). In panel (a), firms with productivity between the two cutoffs now find it profitable to invest. These firms are middle-productivity firms. Also in panel (b), new firms start to invest in productivity, but in this case, they are ex-ante the least productive.

Existing models of international trade focus on the increase in market size generated by new export opportunity, $\frac{\partial A^x(\tau^{exp})}{\tau^{exp}} < 0$. In contrast, this paper examines how derived demand for intermediate inputs can lead to increased productivity among domestic firms. More formally, consider the total differential for the intermediate input demand:

$$\begin{aligned} A^m &= \sum_j \alpha_{ij} y_j(\tau_j^{exp}) \\ \frac{dA^m}{A} &= \sum_j \frac{\alpha_{ij} y_j}{A} \quad -\sigma^{y_j}_{\tau_j^{exp}} \quad \frac{d\tau_j^{exp}}{\tau_j^{exp}}. \end{aligned} \tag{1.1}$$

Equation 1.1 defines the change in derived demand for intermediate inputs as the weighted average change in the export tariff faced by upstream firms. The magnitude of the change depends on three components: the relative importance of downstream industry in the demand for intermediates ($\frac{\alpha_{ij} y_j}{A}$); the elasticity of output to the tariff change ($\sigma^{y_j}_{\tau_j^{exp}}$); and the magnitude of the trade shocks, i.e., the change in export tariffs faced by downstream firms ($\frac{d\tau_j^{exp}}{\tau_j^{exp}}$).

The simple conceptual framework presented here shows how an increase in market size increases firms productivity. The relation between the productivity gains and the initial level of productivity determines which are the firms that invest. All these features are common to and well studied by other models (Lileeva and Trefler, 2010; Bustos, 2011). The novelty in my framework is that I explicitly account for input-output linkages among firms. When the output of some firms can be used as intermediates in the production of another good, a reduction in the export tariff can affect firms' productivity in two ways. First is the direct effect (dA^x): when firms expand into foreign markets, they experience an increase in sales and invest in their productivity. The second effect depends on the derived demand for intermediates (dA^m). The increase in the market size is due to an expansion in the foreign markets of downstream firms.

1.3 Chilean Free Trade Agreements

To asses the impact of international trade on the performance of Chilean firms, I exploit three important episodes of trade liberalization between Chile, the E.U., the United States, and the Republic of Korea. These free trade agreements (FTAs) were entered into force between February 2003 and April 2004. I use the level of tariffs in 2002, before the FTAs, as a proxy to measure improved access to foreign markets among Chilean firms.

Chile has a long tradition of integration into international trade. Starting in the late 1970s it eliminated non-tariff barriers and implemented a single import tariff rate (Pavcnik, 2002; OECD, 2003). Chilean Most Favoured Nations (MNF) tariffs applied to imports from abroad in 2002 were 7 percent for all industries. Together with other market-oriented reforms and a strong commitment to macroeconomic stability, Chile experienced sustained high growth from 1984 to 1997. Since late 1990s, Chile has signed several FTAs with its most important trading partners. These policies were implemented in response to the economic slowdown and were designed to help diversify of the Chilean economy, which relies heavily on natural resources.[2]

This paper focuses on three important FTAs signed with the E.U., the United States and the Republic of Korea. The negotiation with the E.U. started in November 1999, the agreement was signed in November 2002, and the FTA went into force in February 2003. The negotiation with the United States started in December 2000, the agreement was signed in June 2003, and it went into force in January 2004. The FTA with the Republic of Korea entred into force in April 2004 after seven rounds of negotiations, which started in 1999. By the date of entry into force of the three FTAs, almost all barriers to trade had been removed.[3]

[2]Chilean exports are highly concentrated in few products: copper, wood, and some agro-food products.

[3]While tariffs were completely eliminated after the entry into force of the FTAs with the United States and Korea, the same was not true for the E.U. For some goods, tariff elimination was scheduled in 2006. These goods accounted for less than 8 percent of total exports towards E.U. Moreover, for a wide range of agricultural and food products, quota protections were defined. Quotas were increasing over time, and scheduled to be eliminated within 5 to 8 years. All products imported within quotas were tariff free, but

Figure 1.3 shows the dynamics of aggregate export flows. The vertical lines show when the FTAs went into effect. Between 2002 and 2006 the value of aggregate exports almost tripled. Although Chilean exports to other markets also increase substantially,[4] these three markets account for 50 percent of the country's total exports.[5]

One possible concern about aggregate trends is the role of copper. The export of copper products accounts for half of aggregate exports in 2002. Chile is among the world's largest exporters of copper and the price of this metal, in line with other raw materials, greatly increased during the last decade. When I omit copper products from my calculations aggregate exports double.[6]

I use the change in the export tariff to identify the effect of the FTAs on Chilean firms. The tariff changes were exogenous to Chilean firms and mostly unanticipated, since the negotiations took place during a short period of time. I combine data on MFN tariffs applied by partner countries, to construct a weighted export tariff, i.e., the tariffs faced by Chilean firms. For each products p, I define the export tariff as

$$\tau_p^e = \frac{\tau_p^{E.U.} \cdot M_p^{E.U.} + \tau_p^{U.S.} \cdot M_p^{U.S.} + \tau_p^{KOREA} \cdot M_p^{KOREA}}{M_p^{U.S.} + M_p^{E.U.} + M_p^{KOREA}},$$

where τ is the MFN tariffs and M is the value of imports in the destination countries (EU, USA, and Korea). Variables are measured in 2002, the year before the FTAs were entered into force. Tariffs fall on average by 4.1 percent, ranging from 0 percent to 25 percent (the median tariff was 2.8 percent and the standard deviation 3.8). Table 1.1 shows the five industries with highest and the lowest tariff cuts. The heterogeneity across industries reflects different protection schemes applied by destination countries and are not specific to Chile. Indeed the share of Chilean import is less than 1% for the E.U., the United States, and Korea.

tariffs were applied to extra quantities. Quotas were applied on the basis of arrival time. Finally, the entry into force of FTA with the E.U. was provisional and become definitive in 2006. This caveat had no impact on tariff eliminations.

[4] These are the years in which many developing countries started to grow and increase their importance in world trade: the *Asian Tigers* experienced rapid growth after the financial crisis of late 1990s, China joined the World Trade Organization in December 2001; and Latin American countries saw a period of rapid growth and macroeconomic stability after the Argentinean crisis in 2001. Aggregate exports between 2002 and 2006 increased by 231, 194 and 314 percent for the E.U., the United States and Korea, respectively. During the same period, exports to the rest of the world increased by 157 percent.

[5] Manufacturing export shares toward the E.U., the United States and Korea in 2002 were 26.5, 19.9, and 4 percent, respectively.

[6] I exclude 86 HS products (6-digit) that contain the word *copper* or *molybdenum* in the description.

Another important effect of the FTAs was the elimination of Chilean import tariffs, which likely granted foreign firms access to the Chilean market and increased domestic competition. Between 2002 and 2006, aggregate imports from the FTA partners almost doubled. This increase was smaller than the rise in aggregate exports. In addition to the elimination of import tariffs on goods from the three FTA partners, Chile also reduced import tariffs on goods from other countries. During 1998-2005, the Chilean government gradually, unilaterally reduced import tariffs from 11% to 6%. This policy was part of the government's economic growth strategy.

The FTAs brought about a bilateral elimination of tariffs. These policies are expected to have two main effects on firms and the competitive environment: (i) it creates new export opportunitis for domestic firms, and (ii) it opens the domestic market to foreign competition. The evidence discussed above suggests that the FTAs signed by Chile had the main effect of creating new export opportunity. Chile was already open to international trade before the FTAs and the overall level of protection was very low compared to other developing countries.

1.4 Variable Definition and Estimation

1.4.1 Measuring the derived demand

I measure the increase in the derived demand for intermediate inputs using information on the export tariffs faced by downstream firms and an input-output matrix. The idea is that market size for intermediate input suppliers will increase if, all else equal, downstream firms increase their exports.[7] Formally, let U be an I x J input-output matrix, where I is the number of intermediate inputs used in production and J is the number of output products. Let u_{ij} be an entry in matrix U which represents the value of input i used in the production of product j. The value of the input purchased can be expressed as a share of total output $u_{ij} = \alpha_{ij} y_j$. Total output for good i is equal to A_i, which is the sum of all intermediate usage and final consumption. Finally, let τ_j^e be the export tariff faced by product j. The derived demand for product i, denoted as τ_i^{ie}, can be written as:

$$\tau_i^{ie} = \sum_j \frac{u_{ij}}{A} \tau_j^e = \sum_j \frac{\alpha_{ij} y_j}{A} \tau_j^e, \tag{1.2}$$

[7] Amiti and Konings (2007) and Halpern et al. (2011) show that the increased in market size also depend on the elasticity of substitution between domestic and foreign intermediates, since downstream firms can start to source intermediate inputs abroad.

which is the weighted average export tariff faced by all products that use intermediate i as an input.[8] To understand this, suppose that export tariff τ_j^e falls for some product j. The derived demand will increase for those intermediates i used in the production of j (which corresponds to a drop in τ_i^{ie}). The variable τ_i^{ie} can be interpreted as an *indirect export tariff*, meaning that it is a tariff faced by downstream firms.

It is important to stop here and to provide some additional intuition about this measures. Focus, for example, on Chilean wine. Chile has become a worldwide competitor in wine production. After the FTAs went into effect, wine experience the largest drop in export tariffs of any product, mainly due to the high protection of agricultural products applied by the E.U., whose market for wine is among the largest worldwide. Chilean wine producers experienced a huge drop in the export tariff, which helped them enter foreign markets ($\tau_{wine}^e = 25.5$). At the same time, they experienced virtually no change in derived demand: wine is not used as an intermediate input in the production of any other good.[9] Now consider the intermediate inputs used in the production of wine: labels of paper and bottles. Export tariffs on these products dropped by 2.2 and 4.2 percent, respectively, after the FTAs. The impact for these products on the derived demand was bigger. Labels had an indirect tariff cut of 2.8 percent, more than twice the average change in the indirect export tariff (equal to 1.1). Producers of bottles, in comparison, experienced an indirect tariff cut of 1.5 percent, almost 50 percent above the average fall of the indirect export tariff.

I build the indirect export tariff using the Chilean symmetric Use-Supply Input-Output matrix for year 1996, the last year they were compiled before the FTAs were introduced. I work with the table for national transactions at basic prices. The matrix includes 36 manufacturing and 11 agriculture and mining sectors.[10]

[8]The main difference between eq. (1.2) and eq. (1.1) is that the former assumes that the elasticity of output is equal to one for all products. This assumption can downward bias the measure of derived demand, which could be interpreted as lower bound estimates. However to my knowledge, such estimates are not available, and I avoid estimating them.

[9]Although wine is not used as an intermediate product, the IO table has a positive entry for intermediate usage of wine in the production of wine. The CPC product code 24212 that is used by the INE to contract the IO table includes both wine and grape must (see below and the appendix for data description). I also checked for this in the output and input data. The INE generated two different codes for this CPC product, one ending with 01 to refer only to wine, and one ending with 02 that correspond with grape must. Almost all output products are recorded using the INE wine-specific code 2421201. In the input dataset, instead, grape must is the most used inputs. Only a few firms report purchasing wine as an intermediate product.

[10]The matrix is created by the Central Bank of Chile. Further infor-

1.4.2 Productivity estimation

Estimating productivity can be problematic, as pointed out by De Loecker (2011) among others, when real output is measured using aggregate price deflators. In this case, $\widehat{\varphi_{it}}$ can reflect variation both in technical efficiency and in firm markups and market power. Another possible concern arises when material expenditure is computed using aggregate price deflators. The estimated productivity can reflect input price heterogeneity across firms mainly due to quality differences. In a recent paper, Smeets and Warzynski (2013) show the importance of using firm-specific price deflators: when productivity is estimated using aggregate price deflators, the export premia as well the productivity gains from trade are largely underestimated.

One of the main advantages of my Chilean data set in this work is that it allows me to compute plant-specific output and input price deflators and avoid these estimation problems. For each plant in my data, I observe unit values for output produced and intermediate inputs used in production. I follow the methodology used by Eslava et al. (2004) to build plant-specific price indices. Let P_{ipt} and P_{ipt-1} be the prices charged by plant i for product p at time t and $t-1$, respectively. The weighted average of the growth in prices for all individual products is defined as

$$\Delta P_{it} = \sum_{p} \bar{s}_{ipt} \Delta \ln(P_{ipt}),$$

where $\Delta \ln(P_{ipt}) = \ln P_{ipt} - \ln P_{ipt-1}$ and $\bar{s}_{ipt} = \frac{s_{ipt}+s_{ipt-1}}{2}$ (s_{ipt} and s_{ipt-1} are the shares of product p in plant total production at time t and $t-1$, respectively). The price indices for each plant are then constructed using the following formula:

$$\ln P_{it} = \ln P_{it-1} + \Delta P_{it},$$

where the price for the reference year is standardized ($P_{i'0} = 100$). The same methodology can be used to construct intermediate input price deflators using information on prices for intermediate input. I compute two plant-specific price indices: one for output $\ln P^{o}_{it}$ and one for intermediate inputs $\ln P^{m}_{it}$.

With these indices, I compute real variable as follows. Real output is defined as $y_{it} = \ln R_{it} - \ln P^{o}_{it}$, where R_{it} is nominal revenues. Intermediate input expenditure is defined as $m_{it} = \ln M_{it} - \ln P^{m}_{it}$, where M_{it} is the intermediate input expenditure.

mation can be found at `http://www.bcentral.cl/publicaciones/estadisticas/actividad-economica-gasto/aeg06.htm`. Although quite aggregated compared to IO tables available for other developed countries, the classification of industries is very informative for the Chilean economy. First, each of the 17 food manufactures has its own entry. These firms account for 30% of the total. Second, each sector accounts for less than 6% of total firms except for the bread industry.

My empirical analysis focuses on plant productivity, which I measure as follows. Consider the gross output production function:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \varphi_{it} + \varepsilon_{it}, \tag{1.3}$$

where y_{it} is the log of real output, l_{it} is the log of employment measured in efficiency units, k_{it} is capital, and m_{it} are the intermediate inputs.[11] φ_{it} is a productivity parameter, and ε_{it} is an idiosyncratic error term. k_{it} is a state variable, i.e., optimally decided one period in advance by firms. I also consider l_{it} to be a dynamic input. Petrin and Sivadasan (2013), using my same data set, treat employment as a dynamic input when estimating firm productivity due to the rigidities of the Chilean labor market. Materials, instead, are variable inputs, with the optimal choice depending on unobservable productivity: once firms becomes aware of productivity, they optimally choose the amount of material to use in production. The main problem in estimating eq. (1.3) is the unobservable productivity term φ_{it}. This is likely to be correlated with the variable input used in production and thus will cause inconsistent estimates of the elasticities of output. The methodology proposed by Olley and Pakes (1996) and modified by Petrin and Levinsohn (2003) avoids this problem by substituting the unobservable productivity term with a control function that allows the identification of the variable input parameters. This methodology rests on two main identifying assumptions. First, the productivity evolves exogenously following a first order Markov process, i.e. $p(\varphi_{it}|I_{it}) = p(\varphi_{it}|\varphi_{it-1})$. Second, firms optimally choose the amount of some variable, such as investment or intermediate input, that is strictly increasing in productivity.

I use Wooldridge (2009) modified version of these two approaches which has two main advantages: (i) all parameters can be jointly estimated with a Generalized Method of Moment (GMM) approach, and (ii) it also considers the collinearity issues raised by Ackerberg et al. (2006). More formally, let the innovation in productivity be $a_{it} = \varphi_{it} - E[\varphi_{it}|\varphi_{it-1}]$. The innovation is assumed to be uncorrelated with k_{it} and l_{it}, with the past values k_{it-1} and l_{it-1} and with past investments i_{it-1}:

$$E[\varphi_{it}|k_{it}, l_{it}, k_{it-1}, l_{it-1}, i_{it-1}] = E[\varphi_{it}|\varphi_{it-1}] \equiv f(k_{it-1}, l_{it-1}, i_{it-1}).$$

By substituting $\varphi_{it} = f(k_{it-1}, l_{it-1}, i_{it-1}) + a_{it}$ into eq. 1.3, it is possible to derive an estimation equation that allows me to identify all output elasticities:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f(k_{it-1}, l_{it-1}, i_{it-1}) + a_{it} + \varepsilon_{it} \tag{1.4}$$

[11] See the appendix for the exact definitions of capital and labor input.

using m_{it-1} as an instrument for m_{it} and a third degree polynomial approximation for $f()$. Finally, productivity can be calculated as $\widehat{\varphi_{it}} = y_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_k} k_{it} - \widehat{\beta_m} m_{it}$ as a residual. The estimated output elasticities are reported in the appendix. I estimate the production function for each two-digit industry separately and I found reasonable return to scale ranging 0.86 for machinery and equipment to 1.2 for wood industries.

1.4.3 Plant-Specific Tariffs

I use the information on products to construct plant-specific tariff variables.[12] For each plant I define the export tariff as

$$\tau_i^e = \sum_p \omega_{ip} \tau_p^e, \tag{1.5}$$

where ω_{ip} is the share of product p in total revenues. I also construct a plant-specific indirect export tariff:

$$\tau_i^{ie} = \sum_p \omega_{ip} \tau_p^{ie}. \tag{1.6}$$

It is important to stress the differences between the two measures. The export tariff is applied to Chilean exports before the FTAs. The indirect export tariff is the export tariff faced by downstream firms that use other firms' output as intermediate inputs in production.

1.4.4 Estimation Strategy

To establish a link between implementation of the FTAs and firm productivity, I proceed as follows. Consider the following equation:

$$TFPQ_{ijt} = \gamma_0 + \gamma_1 \tau_{ijt}^e + \gamma_2 \tau_{ijt}^{ie} + \delta_{jt} + \delta_i + \eta_{ijt}, \tag{1.7}$$

where i indexes firms, j industries, and t time. The dependent variable is firm productivity $TFPQ_{ijt}$. The main variable of interest is τ_{ijt}^{ie}, which is the plant-specific indirect export tariff. Finally, τ_{ijt}^e is the plant export tariff, δ_{jt} is industry-time fixed effects, and δ_i is an unobservable time invariant plant fixed effect.

Estimating eq. (1.7) using OLS has several drawbacks. Tariffs drop to zero after the FTAs go into effect for all firms, introducing serial correlation across observations. Moreover, productivity is likely to be highly seriallly

[12] To my knowledge, only a few works use firm-specific tariffs to identify the impact of FTAs. Among others, see Lileeva and Trefler (2010).

correlated across time within a firm. The presence of such problems makes estimation of the coefficients with OLS unbiased but will not yield the correct standard errors. Following a solution proposed by Bertrand et al. (2004), which they show performed well in Monte Carlo study, I ignore time series information. Instead, I consider one year *before* the FTAs (2002) and one year *after* (2006). Finally, I estimate eq. (1.7) using the differences to eliminate the unobservable plant fixed effect. The final estimation equation is

$$\Delta TFPQ_{ijt} = \gamma_1 \Delta \tau^{e}_{ijt} + \gamma_2 \Delta \tau^{ie}_{ijt} + \delta_j + \Delta \eta_{ijt}. \tag{1.8}$$

I argued in section (1.3) that the main variables of interest (τ^{e}_{ijt} and τ^{ie}_{ijt}) are likely to be uncorrelated with plant unobserved heterogeneity and the error term η_{ijt}. The variation in tariffs reflects the implementation of the FTAs that is exogenous to firms; thus I can use OLS. The equation also include industry fixed effects δ_j (at four-digit ISIC rev 3), which is possible because tariffs vary at the firm level. The variability I will exploit to identify the parameters is therefore within firms. The specification is parsimonious, as it includes only the tariff variables and the industry fixed effects, but it is sufficient to identify the effect of an increase in derived demand and the new export opportunity generated by the FTAs.

The presence of industry fixed effects, δ_j, will absorb several confounding factors that might lead to biased estimates. The first is an increase in competition in the domestic market due to the elimination of output tariffs imposed by Chile on imports. An increase in domestic competition can lead to a reduction of X-inefficiency (Rodrik, 1988). Chilean tariffs were a flat 7 percent across all industries before the FTA because of the single tariff policy rate. Including δ_j in the regression is sufficient to control for the change in the output tariff. A second confounding factor could be the effect of a fall in import tariffs on intermediate inputs, which allowed firms to source high quality input abroad. Increases in productivity can arise through learning, variety or quality effect (Amiti and Konings, 2007; Halpern et al., 2011). Again δ_j is sufficient to control for this mechanism because the level of Chilean tariffs on imports was flat across industries before the FTAs. Finally, even if the variation in tariff is exogenous, the level of the change reflects the protection scheme applied by partners, i.e., it is correlated with industry characteristics. Thus the presence of industry fixed effects controls for the initial differences in tariff levels across industries.

To increase the precision of the estimates, I add some additional firm controls measured before the FTAs, including the log of employment measured in efficiency units and the log of output per worker. These variables also help control for the presence of observable firm heterogeneity, which partially explains the differences in firm performance.

1.5 Data

Plant-level information comes from the manufacturing survey *Encuesta Nacional Industrial Annual* (ENIA) conducted each year by the Chilean Statistical Agency (INE). The survey, which plants are required by law to fill out, collects information on the universe of plants with 10 or more employees. Data cover the period from 2001 to 2007, with an average of $5,000$ observations per year. Chilean plant data are considered of high quality and have been widely used in the literature (Pavcnik, 2002; Petrin and Levinsohn, 2003; Fernandes and Paunov, 2012; Ackerberg et al., 2006) with only minor data cleaning needed.[13] In addition to information such as employment, revenues, and capital, for each plant I observe *output* produced and intermediate *inputs* used in production at the detailed product level. For each output, I have data on quantities (produced and sold), total revenues, and quantities exported. For each input, I have data on quantities (purchased and used in production), total expenditures, and quantities imported. I use information on outputs and inputs at the product level to build *plant-specific* tariff and price indices for revenues and intermediate input expenditure.

Figure 1.4 shows the export market participation of Chilean firms along the extensive and the intensive margin. The number of exporting firms increases from 19.7 percent in 2002 to 22.1 percent in 2006. The average export share jump from 6.4 percent to 7.8 percent in 2006.

In the empirical analysis, I use two waves of survey data: 2002 and 2006, the year before the first FTA went into effect and one year after the last went into force. I use these two years for several reasons. First, I did not use 2001 data because several changes were made to the survey that year, which could affected the results and the response rate. In addition, the Argentinian financial crisis reached its peak that year and could have affected Chilean firms. I also exclude the three years between 2002 and 2006 because the FTAs went into force at varying times during this period and their effect could take time to be felt. Finally, I exclude 2007 because in this year two other important FTAs between Chile and China and Japan entred into force. My final sample includes only firms that I observe in both periods, because I am interested in within-firm productivity dynamics.

Table 1.2 presents the means for several key variables for the $3,345$ firms in my final sample. Means are reported separately for the years before and after the FTAs, with the standard errors in parentheses. The average firm

[13] See the appendix for a detailed description of data cleaning.

size increases slightly from 3.52 to 3.58 (measured as log employment in efficiency units). The log of real output, the value added per worker, and other variables exhibit similar patterns. The log investment per capita jumps to 5.92 in 2006 from 5.79 in 2002. Neither the number of multi-product firms nor the overall number of products varies, but the number of exported products slightly increases. The last row reports average productivity, which rises from 1.49 to 1.51.

1.6 Results

Table 1.3 presents the results of the OLS regressions of (1.8) that explore the relationship between tariff cuts and increase in productivity. Column 1 shows that a demand shock generated by downstream firms increases productivity among input suppliers. The coefficient of the indirect export tariffs is negative (-1.31) and significant, implying that the average fall in the indirect export tariff increases productivity by 1.4 percent. In column 2, I add firm-level controls (employment and output per worker). The point estimate increases slightly, but the standard errors are reduced. Columns 3 and 4 include only the export tariff and the point estimates remain negative and significant. The implied increase in productivity is about 1.2 percent ($-0.225 * 5.2$). Although the extant literature sometimes has struggled to find a positive effect between exports and productivity (for a review of the literature see Bernard et al. (2011)), my estimates show that productivity increases for Chilean firms directly affected by the FTAs. The last two columns assess the robustness of the baseline results when both tariffs are added contemporaneously to the regression. The coefficients remain negative and significant. The point estimates are similar to the specifications when the tariffs are included separately. The implied increase in productivity is 1.5 percent for the indirect effect and approximately 1.2 percent for the direct effect.

To show that the tariff cuts capture different demand shocks, I classify industries as either comparative advantage (CA) or disadvantage (CD) industries and estimate (1.8) separately.[14] Chilean exports are highly concentrated in a few products: salmon, wine, avocados, pulp wood, and copper.[15] In CA industries the share of exporting firms is three times larger than the rest of the industries (about 45% vs. 15%). The most exported Chilean products are either final consumption goods (salmon, wine, and avocados), or they

[14] I use Baci-Cepii data to compute the Balassa revealed comparative advantage index in 2002.

[15] These products account for 88% of manufacturing exports.

are intermediate inputs not used in the production of any other exported products (pulp wood and copper). Table 1.4, columns 1 and 2 shows the results on the sample of CD industries and CA industries, respectively. In CD industries the coefficient of indirect export tariff is negative and significant (-1.515), implying an increase in productivity of 1.6 percent. The coefficient of the direct export tariff is positive but not significant, meaning that the decrease in the export tariff does not boost firm productivity in CD industries. Column 2 shows the effect of tariff cuts in CA industries. The coefficient on the indirect export tariff is negative but insignificant, while the drop in the export tariff increases firm productivity by 1.9 percent. The Chilean export market is structured such that in CA I find that the decrease in the export tariff positively affects firm productivity; however the derived demand plays no role.

In column 3 and 4, I split the sample according to the share of products that require relationship-specific investment. Borrowing from Nunn (2007), for each industry I compute the average number of products not sold on an organized exchange using the Rauch (1999) classification. When an intermediate input requires specific investment, the relationship between buyers and sellers are stronger and long lasting. The increase in the derived demand should be more important in industries that produce complex intermediate inputs because of the lower degree of substitutability. Column 3 shows the results for industries that produce more differentiated goods. I use the median value to split the sample. The indirect export tariff is negative and significant, suggesting a productivity increase of 2.5 percent. The coefficient for firms that operate in industries with a share of differentiated products below the median (column 4) is negative and significant but smaller (the implied increase in productivity is 1.2 percent). The estimated coefficient on the direct export tariff moves from being insignificant for differentiated goods, to becoming significant, implying an increase in productivity of 1.4 percent.

The baseline results show that the increase in the derived demand for intermediate inputs boosts firm productivity among domestic suppliers. This is the first paper, to my knowledge, that shows a new channel for TFPQ improvements. Both sample splits show that the export tariff cuts and the increase in derived demand are different demand shocks that hit different types of firms. Surprisingly, even though the shocks are very different, I find that the magnitude of the increase in productivity is almost the same. The indirect export tariff depends on the input-output linkages between firms and the tariffs faced by downstream exporting firms. The export tariff, instead, depends on the protection scheme applied by the partner countries. Because of the structure of its exports, Chile is an ideal case study for examining the implications of such differences. Previous works examining the relation between exports and productivity have focused mainly on exporting firms, which tend to increase their productivity in response to an export shock. Because Chilean exports are concentrated in a few well-defined industries, I can to split the sample and further analyze how export shocks shape firms productivity. These are firms affected *directly* by the export shocks. This paper contributes to the literature by showing that productivity also increased for firms that do not export but that are connected to exporting firms through input-output linkages. These firms are *indirectly* affected by the export shock.

Table (1.5) shows some heterogeneity in firm responses, which is not surprising because even when all firms face the same demand shock, only a subset are likely to find it profitable to increase productivity. In the first two columns, I divide firms within each industry by size measured using employment in efficiency units. Column 1 and 2 show the results for firms with employment below and above the median, respectively. The coefficient on the indirect export tariff in column 1 is negative and significant (-2.017), implying an increase in productivity of about 2.2 percent. The direct effect is also negative and significant. Although both coefficients in column 2 are negative, neither is statistically significant, suggesting that only smaller firms find it profitable to increase productivity when market size increases. In the last two columns, I divide firms within each industry according to their sales per worker. The indirect export tariff is negative and significant in both columns, although the implied increased in productivity is larger for smaller firms (1.7 and 1.3 percent, respectively). The direct effect is significant only for firms with output per worker below the industry median.

1.6.1 Alternative Productivity Measures

The results are robust across different productivity measures. In the first column of Table (1.6), I use the gross output production function specification and investment to construct the proxy for unobservable productivity, following the two-step estimation procedure proposed by Ackerberg et al. (2006). In the second column, I use the approach described in the previous section (Wooldridge, 2009) but with a value added production function. Finally, in the last two columns, I consider the change in labor productivity measured using the change in real output per worker and the real value added per worker, respectively. The general pattern remains unchanged. The results of the first column are almost identical to the baseline specification. The point estimates using a value added production function, as expected, are bigger with respect to TFPQ measured using the gross output specification. Productivity almost doubles in response to the increase in the derived demand and the export tariff cut. The increase in output per worker caused by an increase in derived demand almost mimics the productivity gains (-1.242), but the direct effect is smaller and not significant (-0.466). The last column shows the result for labor productivity. Again, the derived demand shock has a positive effect on firms' labor productivity, increasing increase by 2.8 percent.

1.6.2 Alternative Tariff Measures

The indirect export tariff used in Tables (1.3)–(1.6) is calculated using eq. (1.6) and the 1996 IO table, the last year for which the matrix is available before the FTAs. One possible concern is that after several years of economic slowdown and the 2000 Argentinean crisis, this table might not be representative of the Chilean economy in 2002. For robustness, I compute the indirect export tariff using the 2003 IO table. This year's matrix is likely to be partly affected by the implementation of the EU-FTA, but it can show that the results are not sensitive to the use of the 1996 IO table. The second column of Table (1.7) shows that the main results remain unchanged when using this alternative measure. The indirect export tariff is negative and significant, and the point estimates are larger than in the baseline regression (reported in column 1 for reference), implying an increase in productivity of 2.1 percent ($-2.295 * 0.9$). The coefficient of the direct export tariff remains identical.

I aggregate the tariff at the plant level using sales shares measured before the FTAs as weights, which could bias my results by introducing some correlation with unobservable firms characteristic. In Table (1.7), column 3 shows that using unweighted tariffs does not alter the main results. Both coefficients, although smaller, remain negative. The point estimate of the derived demand is comparable to the baseline specification both in magnitude and significance. The direct effect, however, is smaller and insignificant.

Column 4 computes the indirect export tariff using as weights the total output sold as intermediates ($\tilde{\tau}_i^{ie} = \sum_j \tau_j^e \frac{u_{ij}}{A^m}$). The coefficient on the indirect export tariff remains negative and significant. The point estimate is -0.368, and the implied increase in productivity is 2.0 percent. The effect is larger because this measure does not take into account that there are industries that sell a small fraction of their output as intermediates. Formally, the two measures are linked by the following relation:

$$\tau_i^{ie} = \sum_j \tau_j^e \frac{u_{ij}}{A^t} = \frac{A^m}{A^t} \sum_j \tau_j^e \frac{u_{ij}}{A^m} = \frac{A^m}{A^t} \tilde{\tau}_i^{ie}. \tag{1.9}$$

When all output is sold as intermediates, the two measure are identical. In contrast, when only a fraction of the output is sold as intermediate inputs, no matter the value of $\tilde{\tau}_i^{ie}$, the value τ_i^{ie} will always be close to zero. When measuring the impact of the derived demand, it would be misleading not to account for how much of the product is sold as an intermediate input. For example, imagine two different industries (say A and B) that sell their output to a third industry (say C). Industry C faces an export tariff equal to $\tau^x = 10\%$. The main difference between A and B is that while A sells all of its output as an intermediate to C, industry B sells 50% of its output as an intermediate to C and the rest to final consumers. In this simplified example, $\tilde{\tau}_i^{ie}$ is the same for industry A and B, while τ_i^{ie} for industry A is twice as large as that of B. The reason is that the increase in derived demand for industry A is much larger than that of industry B.

1.6.3 Controlling for Import Competition

The entry into force of the FTAs decreased the tariff Chile applied to its imports. Output and input tariffs can affect firms in two different ways. They can have a pro-competitive effect by increasing the number of foreign firms selling their products in the domestic market. Tariff cuts can also push firms to source intermediate inputs abroad. It is possible that part of the increase in productivity that I have documented could be due to import tariff cuts and not to the export shock. I have already argued that main effect of the FTAs was generating new export opportunities for Chilean firms. Unfortunately, I cannot add the change in output and input tariffs to my main specification, because Chile was applying a single import tariff rate during my sample period. All tariffs dropped from 7 percent in 2002 to zero. Although the tariff cuts were of equal magnitude across industries, the effect could have been heterogeneous across industries. The presence of industry fixed effects in the baseline specification should control for this heterogeneity.

Nonetheless, I perform two additional exercises to test the robustness of my results to the change in imports. Table 1.8 shows the results. In the first two columns, I split the industries below and above the median change in aggregate import flows.[16] If the results were driven by a pro-competitive effect, then I expect to find a significant coefficient for tariffs only in those industries that were most affected by the increase in imports

[16] I report the results for change in import flows from the E.U., the United States and Korea, because these are the countries affected by the tariff elimination. I also repeat the exercise considering the imports from other countries, because during this period Chilean import tariffs dropped by 2 percent. Finally, I also consider total imports, and the results are identical.

from abroad (those above the median). The increase in the derived demand has a statistically significant impact on firm productivity in industries with smaller changes in imports. The point estimates are similar also for industries above the median, but the estimates are less precise. Point estimates are remarkably similar to the baseline results.

My second robustness test controls for changes in imports of intermediate input product. For each industry, I compute the share of importing firms before the FTAs and then split the industries below and above the median share. I consider the share of importing firms measured ex ante, because this proportion remains fairly constant at the industry level. Columns 3 and 4 of Table (1.8) show the results. The indirect export tariff is always negative and significant. The effect is larger for firms in industries with a low share of importing firms. This is consistent with the fact that these firms are the ones with ex-ante lower productivity. Both exercises provide some empirical evidence that import tariff cuts following implementation of the FTAs was not the main driver of the observed productivity gains.

1.7 Conclusion

In this paper, I provide empirical evidence of an additional channel of productivity gains generated by international trade. When firms are connected through input-output linkages, an expansion of firms into foreign markets increases the derived demand for domestic input. I propose a measure of exposure of non-trading firms to the export shock, which I define as the average export tariff faced by all downstream industries in the production chain. I estimate plant productivity controlling for output and input price heterogeneity. I show that the positive demand shock induces domestic firms to take actions that boost their productivity. The main drawback of my analysis is that because of data limitations, I am not able to identify the exact mechanism underlining productivity gains: hiring good managers, increasing technological spending, or modifying firm organization (see Syverson (2011) for a detailed review). My work shows instead that demand components are important determinants of productivity dynamics.

Figures and Tables

Figure 1.1: Input Output Linkages

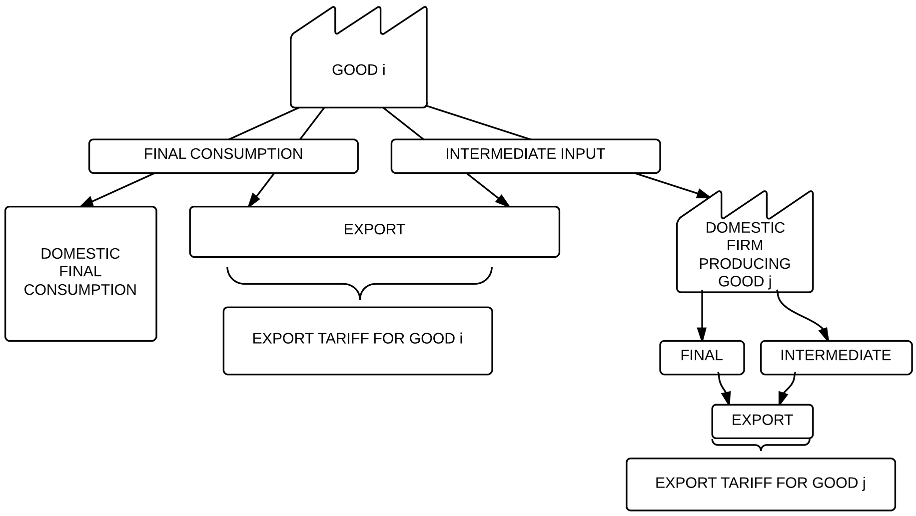


Figure 1.2: Optimal Investment Decision

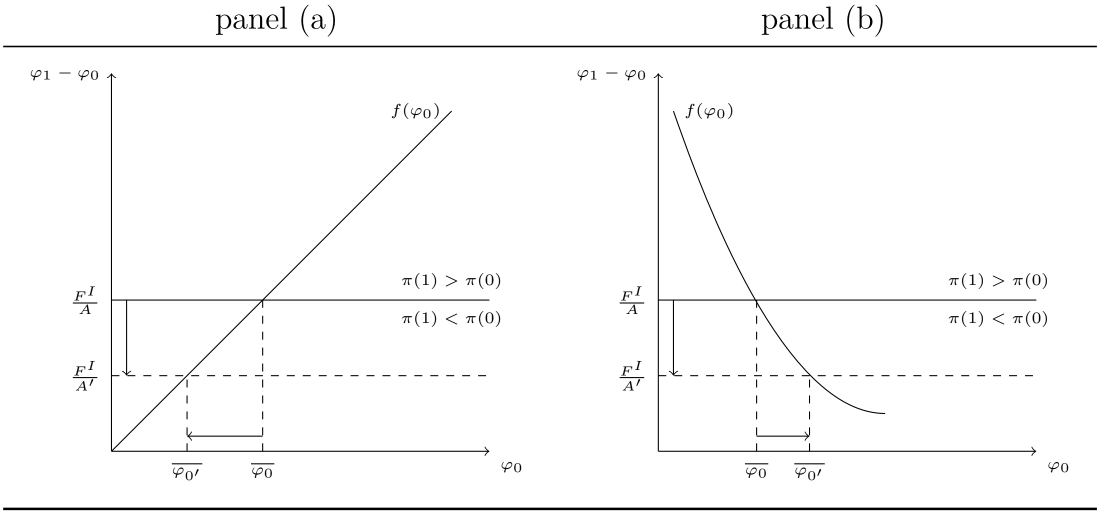
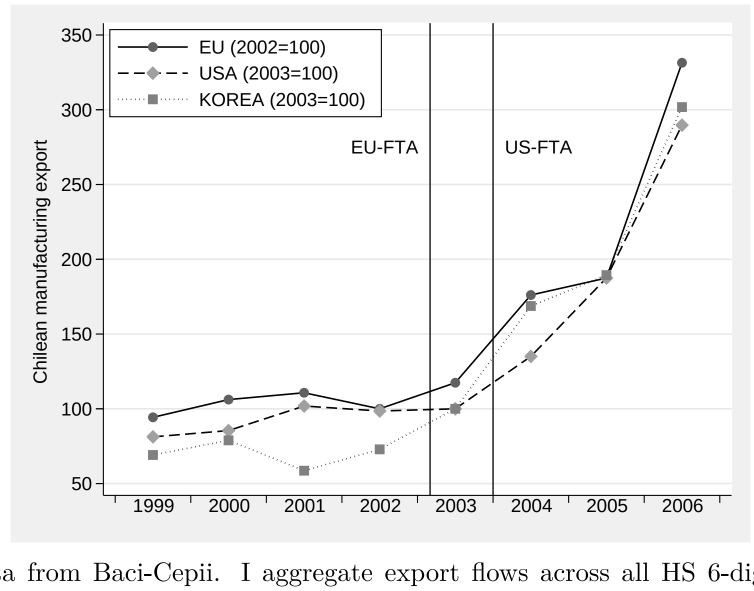
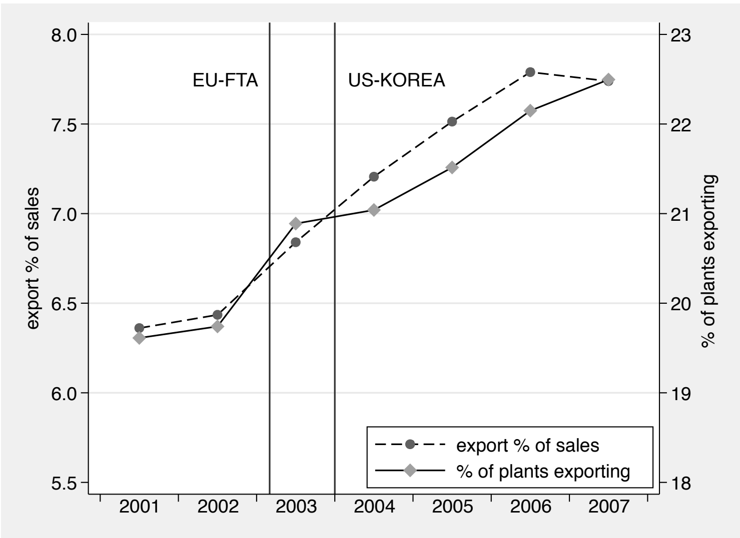


Figure 1.3: Aggregate Export Flows



Notes: Data from Baci-Cepii. I aggregate export flows across all HS 6-digit products. Index numbers equal 100 the year before the entry into force of the FTAs: 2002 for the EU and 2003 for the United States and Korea.

Figure 1.4: Extensive and Intensive Margins of Trade



Notes: Data from ENIA. The solid vertical lines represent the entry into force of the FTAs. The export percentage of sales is the average across firms, calculated as (total exports)/(total sales). Plants with positive exports are classified as exporting.

Table 1.1: Export Tariff for Selected Industries in 2002

Industry description	Tariff
Panel (a) : five industries with highest tariff cuts	
Manufacture of wines	24.7
Manufacture of starches and starch products	18.6
Processing and preserving of fruit and vegetables	15.1
Manufacture of knitted and crocheted fabrics and articles	12.3
Manufacture of wearing apparel, except fur apparel	11.7
Panel (b) : five industries with lowest tariff cuts	
Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy	0.1
Manufacture of coke oven products	0.1
Publishing of books, brochures, musical books, and other publications	0.0
Publishing of newspapers, journals, and periodicals	0.0
Manufacture of machinery for mining, quarrying, and construction	0.0

Notes: Tariffs are aggregated at the industry level according to the 4-digit ISIC Rev.3 classification.

Table 1.2: Means of Key Variables

Variable description	2002	2006
log (employment)	3.525	3.584
	(1.119)	(1.193)
log (real output)	13.348	13.387
	(1.703)	(1.829)
log (value added per worker)	8.616	8.630
	(1.090)	(1.191)
log (capital per worker)	8.678	8.698
	(1.515)	(.535)
log (investment per worker)	5.796	5.924
	(1.968)	(1.943)
% multi-product firms	0.492	0.492
	(0.500)	(0.500)
number of products	2.220	2.221
	(1.889)	(1.887)
number of exported products	0.304	0.318
	(0.779)	(0.805)
TFPQ	1.493	1.511
	(1.314)	(1.360)

Notes: The table uses the final sample of ENIA firms used in the empirical analysis, those that are present both in 2002 and 2006 after data cleaning. Multi-product refers to firms that report more than one output. Number of products is the overall number of outputs reported by the firms. Number of exported products refers only to products with positive exports. Standard errors are reported in parentheses.

Table 1.3: Main Results on Productivity

Dependent Variable: Change in log TFPQ						
$\Delta\tau_{it}^{ie}$	-1.311**	-1.516***			-1.207**	-1.397***
	[0.513]	[0.510]			[0.516]	[0.513]
$\Delta\tau_{it}^{e}$			-0.225**	-0.263**	-0.197*	-0.232**
			[0.107]	[0.106]	[0.107]	[0.106]
Firm Controls		Y		Y		Y
Implied change in TFPQ						
$\Delta\tau_{it}^{ie}$	1.45	1.68			1.34	1.55
$\Delta\tau_{it}^{e}$			1.18	1.38	1.03	1.22
R^2	0.042	0.057	0.041	0.056	0.043	0.058
Observations	3345	3345	3345	3345	3345	3345

Notes: The dependent variable is the log change in firm productivity. All regressions include industry fixed effects. Firm controls include the log of employment in efficiency units and the log output added per worker measured in 2002. The implied change in productivity is the estimated coefficient in the above panel multiplied by the corresponding mean tariff cuts ($\Delta\tau_{it}^{ie} = 1.1$ and $\Delta\tau_{it}^{e} = 5.2$). Standard errors clustered at the industry level are in brackets. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table 1.4: Derived Demand and Industry Characteristics

Dependent Variable: Change in log TFPQ	Comparative Advantage		Differentiated Industries	
	CD	CA	Above	Below
$\Delta\tau_{it}^{IE}$	-1.515***	-1.073	-2.264***	-1.043*
	[0.388]	[1.762]	[0.821]	[0.631]
$\Delta\tau_{it}^{EXP}$	0.0210	-0.369**	-0.157	-0.272*
	[0.163]	[0.138]	[0.217]	[0.139]
R^2	0.0669	0.0349	0.0581	0.0575
Observations	2175	1170	1665	1680

Notes: The dependent variable is the log change in firm productivity. All regressions include industry fixed effects, log employment, and log sales per worker measured in 2002. Comparative advantage (CA) and comparative disadvantage (CD) industries are defined using the Balassa index. For each industry, I divide the share of exports in a certain industry in Chile by the same share calculated using world trade flows. Due to the limited number of industries with a Balassa index greater than one, I use0.6 as the cutoff. In the last two columns, industries are divided according the the median share of differentiated good at the industry level, measured as the share of differentiated products according to the Rauch (1999) classification. Standard errors are in brackets. Robust standard errors in the first two columns due to the limited number of clusters in column 3. Clustered standard errors are presented in the last two columns. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table 1.5: Heterogeneity

Dependent Variable: Change in log TFPQ	Employment		Output per worker	
	Below	Above	Below	Above
$\Delta\tau_{it}^{IE}$	-2.017**	-0.715	-1.606*	-1.185**
	[0.785]	[0.480]	[0.919]	[0.577]
$\Delta\tau_{it}^{EXP}$	-0.289*	-0.147	-0.320**	-0.126
	[0.165]	[0.189]	[0.156]	[0.156]
R^2	0.0927	0.0908	0.0836	0.0802
Observations	1673	1672	1673	1672

Notes: All regressions include industry fixed effects, log employment, and log sales per worker measured in 2002. Firms are divided according to the median value of the within-industry distribution of employment (first two columns) and real output per worker (last two columns). Standard errors clustered at the industry level are in brackets. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table 1.6: Alternative Productivity Measures

Dependent Variable: Change in log TFPQ	(1)	(2)	(3)	(4)
$\Delta\tau_{it}^{IE}$	-1.364**	-2.418**	-1.242**	-2.514***
	[0.586]	[0.993]	[0.493]	[0.941]
$\Delta\tau_{it}^{EXP}$	-0.229**	-0.466*	-0.142	-0.420
	[0.111]	[0.275]	[0.173]	[0.274]
R^2	0.0493	0.0569	0.0992	0.0565
Observations	3344	3297	3360	3299

Notes: This table reports the baseline results using different productivity measures. In the first column, TFPQ is estimated using the two-step Ackerberg et at. (2006) procedure. In the second column, TFPQ is from a value-added production function. In the last two columns, the dependent variables are real output per worker and labor productivity (real value added per worker). All regressions include industry fixed effects, log employment, and log sales per worker measured in 2002. Standard errors clustered at the industry level are in brackets. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Alternative Derived Demand Measures

Dependent Variable: Change in log TFPQ				
	(1)	(2)	(3)	(4)
$\Delta\tau_{it}^{IE}$	-1.397**			
	[0.558]			
$\Delta\tau_{it}^{IE}$ IO93		-2.295***		
		[0.730]		
$\Delta\tau_{it}^{IE}$ simple			-1.281***	
			[0.418]	
$\Delta\tau_{it}^{IE}$ intermediate				-0.368*
				[0.216]
$\Delta\tau_{it}^{EXP}$	-0.232*	-0.218*		
	[0.120]	[0.122]		
$\Delta\tau_{it}^{EXP}$ simple			-0.160	-0.159
			[0.115]	[0.123]
R^2	0.0584	0.0588	0.0583	0.0563
N	3345	3345	3345	3345

Notes: Column 1 reports the baseline results from Table (1.3) for comparison. In column 2, the indirect export tariff is computed using the 2003 IO table. In column 3, both the indirect and the direct export tariff are aggregated at the firm level across products using simple averages. In column 4, I compute the indirect export tariff using the weight in the IO table pertaining only to intermediate production. Tariffs are then aggregated at the firm level using simple averages. All regressions include industry fixed effects, log employment, and log sales per worker measured in 2002. Standard errors clustered at the industry level are in brackets. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Robustness: Controlling for Import Competition

Dependent Variable: Change in log TFPQ				
	Δ Aggregate Import		Share Importing Firms	
	Below	Above	Below	Above
$\Delta\tau_{it}^{IE}$	-1.399**	-1.305	-2.378*	-0.937*
	[0.582]	[0.908]	[1.221]	[0.528]
$\Delta\tau_{it}^{EXP}$	0.127	-0.395***	-0.490***	0.0187
	[0.231]	[0.134]	[0.152]	[0.182]
R^2	0.0636	0.0561	0.0700	0.0575
N	1640	1705	1803	1542

Notes: In the first two columns, industries are split according the the change in aggregate import from the rest of the world above and below the median change (.64). In the last two columns, industries are divided above and below the median share of importing firms (.20) before the FTAs in 2002. All regressions include industry fixed effects, log employment, and log sales per worker measured in 2002. Standard errors clustered at the industry level are in brackets. Significance levels *** p<0.01, ** p<0.05, * p<0.1

Appendix

Plant and Product Data

The ENIA Manufacturing Census, which is considered to be of high quality, has been widely used in research (`http://www.ine.cl/`). I apply the following data-cleaning procedure to the plant data:

- I drop firms with strange patterns: firms that appear and disappear several times in the survey;
- I drop firms with missing employment, wages, revenues, and intermediate input expenditures;
- I drop firms with big variation (factor of 5) in a key variable: employment, wages, or output;
- I *winsorize* data at the 1st and the 99th percentile.

While plant data have been widely used, few works have used product information (Saravia and Voigtländer, 2013; Fernandes and Paunov, 2013). From 2001, all products are recorded according to the Central Product Classification (CPC, Version 1), which is an international classification produced by the United Nations. This important methodological change assure product categories are homogeneous across time, substantially improving data quality.

Products are categorized via seven digits, corresponding to approximately 1100 different products. The first five digit correspond to the official classification as compiled by the United Nations. The last two digits are added by the National Statistical Agency to assure quantities are recorded properly for different product categories. Table 1.9 provides an extract of the official classification.

The product data include information on inventories, quantity produced, and its variable cost of production. Finally, I observe quantity sold, revenues, and the percentage, expressed in term of quantity, of exported products. I apply the following cleaning procedures:

- I check that product categories are recorded with the same unit of measurement;
- I drop all products from section 6 to 9 of CPC classification, which correspond to manufacturing services. These correspond to 902 observations, about 100 firms per year;

- I drop all products with null production or revenues in a given year;
- I drop all products with missing observations in a given year, i.e., I considered only products for which information was available in subsequent years. Such products represent a small share of total output;
- I eliminate products with a reported quantity of production of 1, 2, or 3; and
- I drop observations with big variation (factor of 5), and I winsorize revenues at the 1st and 99th percentiles.

Table 1.9: CPC Classification: an Example

Division	
28	Knitted or crocheted fabrics; wearing apparel
Group	
282	Wearing apparel, except fur apparel
Class	
2822	Wearing apparel, knitted or crocheted
Sub-Class	
28221	Men's or boys' suits, coats, jackets, trousers, shorts and the like, knitted or crocheted
28222	Men's or boys' shirts, underpants, pyjamas, dressing gowns and similar articles, knitted or crocheted
28223	Women's or girls' suits, coats, jackets, dresses, skirts, trousers, shorts and the like, knitted or crocheted
28224	Women's or girls' blouses, shirts, petticoats, panties, nightdresses, dressing gowns and similar articles, knitted or crocheted
28225	T-shirts, singlets and other vests, knitted or crocheted
28226	Jerseys, pullovers, cardigans, waistcoats and similar articles, knitted or crocheted
28227	Babies' garments and clothing accessories, knitted or crocheted
28228	Track suits, ski suits, swimwear and other garments, knitted or crocheted n.e.c.
28229	Gloves, shawls, scarves, veils, ties, cravats and other made-up clothing accessories, knitted or crocheted; knitted or crocheted parts of garments or of clothing accessories

Construction of capital series and output elasticity

Starting from 2001, the ENIA survey annually collects information on the book value of four different categories of capital: building, land, machinery, and vehicles. For each of these categories, the survey also collected investment information. I use the perpetual inventory method to construct a capital series. I apply the following formula; $K_{it} = K_{it-1}(1-\delta)+I_{it}$, where K is capital, δ is a depreciation rate, and I is investment. I use the depreciation rate from Fernandes and Paunov (2013): 3% for building, 7% for machinery, and 11.9% for vehicles. Land is assumed not to depreciate.

Table 1.10: Production Function Estimates

Sector	Elasticities Material	Labour	Capital	Return to Scale
Food beverages	0.783	0.091	0.165	1.039
	(0.016)	(0.025)	(0.035)	(0.040)
Textiles	0.648	0.364	0.122	1.133
	(0.031)	(0.064)	(0.061)	(0.069)
Wearing apparel	0.599	0.281	0.205	1.086
	(0.026)	(0.068)	(0.089)	(0.108)
Leather, footwear	0.702	0.059	0.300	1.061
	(0.046)	(0.078)	(0.111	(0.130)
Wood	0.711	0.207	0.301	1.219
	(0.061)	(0.070)	(0.085)	(0.090)
Paper	0.608	0.106	0.241	0.956
	(0.036)	(0.070)	(0.060)	(0.081)
Publishing	0.616	0.307	0.278	1.201
	(0.037)	(0.064)	(0.088)	(0.097)
Chemicals	0.698	0.115	0.179	0.992
	(0.029)	(0.055)	(0.071)	(0.088)
Rubber, plastics	0.717	0.238	0.213	1.168
	(0.032)	(0.053)	(0.053)	(0.069)
Non-metallic min	0.797	0.076	0.284	1.158
	(0.025)	(0.049)	(0.081)	(0.093)
Basic metal	0.694	0.081	0.280	1.054
	(0.041)	(0.051)	(0.099)	(0.082)
Fabricated metal	0.641	0.232	0.133	1.006
	(0.032)	(0.045)	(0.092)	(0.096)
Machinery and equipment	0.630	0.311	-0.075	0.866
	(0.034)	(0.075)	(0.077)	(0.094)
Electrical mach	0.706	0.087	0.088	0.880
	(0.038)	(0.076)	(0.106)	(0.123)
Motor vehicles	0.591	0.311	0.248	1.151
	(0.053)	(0.153)	(0.142)	(0.145)
Other transport	0.572	0.281	0.232	1.085
	(0.105)	(0.166)	(0.189)	(0.220)
Furniture; man.	0.638	0.413	0.134	1.185
	(0.040)	(0.075)	(0.062)	(0.084)

Notes: The first three columns report the estimated output elasticities. The last column reports the implied return to scale. See the text for more detail about the estimation procedures. Standard errors are in parentheses.

Tariff Data

Export, output, and input tariff data are constructed as follows. Tariff data come from the TRAINS database from the World Bank. Import tariffs data for 2002 are used to construct export tariffs, and Chilean import tariff data are used to construct output and input tariff data. All tariff data are registered according to the HS02 (6-digit) classification system, which is the native classification used by TRAINS. World trade flows comes from BACII-CEPI, which builds on UN-COMTRADE but harmonizes the data to reconcile flows reported by importing and exporting countries. These data are reported using the HS96 (6-digit) classification.

The correspondence table between HS (6-digit) and CPC (5-digit) classification comes from the UN classification registry (`http://unstats.un.org/unsd/cr/registry/`), which provides correspondence tables from HS1996 to CPCV1 and from HS2002 to CPCV11. Product data from ENIA are collected according to CPCV1 classification system (7-digit). The major changes between CPCV1 and CPCV11 are in section 5 to 9 of CPC system, the services sector. Raw material and manufactured products are not affected by the change in the classification system. I aggregate raw tariff data using as weights the value of imports of the reporting country.

There are almost 5000 HS 6-digit products. These products correspond to almost 1100 CPC 5-digit products. the ENIA database report almost 1100 CPC 7-digit products. Finally, after all conversions, I am left with tariff information on 700 products.

IO table and the Indirect Export Tariff

To construct the *indirect export tariff*, I use import tariff and the IO table provided by the Central Bank of Chile (`http://www.bcentral.cl/publicaciones/estadisticas/actividad-economica-gasto/aeg06.htm`). Activities in the IO table are registered according to the Chilean classification scheme: CAE (Clasificaciones Actividad Economica). Overall, the economy is composed of 73 sectors, 37 of which are manufacturing. The Central Bank of Chile provides correspondence between CAE and CIIU Rev. 3. I use the *supply-use* table for national transactions at basic prices. I construct the *indirect export tariff* as follows. I take tariffs from WITS. I aggregate the tariffs using import values for each reporting country at the CAE level. I am left with one export tariff for each CAE sector. I use the IO table (Tablas de Utilizacion Nacional, Precios Basicos) to construct the weight. See the text for further detail on this calculation.

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Chapter 2

Free Trade Agreements and Firm Product Markups in Chilean Manufacturing

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2.1 Introduction

Recent models of international trade (Melitz, 2003; Bernard et al., 2003) have stressed how firms self select into foreign markets based on their predetermined productivity where prices and markups reflect the degree of competition on the markets where firms sell their product (Melitz and Ottaviano, 2008; Bernard et al., 2011; Mayer et al., 2012; Dhingra, 2013).[1] Prices and productivity adjust as soon as firms manage to get access to international markets, and they often represent two distinct channels of adjustment. Nevertheless, standard empirical applications estimate productivity by the way of proxies that mix up the two channels, as sales per employee and productivity measure based on real value added (see e.g. Klette and Griliches, 1996; Foster et al., 2008; De Loecker, 2011). Unfortunately, any quality upgrade, product diversification or marketing strategy that changes the market power and the pricing strategy of the firm, without changing its technical productivity –that is the amount of input needed to produce one unit of output–

[1]Further developments of this class of models allow firms to change their productivity by adopting better technologies or innovating (Yeaple, 2005; Verhoogen, 2008; Lileeva and Trefler, 2010; Bustos, 2011). The most recent development consider multi-product firms and allow firms' productivity to change according to their product mix.

will affect these measures of productivity in the same way as innovation or technological adoption do.

Boosted by improved data availability, recent theoretical and empirical work in industrial organization have proposed methodologies to estimate productivity measures that control for input and output price heterogeneity and are therefore able to distinguish adjustments of markups and prices from those of quantity-based total factor productivities (see e.g. Eslava et al., 2004; Foster et al., 2008; De Loecker, 2011; De Loecker et al., 2012; Smeets and Warzynski, 2013).

In this paper, we take advantage of a unique dataset where firms agree to declare the costs of each good that they produce in order to improve our measurement of markups and productivity. We use detailed information about firms' product portfolio to estimate a measure of productivity that controls for both output and input price heterogeneity, and use our firm-product level measure of the unit average cost to compute a firm product level measure of the margin (we use the term markup) that a firm can generate. The advantage of our methodology is that we do not rely on estimated average costs, but we source this information directly from the firm for each product that it sells.

As a consequence, we obtain precise measures of price, average cost, markup and physical total factor productivity (TFPQ) at the firm-product level in Chilean manufacturing over the period 2001-2007. We relate adjustment along these margins to the tariff drop that occurred during this period when Chile signed two important Free Trade Agreement (FTA) with European Union, United States and Korea.

Using the fall in export tariff generated by the implementation of the FTAs , we document three main findings. First, export market participation of Chilean products increased as a result of tariff cuts. The probability for a product to be exported increased by 1% to 4%. Second, the entry into export markets led to a drop in the average unit cost as well as in price. Finally, when we distinguish between homogeneous and differentiated goods, we find evidence of an increase in markups only for differentiated products.

Several authors have previously used similar data to study price behavior in the US, Colombia, Belgium, Denmark and other countries (see e.g. Roberts and Supina, 1996, 2000; Foster et al., 2008, 2012; Kugler and Verhoogen, 2012; De Loecker et al., 2012). These papers have generated stylized facts and methodologies to deal with these transaction dataset, but they did not have information about firm-product level costs. One exception is a recent paper by Garcia Marin and Voigtländer (2013) that uses the same Chilean dataset. However, their focus is on the proper measurement of learning-by-exporting effect, while we are mostly interested in the evolution of markups, prices and efficiency following trade liberalization.[2]

The rest of the paper is structured as follows. Section 2.2 describes our unique database. Section 2.3 introduces our methodology to derive measures of markups and physical productivity at the firm-product level. Section 2.4 discusses trade liberalization in Chile, presents our identification strategy and shows our results. Section 2.5 concludes.

2.2 Data

The plant level information that we use in this paper, the *Encuesta Nacional Industrial Annual* (ENIA) collected by the *Instituto Nacional de Estadisticas* (INE), is well known and has been used in several important contributions in the productivity literature (Pavcnik, 2002; Levinsohn and Petrin, 2003; Ackerberg et al., 2006). It contains all standard variables that researchers need to properly estimate production functions. The survey covers the universe of plants in manufacturing with at least 10 employees. Plants are required to answer by law. The survey is conducted at the plant level, but more than 90% of the firms are single plant. We use several waves covering the period 2001-2007.

We complement this standard dataset with more detailed information about firms' product mix. The survey also contains two additional forms that ask firms precise information about which product they make, and which intermediate products they buy. Starting from 2001, INE adopted the Central Product Classification V.1 (CPC) compiled by the UN.[3] The first 5 digits correspond exactly the official classification, while the last 2 digits are country specific. The adoption of the CPC substantially improves data quality. The new classification is homogeneous over time and the units of measurement are consistent within product category. Overall, we observe 1000 distinct products, table 2.1 illustrates an example of product classification and its level of detail.

At the product level, firms are asked about the value produced or bought, and the quantity produced or bought. For goods produced by the firm, it also indicates the quantity exported. More interestingly, it also contains a question about the total variable cost incurred by the firm to produce each product. We can therefore compute the average cost per unit produced, as

[2] They also only use this variable as a robustness check, since they estimate markups using the De Loecker et al. (2012) methodology.

[3] Before 2001 INE used an ENIA specific product classification CUP (*Clasificador Unico de Producto*). More information about the CPC classification can be found on the UN classification registry Web Page.

well as the average revenue per unit produced (unit value, used as proxy for price). We also construct the ratio of our price proxy to average cost and refer to it as our firm-product level "markup" (μ).

We implement several data cleaning procedure both at plant and product level to reduce the influence of outliers, missing data and misreported information. In the plant dataset, we exclude from the sample all plants reporting zero or with a missing key variable such as employment, sales and intermediate input expenditure. We also exclude plants whose growth rate of quantity sold and revenues between adjacent periods is larger than the average by more than 5 standard deviations.

In the product dataset, we first match product descriptions to build a unique product identifier within firms.[4] Second, we drop all products that are reported only once in the dataset and firms whose number of products changes between adjacent periods by more than 5. Third, we drop from the sample those products whose quantity produced, quantity sold and total revenue growth rates exceed their averages by more than 5 standard deviations. Finally, following De Loecker et al. (2012), we trimmed unit values, average unit costs and markups below the 3rd and above the 97th percentile.

The final dataset, which includes all firms with available product information, is well suited to study the determinants and the evolution of markups and prices during a period of extensive trade liberalization. Other papers have the same information for other countries (e.g. India and Colombia) but our dataset is unique along two dimensions. First, it contains firm's proprietary information that allows us to compute markups, without having to implement any particular estimation procedure. Second, during the period of our analysis, we observe the entry into force of three FTAs that created many new export opportunities for Chilean products, thus enabling us to study the effect of an export shock. Most of the existing literature focuses mainly on the effects of output tariff reduction.

Table 2.2 shows the number of firms in our final sample after data cleaning according to how many products they make. The number of firms increased from 2001 to 2005, then dropped sharply afterwards. We also observe a slight decline in the proportion of single product firms.

[4]This procedure allows us to treat as different, products within firms recorded using the same CPC 7-digit code.

2.3 Firm-product productivity and markups

2.3.1 Firm-product productivity

We adapt the standard cost base measurement of physical total factor productivity (henceforth TFPQ; see e.g. Foster et al., 2008) to a multi-product setting. We use the fact that we know the share of total variable costs allocated to each product to weight the use of inputs for each product accordingly.[5] We therefore end up with a "double cost based" measure of TFPQ.

We define $TFPQ$ of product j made by firm i at time t as:

$$TFPQ_{ijt} = q_{ijt} - \alpha_{it}^{j}\alpha_{jt}^{L}log(L_{it}) - \alpha_{it}^{j}\alpha_{jt}^{M}log(M_{it}) - \alpha_{it}^{j}\alpha_{jt}^{K}log(K_{it})$$

where q_{ijt} is the physical quantity of good j produced by firm i at time t, L is employment, M is material (deflated by a firm-specific material price index), K is capital, α_{jt}^{X} for $X = L, M, K$ is the average cost share of each input in the total cost of the firm and α_{it}^{j} is the share of the cost of product j in the total cost of the firm.[6] Our measure controls for both output and input price heterogeneity, since we compute for each firm its specific input price deflator.

Figure 2.1 shows the distribution of the demeaned variable for a few products with different degree of differentiation (bread, wine and jeans). We observe that dispersion is larger for the more differentiated goods like wine and especially jeans.

2.3.2 Firm-product markups

We use our firm-product level measure of the unit average variable cost to compute a firm-product level measure of the margin (we use the term markup) that a firm can generate. We then relate our price, average cost and markup measures to firm-product and firm level characteristics such as export status, being a multi-product firms and firm size.

Table 2.3 shows our measure of the average markup by sector. We find realistic estimates between 1.32 and 1.88, in line with previous findings in the literature. Table 2.4 shows the evolution of the average markup over

[5] We avoid the task of estimating this shares. See e.g. De Loecker et al. (2012).

[6] Factor costs shares are computed in two steps. First, we computed the cost shares for each firms and for each factors. Second, we take the averages of these costs shares across products. The user cost of capital is computed using the real interest rate from Bank of Chile and capital specific depreciation rates (3% for building, 8% for machinery and 11% for vehicles; land is assumed not to depreciate).

our period of analysis. The measure remains surprisingly stable over time, although we observe a small increase.

However, these figures represent averages over very different products. Figure 1 shows the distribution of the markups for three products: bread, jeans and wine. We expect bread to be the most homogeneous product, and therefore to display less dispersion in the markup. This is exactly what we observe. On the other, hand, for more differentiated products such as jeans but especially wine, we observe a more dispersed distribution.

2.3.3 The determinants of markups

We start our analysis by relating the firm-product price, average cost and markup to firm and firm-product characteristics. Our dependent variables y are the logs of prices, log of average unit costs and the markup:

$$y_{ijt} = \alpha + \beta x_{fit} + \delta_{jt} + \varepsilon_{ijt}$$

The explanatory variables include the log of firm size (number of employees), the log of the level of firm's output, the log of total factor productivity (TFPQ), a dummy which takes value 1 if the firm is a multi-product firm, and a dummy which takes value 1 if the firm exports. All regressions include product-time fixed effect (δ_{pt}). Standard errors are clustered at the product level.

Results are shown in table 2.5. We find a negative relationship between TFPQ and both price and marginal cost. Because the coefficient is slightly lower for average cost, the relationship with the markup is positive. These correlations are in line with previous results in the empirical literature (e.g. Foster et al., 2008) and with the predictions of several theoretical models, such as Melitz and Ottaviano (2008). When we control for export status and the multi-product dummy, we find that both measures have positive and significant coefficients in the price and average costs specifications. When we look at the markup, we find that exported products have on average higher markups, but multi-product firms have lower markups. This is because the coefficient is larger in the cost specification than in the price specification. From a theory point of view, it can be explained by the fact that multi-product firms sell many products that might not be in their core competence (see e.g. Mayer et al., 2014) or sell in larger quantity.

Adding firm size as an additional control does not change the basic message. Firm size is positively correlated with price, marginal cost and the markup. This might indicate that larger firms have access to better inputs and produce higher quality goods (see e.g. Kugler and Verhoogen, 2012).

2.3.4 Product-specific analysis

We next shift our focus to a few specific products: Bread, Jeans and Wine (tables 2.6, 2.7 and 2.8). For all three products, prices and average costs are negatively related to productivity. However, the markup is only positively and significantly related to TFPQ in the case of bread. Prices, average costs and markups are not related to firm size for bread and wine, but the relationship is positive and significant in the case of jeans. Multi-product firms have higher prices and average costs in the case of wine and jeans but not in the case of bread. Finally, exporters have higher prices and marginal costs for wine, but there is no significant effect in the case of jeans. For bread, they were simply not enough exporters.

The last column of tables 2.6 to 2.8 looks at the input prices for our three products. We find that exporters also have higher input prices in the case of wine. We find little evidence of a correlation with our variables in the case of jeans. Larger bread producers appear to have lower input prices, while more productive wine producers pay lower prices for their intermediates. This tend to suggest that both productivity and quality matter when competing in the wine business.

2.4 Trade Liberalization

2.4.1 Trade Policy Background

Chile's integration into international trade has a long tradition. Starting in the late 70s, the country progressively reduced import tariffs, eliminating all differences across industries. As a consequence, Most Favored Nation (MFN) tariffs applied to imports from abroad in 2002 equal 8% in all industries. Among developing economies, Chile can be considered as one of the most open and integrated into international trade.

More recently, Chile has signed several Free Trade Agreements (FTAs) with its most important trading partners. In this paper we will focus on three important FTAs signed respectively with the EU, the US and Korea. The negotiation with the EU started in November 1999, the agreement was signed in November 2002 and the FTA started in February 2003. The negotiation with the US started in December 2000, the agreement was signed in June 2003 and the application started in January 2004. The FTA with Korea entry into force in Apr-2014 after 7 rounds of negotiations started in 1999. By the date of entry into force of the FTAs, almost all barriers to trade were removed.[7]

The entry into force of these FTAs had a big impact on Chilean exports. Overall, these three markets accounted for 50% of aggregate exports in 2002 and exports almost tripled between 2002 and 2006 (see Figure 2.3). We will use the change in export tariff as source of variation to identify the effect of the FTAs on Chilean products.

We combine the information on MFN tariff applied by partner countries in 2002 to construct a weighted export tariff, i.e. the tariffs faced by Chilean products before entry into force of the FTAs. For each product j, we define the export tariff as:

$$\tau_j^{exp} = \frac{\tau_j^{EU} \cdot M_j^{EU} + \tau_j^{US} \cdot M_j^{US} + \tau_j^{KOREA} \cdot M_j^{KOREA}}{M_j^{US} + M_j^{EU} + M_j^{KOREA}}$$

where τ are the MFN tariffs and M are the values of imports. Tariffs are aggregated at 4-digit ISIC level.

Table 2.9 reports summary statistics for MFN tariff cuts. Export tariffs faced by Chilean products fell on average by 5,2%, ranging from 0 to 25%. The heterogeneity across industries reflect different protection schemes applied by partner countries which are not specific to Chile. Indeed, the share of Chilean imports is less than 1% for all countries.

2.4.2 Identification Strategy

In this section, we try to relate the changes in prices, markups, average costs and firm-product productivity to the fall in export tariff experienced by Chilean products. Consider the following equation:

$$y_{ijst} = \gamma_0 + \gamma_1 \tau_{jt}^e + \delta_{ij} + \delta_{st} + \eta_{it} \tag{2.1}$$

where j is a product index, i is a firm index, s is a sector index and t time. The dependent variable y_{ijst} is in turn prices, markups, average costs and firm-product productivity. Our main coefficient of interest is γ_1, which identify the causal effect of a fall in the export tariff τ_{jt}^e. δ_{ij} represent firm-product

[7] While the application of FTA with the US and Korea was sharp, the same is not true for EU For some goods tariff elimination was scheduled in 2006, they accounted for less than 8% of total export towards EU For a wide range of agricultural and food products quotas protections were defined. Quotas were increasing over time, and scheduled to be eliminated within 5 to 8 years. All products imported within quotas were tariff free, while tariffs were applied to extra quantities. The application of quotas were applied on the basis of arrival time. Finally, the entry into force of EU FTA was *provisional* and become definitive in 2006, this caveat had no impact on tariff eliminations.

fixed effects that will allow us to control for unobserved heterogeneity and exploit the time variation of the tariff cut. Finally, δ_{st} are sector time fixed effects which control for sector characteristic that varies over time.

Bertrand et al. (2004) discuss several pitfalls in estimating eq. 2.1 using OLS. Export tariffs drop to zero after FTAs for all firms product introducing serial correlation across observations. Moreover, our main dependent variables are likely to be highly serial correlated across time. The presence of such problems make estimation of the coefficients with OLS unbiased, but will not yield the correct standard errors. We will solve these problems in two steps following one of the proposed solutions by Bertrand et al. (2004). First, we take averages of our main variables before the FTAs (years 2001 and 2002) and after (from 2003 to 2007).

$$\overline{y_{pijst}} = \frac{1}{T}\sum_{t}^{T} y_{pijst}$$

Second, we take differences in order to eliminate the unobserved firm-product fixed effect δ_{pi}. In order to increase the precision of our estimates we will add some additional firms and industry controls measured before the FTAs. The final estimation equation is:

$$\Delta\overline{y_{pijst}} = \gamma_0 + \gamma_1 \Delta\tau^{e}_{jt} + Z_{ijsB} + X_{jsB} + \delta_s + \Delta\eta_{it} \tag{2.2}$$

Since the tariffs measure varies at 4-digit ISIC industry level, we cluster our standard errors at this level. Firm controls Z_{ijsB} include the log of employment measured in efficiency units and the log of firm productivity measured before the FTAs. The inclusion of these variables is aimed at controlling for the presence of observable firm characteristics that have an impact on prices, markups and average unit costs. Industry controls X_{jsB} (elasticity of demand, skill shares and capital intensity measured at 4-digit ISIC industry in the US) controls for the differences in the magnitude of tariffs cuts across industries.

2.4.3 Entry into the Export market

In this subsection, we describe entry into the export market observed in Chile after the FTAs. Overall, 336 new products out of 8043 in our sample start to be exported after 2003 (197 exit the export market, 1027 are always exported). Among those newly exported products, 190 are exported by firms that were not exporting before the FTAs. The probability for a product to be exported passes from 15.1% to 16.9%, suggesting that the FTAs created several new export opportunities for Chilean products and firms.

Table 2.10 shows that the new products start to be exported in response to the cut in export tariff. For each observation we created a dummy equal 1 if the product is exported ($dummy_{exp}$). In the first column, the dependent variable is the difference of the variable before/after. In the second column, the dependent variable is the dummy for the period after the trade liberalization, but we add as control the past export status. This specification controls for the fact that in presence of sunk export costs, current export status might depend on past export status. In column (c), we restrict the analysis to the sub sample of firms-products that were not exported before the FTAs. Finally, in the last column, we restrict the sample to firms that were not exporting before the FTAs. The estimated coefficients are always negative, as expected, and significant. They imply that the average fall in tariff (5.2%) increases the probability of export between 1.6% and 4.4%.

Comparing the results from the first and the second specification, the estimated coefficients decrease substantially. It suggests that Chile has a comparative advantage in industries that were highly protected before the trade liberalization (e.g. fishing and wine industry). By restricting the analysis to the sub sample of non exported products or non exporting firms, the point estimate passes from $-.85$ to $-.76$ and $-.47$. This is likely to be the case because Chile before the FTAs exports products with high tariffs. In these industries non exporting firms and products are likely to be less productive then in industries with low tariffs, generating a negative correlation between export tariffs and unobserved productivity. Coefficients drop after the inclusion of firms and industry controls, but the estimated coefficients are always negative and significant.

2.4.4 Main results

Table 2.11 shows the effect of the fall in tariffs on prices, average unit costs, markups and productivity. Panel A, B and C show three different specifications, with an increasingly sharper control for unobserved heterogeneity, obtained by adding firm controls (employment and sales per worker) in Panel B and industry controls (elasticity of demand and skill intensity measured at 4-digit ISIC industry in the US) in Panel C.

In column 2, the estimated coefficient is positive implying that the average tariff cut (5.2%) reduces prices by 1 to 1.5%. Tariff cuts lower factory-gate prices of exported products in destination markets. Chilean firms face tough competition in larger market such as EU and US. In both cases, a decline in export tariff is associated with a decline in prices. This is a standard result in modern trade literature as trade has a pro-competitive effect.

The richness of our data allow us to explore more deeply which are the determinants and the margins along which adjustment occurs at firm-product level in response to the FTAs. The reduction in prices, in fact, can be due both to an increase in productivity or a reduction in markups. On the one hand, a larger market allows firms to invest in better technology (Yeaple, 2005; Verhoogen, 2008; Bustos, 2011), thus allowing an increase in productivity and a decrease in marginal costs. Following a fall in variable trade costs, productivity may also increase because of selection, that is reallocation of resources across firms (Bernard et al., 2003; Melitz, 2003) or across products within the firm (Bernard et al., 2011; Mayer et al., 2012). On the other hand, in a larger market, firms face tougher competition, thus are force to reduce their markups (Melitz and Ottaviano, 2008).

In column 3, we report the effect of the tariff cut on our measure of average unit costs and surprisingly we do not find any effect. In two specifications, the estimates are positive, implying a reduction in average unit cost following the trade liberalization, but they are not significant. The last column reports the effect on product TFPQ. All estimated coefficients are negative and significant. The implied jump in productivity ranges between 5.2% to 5.8%. This is the first important result of our paper. While the existing literature sometimes has struggled to find a positive effect of export entry on productivity (for a review of the literature see (Bernard et al., 2011)), our estimates show that productivity increases for Chilean products mostly affected by the FTAs. Our results differ from the most of the existing literature along two important dimension. First, our product TFPQ do not suffer from price and markup heterogeneity, because we measure it starting from physical quantities. Second, our identification relies on two important episodes of trade liberalization that increase substantially export opportunities for Chilean firms.

Column 1 shows the estimated effect of tariff cuts on markups. All coefficients are positive, meaning that a reduction in variable trade costs reduced markup of Chilean products. The estimated decline without controlling for firms and industry characteristics is 1.2%; the sign of the relation between trade liberalization and mark-ups remains positive in the specification with industry and firms controls, but the estimates are less precise. We attribute this poor precision to a composition effect between homogeneous and differentiated goods: since in the first part of this paper we document substantial heterogeneity on the determinants of markups at firm level, when distinguishing between homogeneous and differentiated goods we deem that estimates conceal different markups adjustment for different product category. We investigate such heterogeneity by adding to our main specification an interaction term of the tariff cut with the degree of differentiation measured at industry level.

$$\Delta\overline{y_{pijst}} = \gamma_0+\gamma_1\Delta\tau^e_{jt}+\gamma_2\Delta\tau^e_{jt}*Diff_j+Diff_j+Z_{ijsB}+X_{jsB}+\delta_s+\Delta\eta_{it} \quad (2.3)$$

Following Nunn (2007), we measure the share of differentiated products for each industry ($Diff_j$) starting from Rauch's original classification (Rauch, 1999). The average share of differentiated product per industry is .66 (std. dev .37). Table 2.12 shows the main results. The first column shows that on average markups drop by 2% ($= .3921 * -0.52$). The interaction term is negative and significant, implying that markups increase for industry with larger shares of differentiated products. In industries where all products are differentiated, the implied average net increase in markup is around 1.2%. Columns 2 to 4 of table 2.12 show the results on prices, average unit costs and product TFPQ. The estimated coefficient on prices are positive but not significant confirming our previous results that tariff cuts led to drop in prices. Product TFPQ falls exactly by the same amount as estimated in the baseline specification and there is no differences between homogeneous and differentiated products. Finally, there is some evidence on the reduction of average unit costs only for differentiated industries.

In line with the recent theoretical and empirical literature, our results suggest that the new export opportunities generated by the Free Trade Liberalization led to a reduction in average unit costs due to an increase in TFPQ. Firms as a consequence reduced their prices. Markups adjustment depend on the type of products firm exports. We find evidence of markups reduction for homogeneous products and increase in markups for differentiated ones.

2.4.5 Robustness

We now discuss several robustness checks to our baseline results. Panel A of table 2.13 shows the baseline results when we drop from our sample years 2003 and 2004. We discussed earlier that the implementation of the FTAs took place in different periods, February 2003 with the EU and January 2004 with the US. Given that we do not observe export destination at product level, we do not know how long it took for firms to react to this new export opportunity and with respect which market. This my bias our baseline results downward, since the *treatment* my have started later than we think. Panel A shows that our point estimates increase, as well as their precision. Productivity increases by 7.5%, prices fall by 2.4% and markup drop by 1.8%.

In panel B, we restrict the analysis to the sample of firms which were not exporting before the FTAs. We want to be sure that the patterns that we documented so far are not driven by product exported by already exporting firms. Not surprisingly we find that non exporting firms experience larger productivity gains. Productivity soars by 12%. These firms were the least productive. We also find that prices and average unit costs fall by 3.9% and 3.2%.

Finally, we want to check that observed productivity gains and price falls are not driven by an increase in competition faced by Chilean firms in domestic markets or by the access to foreign intermediate input. The entry into force of FTAs generated new export opportunity for Chilean firms abroad, but at the same time, the Chilean import tariff elimination increases the export opportunity for European and US firms in Chile. Thus Chilean firms could have faced higher foreign competition in domestic market. We control for these trends by adding the change in share of import before/after from EU and US measured at industry level in our main specification. Our baseline results, as we expected, remain unchanged both in magnitude and significance. Chile undertook unilateral trade liberalization starting in the late 70s. The level of protection were low compared to other developing economies when the FTAs were signed. Moreover all industries were protected with the same tariff. As a consequence the Chilean output tariff elimination was orthogonal to change in export tariff, leaving estimates unchanged.

2.5 Conclusion

In this paper, we use detailed information about firms' product portfolio and input decisions to understand firm-product markup heterogeneity in Chilean manufacturing. In line with the recent theoretical and empirical literature, we find that, on average, more efficient firms have lower average costs, charge lower prices and have higher margins. Firms also have higher prices and margins when they export their product, even controlling for productivity, but do not necessarily have lower costs. Once we distinguish between differentiated and homogeneous products, we find that larger firms have higher prices and also higher marginal costs when there is scope for differentiation. This suggests that larger firms produce higher quality goods, and more efficient firms charge lower prices conditional on size.

We use our measures to look at the effect of trade liberalization on prices, average costs, margin and productivity. We find that both prices and average costs are decreasing after a drop in tariffs, while firm-product productivity is increasing. Markups appear to be unaffected on average, but are increasing for more differentiated products. This indicates that firms do not fully pass-through increases in productivity on prices. Our paper complements several recent contributions using Colombian and Indian data. An additional channel through which trade liberalization could affect firms' competitiveness is product upgrading. We plan to study this topic in future research.

Figures and Tables

Figure 2.1: Firm-Product Level Productivity Distribution for Bread, Jeans and Wine

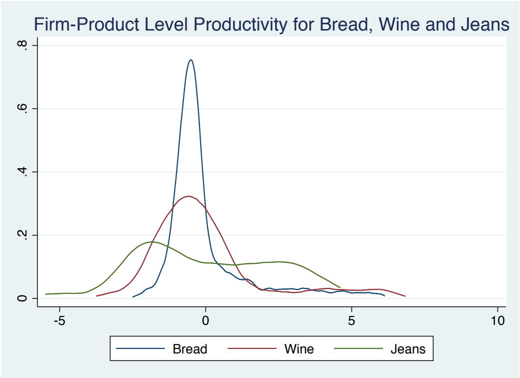

Figure 2.2: Markup Distribution for Bread, Jeans and Wine

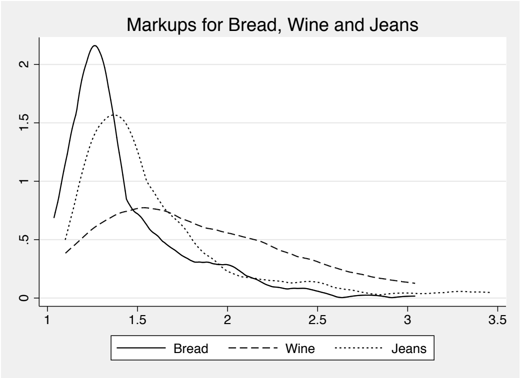

Figure 2.3: Evolution of Aggregate Export Flows

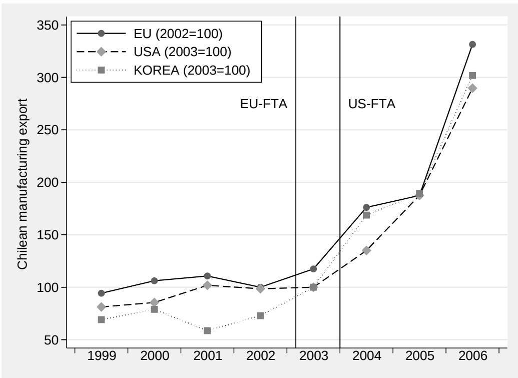

Table 2.1: Example of Central Product Classification (CPC)

Class	INE	Unit	Description
2			Food products, beverages and tobacco; textiles, apparel and leather products
24			Beverages
242			Wines
2421			Wine of fresh grapes, whether or not flavoured; grape must
24211			
	2421101	l	Sparkling wine of fresh grapes
24212			
	2421201	l	wine of fresh grapes, except sparkling wine
	2421202	kg	grape must
24213			
	2421301	l	Vermouth and other wine of fresh grapes flavored with plats or aromatic substances

Notes: This table provides an example of product classification. Columns Section to Subclass correspond to the original UN CPC V.1 classification. The column INE refers to the actual product classification with the last two digits added by the Chilean statistical agency (INE). In some cases, the last two digits refers to products recorded with different unit of measurement. In our final dataset, we observe 1,061 7-digit products which correspond to 650 different 5-digit products. Notice that 463 INE products correspond exactly to the CPC products, like products 24211 and 24213 int the table.

Table 2.2: Number of Firms by Product Category

year	Single product		between 1 and 5		between 5 and 10		more than 10		Total	
	Number of products									
	No.	%	No.	%	No.	%	No.	%	No.	%
2001	1971	52.23	1503	39.83	227	6.01	73	1.93	3774	100.00
2002	1998	49.28	1660	40.95	318	7.84	78	1.92	4054	100.00
2003	1925	48.05	1678	41.89	329	8.21	74	1.85	4006	100.00
2004	2064	48.71	1728	40.78	354	8.35	91	2.15	4237	100.00
2005	2216	50.06	1756	39.67	358	8.09	97	2.19	4427	100.00
2006	2119	50.01	1668	39.37	354	8.35	96	2.27	4237	100.00
2007	1807	48.73	1505	40.59	307	8.28	89	2.40	3708	100.00
Total	14100	49.57	11498	40.42	2247	7.90	598	2.10	28443	100.00

Notes: The table categorizes firms according to the number of products manufactured. Products are defined according the the CPC classification. For each category, the first column report the absolute number of firms, while the second the percentage distribution by year. The last row shows the overall figure.

Table 2.3: Distribution of Markups by Sector

Sectors	Mean	Standard Deviation	1st Percentile	Median	99th Percentile
Food & beverages (28%)	1.53	0.38	1.06	1.40	2.76
Textiles (4%)	1.58	0.40	1.08	1.45	2.69
Wearing apparel (7%)	1.62	0.45	1.10	1.47	3.16
Leather,footwear (2%)	1.63	0.54	1.10	1.44	3.77
Wood (5%)	1.50	0.38	1.03	1.38	2.86
Paper (3%)	1.62	0.42	1.08	1.51	2.93
Publishing (3%)	1.54	0.35	1.11	1.43	2.66
Coke, petroleum (0%)	1.32	0.34	1.05	1.15	2.46
Chemicals (8%)	1.88	0.76	1.04	1.64	4.64
Rubber,plastics (6%)	1.64	0.45	1.10	1.51	3.13
Non-metallic mineral (4%)	1.57	0.40	1.08	1.43	2.94
Basic metal (2%)	1.56	0.50	1.00	1.40	3.24
Fabricated metal prod (7%)	1.53	0.37	1.10	1.41	2.81
Machinery and equip (4%)	1.60	0.41	1.10	1.47	2.90
Electrical mach n.e.c (1%)	1.53	0.38	1.08	1.43	2.78
Medical mach, watches (0%)	1.87	0.55	1.09	1.75	3.36
Motor vehicles (1%)	1.57	0.35	1.11	1.48	2.66
Other transport equip (0%)	1.41	0.25	1.06	1.32	2.30
Furniture; man. n.e.c (7%)	1.55	0.38	1.08	1.43	2.70
Total (100%)	1.59	0.46	1.07	1.44	3.09

Notes: The table displays summary statistics by sector for the sample over the period 2001-2007. Markups are trimmed above and below the 3rd and the 97th percentiles within each sector. The share of observations by sector in the overall sample is reported in parentheses.

Table 2.4: Distribution of Average Markup by Sector and Year

	year							
Sectors	2001	2002	2003	2004	2005	2006	2007	Total
Food % beverages (28%)	1.48	1.52	1.51	1.52	1.53	1.55	1.56	1.53
Textiles (4%)	1.56	1.58	1.62	1.59	1.57	1.58	1.58	1.58
Wearing apparel (7%)	1.57	1.64	1.64	1.63	1.61	1.62	1.66	1.62
Leather,footwear (2%)	1.57	1.61	1.71	1.63	1.62	1.65	1.65	1.63
Wood (5%)	1.42	1.50	1.47	1.50	1.52	1.54	1.55	1.50
Paper (3%)	1.58	1.57	1.67	1.64	1.60	1.62	1.65	1.62
Publishing (3%)	1.46	1.51	1.52	1.52	1.54	1.56	1.64	1.54
Coke, petroleum (0%)	1.30	1.33	1.28	1.32	1.31	1.29	1.42	1.32
Chemicals (8%)	1.88	1.98	1.83	1.91	1.86	1.80	1.89	1.88
Rubber,plastics (6%)	1.63	1.65	1.65	1.62	1.60	1.62	1.68	1.64
Non-metallic mineral (4%)	1.57	1.60	1.64	1.60	1.55	1.51	1.56	1.57
Basic metal (2%)	1.49	1.46	1.55	1.58	1.58	1.57	1.67	1.56
Fabricated metal prod (7%)	1.50	1.52	1.54	1.53	1.55	1.51	1.53	1.53
Machinery and equip (4%)	1.50	1.65	1.63	1.64	1.59	1.60	1.59	1.60
Electrical mach n.e.c (1%)	1.48	1.45	1.52	1.52	1.54	1.57	1.66	1.53
Medical mach, watches (0%)	1.81	1.80	1.85	1.81	1.86	1.77	2.11	1.87
Motor vehicles (1%)	1.57	1.62	1.62	1.59	1.51	1.53	1.56	1.57
Other transport equip (0%)	1.29	1.45	1.36	1.37	1.42	1.46	1.47	1.41
Furniture; man. n.e.c (7%)	1.52	1.58	1.59	1.54	1.53	1.53	1.56	1.55
Total (100%)	1.55	1.59	1.59	1.59	1.58	1.58	1.62	1.59

Notes: The table displays the average markup by sector and by year. Markups are trimmed above and below the 3rd and the 97th percentiles within each sector. The share of observations by sector in the overall sample is reported in parentheses.

Table 2.5: Correlation between Prices, Markup and Costs and Firm's Characteristics

	$log(Price)$	Markup	$log(AverageCost)$
Product TFPQ	-0.3565***	0.0075***	-0.3624***
	[0.007]	[0.001]	[0.007]
Multiproduct dummy	1.2670***	-0.0339***	1.2901***
	[0.043]	[0.010]	[0.043]
Exporter dummy	0.0774*	0.0293**	0.0648
	[0.041]	[0.015]	[0.041]
Log Employment	0.2793***	0.0209***	0.2688***
	[0.016]	[0.005]	[0.015]
Product-Year effects	Y	Y	Y
Industry effects	Y	Y	Y
Observations	67,670	67,717	67,661
R^2	0.821	0.199	0.824

Notes: The table uses the 2001-2007 sample. The dependent variables are reported at the top of each columns: log of unit values, markups and log unit average costs. The table trim the observations above and below the 3rd and the 97th percentiles within each sector. Coefficients from regressions with product-time and firms main industry fixed effects. Industry effects are defined as the industry category with the greatest share of plant sales. Standard errors in brackets clustered at firm level. * 0.10, ** 0.05, *** 0.01 Significance level.

Table 2.6: Bread Prices, Markup and Costs and Firm Characteristics

	Output Price	Average Cost	Markup	Material Price
Product tfpq	-0.0303*	-0.0442***	0.0195***	0.0053
	[0.016]	[0.017]	[0.006]	[0.004]
Log Employment	0.0148	0.0059	0.0198	-0.0252**
	[0.018]	[0.020]	[0.013]	[0.011]
Multiproduct dummy	0.1478***	0.1667***	-0.0304	0.0350
	[0.028]	[0.030]	[0.021]	[0.026]
Constant	5.8342***	5.5139***	1.3908***	3.4746***
	[0.093]	[0.099]	[0.047]	[0.042]
Observations	4,283	4,283	4,214	25,023
R^2	0.124	0.085	0.024	0.962

Notes: The table uses the 2001-2007 sample. The dependent variables are reported at the top of each columns: log of unit values, markups, log unit average costs and log price of intermediates inputs. Markups are trimmed above and below the 3rd and the 97th percentiles within each sector. In the last column we add to the regressions material-time fixed effects. Standard errors in brackets clustered at firm level. * 0.10, ** 0.05, *** 0.01 Significance level.

Table 2.7: Jeans Prices, Markup and Costs and Firm Characteristics

	Output Price	Average Cost	Markup	Material Price
Product tfpq	-0.0893***	-0.0941***	0.0116	0.0091
	[0.030]	[0.031]	[0.009]	[0.026]
Log Employment	0.2940***	0.2628***	0.0707***	0.0383
	[0.050]	[0.045]	[0.022]	[0.046]
Multiproduct dummy	0.5566**	0.6327***	0.0023	-0.1753
	[0.259]	[0.226]	[0.107]	[0.192]
Exporter dummy	-0.2244	-0.1936	-0.0256	-0.0201
	[0.156]	[0.121]	[0.099]	[0.116]
Constant	0.9945***	0.6272***	1.2273***	1.2913***
	[0.269]	[0.220]	[0.143]	[0.237]
Observations	822	822	811	2,506
R^2	0.239	0.234	0.061	0.813

Notes: The table uses the 2001-2007 sample. The dependent variables are reported at the top of each columns: log of unit values, markups, log unit average costs and price of intermediates inputs. Markups are trimmed above and below the 3rd and the 97th percentiles within each sector. In the last column we add to the regressions material-time fixed effects. Standard errors in brackets clustered at firm level. * 0.10, ** 0.05, *** 0.01 Significance level. s.

Table 2.8: Wine Prices, Markup and Costs and Firm Characteristics

	Output Price	Average Cost	Markup	Material Price
Product tfpq	-0.1010***	-0.0917***	-0.0092	-0.0264*
	[0.020]	[0.018]	[0.010]	[0.016]
Log Employment	-0.0287	-0.0388	0.0208	-0.0035
	[0.037]	[0.038]	[0.024]	[0.036]
Multiproduct dummy	0.6739***	0.6341***	-0.0421	0.1927*
	[0.137]	[0.132]	[0.071]	[0.113]
Exporter dummy	0.4807***	0.3851***	0.0470	0.4144***
	[0.117]	[0.105]	[0.063]	[0.089]
Constant	-0.0695	-0.5459**	1.7566***	2.4213***
	[0.236]	[0.223]	[0.107]	[0.148]
Observations	662	662	620	3,151
R^2	0.216	0.191	0.042	0.876

Notes: The table uses the 2001-2007 sample. The dependent variables are reported at the top of each columns: log of unit values, markups, log unit average costs and price of intermediates inputs. Markups are trimmed above and below the 3rd and the 97th percentiles within each sector. In the last column we add to the regressions material-time fixed effects. Standard errors in brackets clustered at firm level. * 0.10, ** 0.05, *** 0.01 Significance level.

Table 2.9: Tariffs Reduction by Sector

Sector	Average	Standard Deviation	Minimun	Median	Maximun
Food & beverages	-0.075	0.042	-0.247	-0.063	-0.021
Textiles	-0.089	0.021	-0.123	-0.093	-0.061
Wearing apparel	-0.117	0.000	-0.117	-0.117	-0.117
Leather,footwear	-0.087	0.024	-0.104	-0.104	-0.043
Wood	-0.012	0.015	-0.049	-0.002	-0.002
Paper	-0.023	0.004	-0.028	-0.021	-0.016
Publishing	-0.010	0.008	-0.019	-0.010	-0.000
Coke, petroleum	-0.045	0.000	-0.045	-0.045	-0.045
Chemicals	-0.032	0.018	-0.063	-0.039	-0.007
Rubber,plastics	-0.056	0.011	-0.060	-0.060	-0.024
Non-metallic mineral	-0.026	0.015	-0.066	-0.020	-0.010
Basic metal	-0.024	0.005	-0.029	-0.019	-0.019
Fabricated metal prod	-0.028	0.002	-0.038	-0.030	-0.025
Machinery and equip	-0.017	0.011	-0.049	-0.015	-0.000
Electrical mach n.e.c	-0.029	0.007	-0.037	-0.024	-0.022
Medical mach, watches	-0.014	0.012	-0.035	-0.015	-0.003
Motor vehicles	-0.031	0.010	-0.080	-0.030	-0.025
Other transport equip	-0.029	0.027	-0.072	-0.017	-0.007
Furniture; man. n.e.c	-0.009	0.008	-0.038	-0.006	-0.006
Total	-0.052	0.042	-0.247	-0.047	-0.000

Notes: Authors' calculations using WITS-World Bank dataset. MFN tariffs refer to 2002.

Table 2.10: Entry into Export Market

	$\Delta dummy_{exp}$ (a)	$dummy_{exp}$ (b)	$dummy_{exp}$ (c)	$dummy_{exp}$ (d)
Panel A				
$\Delta\tau$	-0.1424	-0.8509***	-0.7624***	-0.4665***
	[0.095]	[0.185]	[0.221]	[0.124]
Firm-level controls	no	no	no	no
Industry-level controls	no	no	no	no
Sector dummies	yes	yes	yes	yes
Observations	8,043	8,043	6,825	6,214
R^2	0.004	0.577	0.021	0.017
Panel B				
$\Delta\tau$	-0.0455	-0.6093***	-0.4371*	-0.3121**
	[0.105]	[0.195]	[0.226]	[0.120]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	no	no	no	no
Sector dummies	yes	yes	yes	yes
R^2	0.005	0.596	0.074	0.046
Panel C				
$\Delta\tau$	-0.0740	-0.6467***	-0.5577**	-0.3974***
	[0.090]	[0.180]	[0.261]	[0.120]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
R^2	0.005	0.596	0.075	0.046

Notes: The dependent variable at the top of the column. Column (c) includes only non exported products before FTAs. Column (d) includes only non exporting firms before FTAs. Δ denotes changes in a variable before/after the FTA. Firm level controls includes employment measured in efficiency unit and output per worker measured before FTA. Industry controls includes demand elasticity and skill intensity measured at 4-digit ISIC industry in the US. Standard errors in brackets clustered at 4-digit ISIC industry level. * p<0.10, ** p<0.05, *** p<0.01. Significance level.

Table 2.11: Main Results

	Δ Markup (1)	Δ Prices (2)	Δ Costs (3)	Δ TFPQ (4)
Panel A				
$\Delta\tau$	0.2400*	0.2055	-0.0345	-1.1500***
	[0.142]	[0.125]	[0.175]	[0.411]
Firm-level controls	no	no	no	no
Industry-level controls	no	no	no	no
Sector dummies	yes	yes	yes	yes
Observations	8,043	8,043	8,043	8,043
R^2	0.014	0.009	0.007	0.007
Panel B				
$\Delta\tau$	0.1672	0.2512*	0.0839	-1.0079**
	[0.133]	[0.137]	[0.145]	[0.437]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	no	no	no	no
Sector dummies	yes	yes	yes	yes
R^2	0.016	0.009	0.008	0.007
Panel C				
$\Delta\tau$	0.1593	0.2998**	0.1405	-1.1277***
	[0.155]	[0.127]	[0.162]	[0.393]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
R^2	0.017	0.010	0.008	0.008

The dependent variable at the top of the column: log of unit values, markups, log unit average costs and log product tfpq. Δ denotes changes in a variable before/after the FTA. Dependent variable trimmed below the 3rd and above the 97th percentile. Firm level controls includes employment measured in efficiency unit and output per worker measured before FTA. Industry controls includes demand elasticity and skill intensity measured at 4-digit ISIC industry in the US. Standard errors in brackets clustered at 4-digit ISIC industry level. * p<0.10, ** p<0.05, *** p<0.01. Significance level.

Table 2.12: Differentiated vs. Homogeneous Products

	Δ Markup	Δ Prices	Δ Costs	Δ TFPQ
$\Delta\tau$	0.3921***	0.1279	-0.2643	-1.2985***
	[0.142]	[0.188]	[0.160]	[0.408]
$\Delta\tau$ x $Diff_j$	-0.6679*	0.5472	1.2151**	1.6445
	[0.365]	[0.483]	[0.489]	[1.310]
$Diff_j$	-0.0271	0.0163	0.0433	-0.0598
	[0.021]	[0.033]	[0.032]	[0.066]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
Observations	8043	8043	8043	8043
R^2	0.017	0.010	0.009	0.009

The dependent variable at the top of the column: log of unit values, markups, log unit average costs and log product tfpq. Δ denotes changes in a variable before/after the FTA. Variable $Diff_j$ is defined as the share of products within an industry that is non exchanged on a organized base. Firm level controls includes employment measured in efficiency unit and output per worker measured before FTA. Industry controls includes demand elasticity and skill intensity measured at 4-digit ISIC industry in the US. Standard errors in brackets clustered at 4-digit ISIC industry level. * p<0.10, ** p<0.05, *** p<0.01. Significance level.

Table 2.13: Robustness

	Δ Markup	Δ Prices	Δ Costs	Δ TFPQ
	(1)	(2)	(3)	(4)
Panel A: Exclude from sample 2003 and 2004				
$\Delta\tau$	0.3559**	0.4591**	0.1032	-1.4476**
	[0.147]	[0.183]	[0.265]	[0.682]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
Observations	5890	5890	5890	5890
R^2	0.028	0.012	0.015	0.008
Panel B: Sub Sample of non exporting firms				
$\Delta\tau$	0.1242	0.7546**	0.6303**	-2.3535***
	[0.158]	[0.288]	[0.279]	[0.670]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
Observations	6209	6209	6209	6209
R^2	0.018	0.011	0.011	0.014
Panel C: Control for import competition				
$\Delta\tau$	0.1653	0.2969**	0.1315	-1.0605***
	[0.155]	[0.126]	[0.160]	[0.402]
Firm-level controls	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
Observations	8,036	8,036	8,036	8,036
R^2	0.017	0.010	0.008	0.008

The dependent variable at the top of the column: log of unit values, markups, log unit average costs and log product tfpq. Δ denotes changes in a variable before/after the FTA. Dependent variable trimmed below the 3rd and above the 97th percentile. Firm level controls includes employment measured in efficiency unit and output per worker measured before FTA. Industry controls includes demand elasticity and skill intensity measured at 4-digit ISIC industry in the US. In Panel C we add to the regression the change in the share of import from EU and US measured at industry level as additional control. Standard errors in brackets clustered at 4-digit ISIC industry level. * p<0.10, ** p<0.05, *** p<0.01. Significance level.

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Chapter 3

Export-Driven Innovation? Firm-Level Evidence on Exports and Patents

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3.1 Introduction

Innovation is a key driver of productivity and economic growth (Grossman and Helpman, 1991). A large body of economic literature explored the determinants of innovation at the micro level, ranging from the skill level of the workforce to managerial quality and practices (Bloom and Reenen, 2006), from a firm's financial structure to the availability of external sources of financing (Hall and Lerner, 2009).

In this paper, we study how the exposure to foreign demand might affect a firm's innovation activity. Using Italian firm-level data and European Patent Office (EPO) records, we find that an increase in exports has a positive effect on the probability that a firm applies for a patent, which is our measure of innovation.

Previous empirical studies of firm innovation rely either on R&D activity measures or on self-declared product or process innovation data. Instead of measuring innovative inputs, as R&D activity does, our measure of innovation — firms' patent application — have the advantage of measuring a realized innovative output. In addition, patent applications are less likely to suffer from measurement errors than self-declared indicators of innovation, allowing us to focus on innovations that are not marginal but in some way relevant to the market.[1]

We also contribute to the literature dealing with endogeneity using an instrumental variable approach that relies on the exogenous developments of world imports. For each firm in our data set, we construct an instrument that measures foreign market size using aggregate import flows in destination countries and the heterogeneity of export destinations for firms located in different provinces. We exploit the fact that two otherwise identical firms face different foreign demand because they are located in provinces that serve different markets.

In our empirical exercise, we show that passing from the 25th to the 75th percentile of export distribution increases the probability of patenting by 15 percent (one half of a standard deviation). To guide the interpretation of the results, we first present a simple model that is slightly modified version of Melitz's (2003) partial equilibrium, where we add a role for innovation. As this model predicts, we find that exporting has a positive and statistically significant effect on patenting only for firms that are larger and more productive that the median.

Starting from Bernard and Jensen's (1995) seminal paper on US firm-level data, a rich literature covering many advanced and emerging economies has shown that exporting firms are larger, more productive, and more innovative than non-exporters. Three possible explanations have emerged for the positive correlation between exports and innovation. The first relies on a *self-selection* mechanism. As Griliches (2000) points out, the effect of R&D investment on firm-level productivity growth is immense. Productivity level, in turn, influences the exporting behavior of firms, since only ex ante more productive firms *self-select* into international markets (Melitz, 2003). Therefore, firms investing in R&D end up being more competitive in international markets, implying that causality runs from innovation to trade. The second explanation is based on the *complementarity* between market size and technological change. As Rodrik (1988) and Yeaple (2005) illustrate, the expected profits, and therefore the incentives to invest in new technologies or products, rise with the size of the final markets; in this context, the exporting activity can be seen as an enlargement of the market size for a firm's output. In other words, *complementarity* implies that the size of the export flows

[1] Some common drawbacks to using patent data in economics have been widely documented (Griliches, 1990). First, patent counts do not reveal the economic value of patents: within the same industry, it is not possible to distinguish between a patent worth ten dollars and one worth a billion dollars. Second, the use of patents varies across industries for reasons that might not be related to innovation propensity. Third, it is not clear how long it takes from when a firm pays the fixed costs to set up a research lab or to start a new innovative project to when a successful project gives rise to a patent application.

matters for innovation. The third explanation relates to the fact that trade flows facilitate international knowledge spillovers (Coe and Helpman, 1995) and therefore may contribute to the adoption of new technologies and the development of new, higher quality products. This is known as the *learning by exporting* hypothesis,[2] which posits that export participation enhances innovation and productivity.

While the *self-selection* mechanism has received wide and robust empirical support, the literature has struggled to prove that exports have a convincing causal impact on firm productivity and innovation. Both Clerides et al. (1998), who study Mexican and Moroccan firm-level data, nor Bernard and Jensen (1999), who use US plant-level data, find that exporting has any effect on productivity. In a cross-country harmonized exercise, the International Study Group on Exports and Productivity (ISGEP, 2007), found some support for the *learning by exporting* hypothesis but only for Italian firms, particularly the smaller ones. Aw et al. (2011) estimate a structural model and find that productivity evolves depending on export and R&D spending. Their results suggest that investment in R&D has a greater impact on productivity than exports, and that exports have little impact on the decision to invest in R&D and the associated productivity dynamics. In contrast, De Loecker (2007), using data on newly exporting firms in Slovenia, finds that these firms become more productive after entry and that their productivity gap with respect to domestic firms increases over time. Crespi et al. (2008) use Community Innovation Survey data to show that exporters report that they indeed learn from foreign buyers; these firms also record higher productivity growth compared to domestic firms. Using the Canada-U.S. Free Trade Agreement to improve the identification strategy, Lileeva and Trefler (2010) shows that labor productivity of Canadian firms increases as a consequence to U.S. tariff cut and that this effect is stronger among ex-ante smaller and less productive firms.

This is not the first study to analyze the relationship between exports and firm innovation. Salomon and Shaver (2005) find that the exporting activity of Spanish firms is associated with ex-post increases in patenting and product innovation; Salomon and Jin (2010) build on this research by showing that the effect is stronger among technologically advanced firms. Using a sample of Irish and British firms, Girma et al. (2008) conclude that previous exporting experience enhances the research and development (R&D) propensity of Irish firm but not of British ones. According to Damijan et al. (2010), ex-

[2]There is a parallel *learning by importing* hypothesis, which posits that a firm can improve its efficiency via technology and quality embedded in imported intermediate inputs (Amiti and Konings, 2007; Goldberg et al., 2010; Khandelwal and Topalova, 2011; Colantone and Crinò, 2011).

ports increase the probability of process innovation and productivity growth among Slovenian firms. Similarly, Bustos (2011) shows that Argentinean firms respond to the MERCOSUR Free Trade Agreement by increasing both their export market participation and their technology spending. She also finds that the impact of the exogenous reduction in tariffs on technological adoption is heterogeneous across firms, and stronger among firms in the middle-upper tail of the distribution in terms of size.

The remainder of this paper is organized as follows. The next section presents a simple theoretical model for exports and product innovation that serves as the conceptual framework for the empirical analysis. Section 3.3 describes the empirical specification and our identification strategy. Section 3.4 discusses our dataset, and section 3.5 presents the results of the estimates. Section 3.6 concludes.

3.2 Theoretical underpinnings

We start by describing a simple theoretical model aimed at guiding the empirical analysis. Following Helpman (2006), our model is a modified version of Melitz's (2003) partial equilibrium in which we allow firms to choose whether to start an innovative project or not.

As in Melitz (2003), consider an economy with two countries, home and abroad, populated by I firms indexed by i. Following convention, we denote abroad variables using $*$. Firms face a domestic isoelastic demand function $q(i) = p(i)^{-\sigma}A$ in a monopolistic competitive market. Foreign demand is given by $q^*(i) = p^*(i)^{-\sigma}A^*$. $\sigma > 1$ is the elasticity of substitution between any pair of varieties. A and A^* measure, respectively, the size of the domestic and foreign markets. $p(i)$ and $p^*(i)$ are the prices charged by firms in the domestic and foreign markets, the latter including the *ad valorem* tariff paid by firms when selling products abroad. Exporting firms also have to pay a fixed cost F^X.[3] Firms are heterogeneous in terms of productivity φ', and their cost function is $(c/\varphi')q(i)$. We focus on the static optimization problem; thus we assume A and A^* to be exogenous, and we normalize c to one.

We add innovation to this standard setup. We assume that firms can start an innovative project after paying a fixed cost related, for example, to the need of setting up a research lab. The fixed cost is ex-ante uncertain and equal to $F^I(1+\varepsilon_i)$, where ε_i is a random variable drawn from a uniform distribution with support $[0, \gamma]$. Two otherwise identical firms could come

[3] For simplicity, we assume that all firms have a productivity level above the survival threshold determined by the set-up fixed cost F^E so that the entry/exit decision is not relevant in our case.

up with innovative ideas that entail different implementation costs: as a result, it is more likely that the cheapest projects are undertaken and then patented. Moreover, the model implies that larger and more productive firms can bear higher fixed costs and therefore have a higher (ex-ante) probability of patenting.

The timing of the model is as follows. At the beginning of each period, a firm observes the realization of the productivity level and the fixed cost of innovation. Then it makes decisions about whether to export and whether to start the innovative project.[4] When a firm patents a new invention, it gets $\delta > 1$ extra profits.[5] A firm's profit function depends on the exporting and innovation decisions ($\pi(E, I)$ with $E = \{0, 1\}$ and $I = \{0, 1\}$) in the following way:

$$\begin{aligned}
\pi(0,0) &= \varphi A \\
\pi(0,1) &= \delta\varphi A - F^I(1+\varepsilon_i) \\
\pi(1,0) &= \varphi[A + \tau^{-\sigma}A^*] - F^X \\
\pi(1,1) &= \delta\varphi[A + \tau^{-\sigma}A^*] - F^X - F^I(1+\varepsilon_i),
\end{aligned}$$

where φ is a transformation of productivity φ', namely, $\varphi \equiv [\varphi'(\sigma-1)]^{\sigma-1}\sigma^{\sigma}$.

We solve the model by equating the profit functions and finding the productivity cutoffs that make a firm indifferent between any two alternatives. We make some simplifying assumptions to stay as close as possible to the empirical patterns we observe in our data. In our firm level data we observe that almost all firms export but that only a subset patent an innovation. Hence, we assume that $F^X < F^I$, which implies that there cannot be non-exporting patenters, as our data suggest. Our main focus in the empirical analysis is the intensive margin of exports. Moreover, in our firm-level data, only a few firms do not export; therefore, we also rule out the possibility that a domestic non-innovative firm start both exporting and innovating simultaneously.[6] As a result, there are only two relevant transitions: from domestic to exporting firm and from exporting to exporting and patenting firm.

[4] The structure of the model is such that once all the uncertainty is resolved, i.e. the productivity level and the fixed cost of innovation are observable, each innovative project that is being undertaken ends with a patent.

[5] Firm can patent product or process innovations. Product innovation can refer to the introduction of new products, or upgrade in the quality of existing product lines. Process innovation, instead, can be thought of as cost saving. We are not able to distinguish between product and process innovation from patent records; therefore, we assume only that patents will increase revenues and hence firms profits. We also assume that no firm is large enough to alter the equilibrium market condition when patenting.

[6] Bustos (2011) shows the importance among Argentinean firms of the joint decision to

As in Melitz (2003), a firm is indifferent between exporting and selling only in the domestic market if $\pi(0,0) = \pi(1,0)$: this gives the standard cutoff $\varphi^X = \frac{F^X}{\tau^{-\sigma}A^*}$. Analogously, exporting firms are indifferent between investing in innovation or not if $\pi(1,0) = \pi(1,1)$. Interestingly, this productivity cutoff depends on the realization of the fixed cost of innovation. Specifically, there are two thresholds. If ε_i is equal to its minimum (i.e. $\varepsilon_i = 0$), $\pi(1,0) = \pi(1,1)$, we get $\underline{\varphi^I} = \dfrac{F^I}{(A+\tau^{-\sigma}A^*)}$, which is the minimum productivity level below which no firm ever finds it profitable to undertake an innovative project (independent of the innovation cost). If, however, ε_i is equal to its maximum (i.e. $\varepsilon_i = 1$), the threshold $\overline{\varphi^I} = \dfrac{\gamma F^I}{(A+\tau^{-\sigma}A^*)}$ corresponds to the productivity level above which all firms always undertake innovative projects (again independent of the innovation cost). For all firms with productivity lying within these two thresholds, the innovation decision will depend on the realization of the fixed cost. For these firms, the ex-ante probability of realizing an innovation and patenting it is

$$\begin{aligned} Prob[Patent] &= Prob[\pi(1,1) \geq \pi(1,0) \mid \varphi \in (\underline{\varphi^I}; \overline{\varphi^I})] \quad (3.1) \\ &= Prob[\varepsilon_i \leq \frac{\varphi(A+\tau^{-\sigma}A^*)}{F^I} - 1 \mid \varphi \in (\underline{\varphi^I}; \overline{\varphi^I})], \quad (3.2) \end{aligned}$$

The probability of investing in innovation is increasing in productivity as long as the gains of innovation are proportional to the revenues while the costs are fixed; hence, more productive firms are better placed to bear the fixed costs.

Fig. 3.1 describes how the probability of patenting (red line) is related to productivity before a firm gets to know its own ε_i and how this relationship changes with trade (green dashed line). There are three different productivity cutoffs that allow us to distinguish four types of firms:[7] i) firms selling only in the domestic market ($\varphi \leq \varphi^X$); ii) firms exporting without innovating ($\varphi \in (\varphi^X; \underline{\varphi^I})$); firms exporting and innovating with some probability smaller than 1 ($\varphi \in (\underline{\varphi^I}; \overline{\varphi^I})$); and firms that are continually exporting and innovating ($\varphi \geq \overline{\varphi^I}$).

begin exporting and upgrading technology. In our empirical analysis, we use data from a survey of Italian manufacturing firms with more than 20 employees and find that only small fraction of the sample firms do not export. Thus, we chose not to make predictions about this margin that we could not test in the data.

[7]Because $F^X < F^I$ and $\tau^{-\sigma}A* < \tau^{-\sigma}A * + A$, the thresholds can be depicted as in Figure 3.1 as long as $\dfrac{F^I}{F^X} \geq \dfrac{\tau^{-\sigma}A^* + A}{\tau^{-\sigma}A^*}$. In other words, the innovation cost cannot be so low that all firms find it convenient to bear it and patent their innovation.

Using our simple model, we can show what happens to the probability of patenting when firms face either a decrease in trade costs ($\downarrow \tau$) or an increase in foreign market size ($\uparrow A^*$). If trade costs decrease, all thresholds move leftward so that the probability of patenting increase:

$$\frac{\partial \, Prob[Patent]}{\partial \, \tau} < 0, \tag{3.3}$$

The green dashed line represents the new relationship between the probability of patenting and the level of productivity. As Figure 3.1 and eq. 3.2 show, an export shock increases the probability of innovation along two margins. On the one hand, for firms with intermediate productivity levels the probability of patenting increases. On the other hand, firms with a productivity level that was just below $\underline{\varphi^I}$ before the shock have a positive probability of starting to innovate.

3.3 Empirical Design

We want to assess the impact of the size of a firm's export flows on its innovation activity, which we measure through patenting. To this aim, we estimate the following equation:

$$D\{Patent\}_i^{\{t+1,t+4\}} = \alpha + \alpha_s I_s + \alpha_t I_t + \alpha_p I_p + \beta X_i^t + \gamma Z_i^t + \varepsilon_{istp}, \tag{3.4}$$

where firms, sectors, years, and provinces are indexed, respectively, by i, s, t, and p. $D\{Patent\}_i^{\{t+1,t+4\}}$ is a dummy variable that in each year takes a value of 1 if firm i will apply for a patent in the following four years (i.e., between $t+1$ and $t+4$). I_s, I_t, and I_p are sector, year, and province fixed effects, respectively. X_i^t is our main variable of interest and is equal to $\ln(export)_i^t$ if $export_i^t > 0$ and 0 otherwise. Z_i^t is a set of firm-level time-varying controls.

Our firm-level data cover a relatively short time span and have some attrition. We cannot add firm-level fixed effects to equation (3.4). To minimize the bias from unobservable time-invariant firm-level features, Z_i^t includes past employment and a set of dummies for past patent status. These dummies allow us to also control for the fact that, because of huge start-up costs, patenting is much easier (less costly) for firms that have patented in the past.

Patenting is a rare, uncertain, and often strategic activity. A firm may decide not to apply or to postpone the application for a patent to avoid the disclosure of specific knowledge required when filing a patent application (Reinganum, 1983, 1984, 1986). For this reason, we measure patents over more than one year. We choose a four-year period to represent the time lag between the start of an R&D activity and the subsequent patent application. Four years is the median and average citation lag found in NBER patent data: the citation lag is the time difference between the application of the citing patent, and that of the cited patent. The distribution of foreword citations in our sample is represented in Fig. 3.2: the median citation lag is 4.83 years (the average is 6.3).

3.3.1 Causality

OLS estimation of equation (3.4) is potentially plagued by endogeneity issues. A first concern is related to omitted variables. Firm productivity or managerial capabilities, for example, can drive both the exporting and innovation decisions of firms, thus creating an upward bias in the OLS estimation. Another concern is reverse causality related to the self-selection mechanism described in the introduction. Consider, for example, the case of an innovative firm that has become productive enough to face the fixed cost of export. If this firm continues to have a relatively stronger patent propensity, then OLS would suffer from an upward bias; if, instead, this firm, already close to the technological frontier, curbs its patent activity, then there would a downward bias.

To address these issues, we estimate equation (3.4) using instrumental variables (IV). To build an exogenous instrument for a firm's level of exports, we use data on world sectoral imports. The ideal instrument would be computed by applying the growth rate of world sectoral imports by destination market to each firm's initial (and historic) level of exports. Unfortunately, we do not have historic data on firm-level exports by destination market. Thus, we exploit the location of the firm and the availability of aggregate trade flows at the sector-province-destination country level to compute the exports of a representative firm in sector s and province p to country c in 1995.[8]

We do so in three steps. First, we compute the fictional export flow at the province-sector-year level by attaching the yearly dynamics of imports by sector s and country c to the corresponding (sector-destination country) provincial level of exports in 1995:

$$\hat{X}^t_{sp} = \sum_c X^{1995}_{csp} \frac{M^t_{cs}}{M^{1995}_{cs}}, \quad t = 2001, \ldots, 2005, \tag{3.5}$$

where X^{1995}_{csp} is the export value of sector s and province p to country c in 1995 and M^t_{cs} and M^{1995}_{cs} are the imports of country c in sector s in,

[8] 1995 is the first year for which we have data on bilateral trade flows.

respectively, time t and 1995. Thus, $\hat{X}^t_{sp}$ is the time series of exports of sector s and province p that are (exogenously) determined by the evolution of foreign demand for imports. The exclusion restrictions are not violated if world demand in a certain sector is not affected by Italian provinces' export performance. We confirm this is indeed the case because in 1995 the largest share of world exports held by a single province is almost negligible (that of Milan, which produced 0.03 percent of worldwide exports of electronic apparel). Our instrument also retains some variability across provinces that we can exploit in the empirical analysis because in 1995 the composition of exports in terms of destination markets is very heterogeneous across sectors and provinces. The number of destinations served by each sector-province varies between 1 and 196 (the average is 80), the mean export share per destination is 2%, and the standard deviation is 0.7. In a second step, we take care of the fact that the scale of $\hat{X}^t_{sp}$ is far larger than that of firm-level exports by dividing $\hat{X}^t_{sp}$ by the total number of active firms in sector s and province p in 1995 ($\hat{X}^t_{sp} = \hat{X}^t_{sp}/N^{1995}_{sp}$).

Finally, we further adjust the instrument for possible nonlinear effects in the first stage regression, which could stem from firms with different export levels having different sensitivities to foreign demand shocks: the *compliers*, whose exports significantly expand in response to an increase in foreign demand; the *always-takers*, whose level of exports is not very sensitive to changes in world demand; and the *never-takers*, which never export even when world demand is particularly buoyant (see Angrist and Pischke, 2009). To get the best fit for this non-linear relationship, we discretize $\hat{X}^t_{sp}$ by computing a set of mutually orthogonal dummies using the quartiles of its within-sector distribution. For a similar approach, see Lileeva and Trefler (2010) and Angrist and Imbens (1995).

Operationally, if we call $q^n_{\ln \hat{X}_{st}}$ with $n = 25, 50, 75, 100$ the upper bound of, respectively, the 1st, 2nd, 3rd, and 4th quartile of the within-sector distribution of $\hat{X}^t_{isp}$, then we build the following set of dummies:

$$D^1_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } \ln \hat{X}^t_{ps} \leq q^{25}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{3.6}$$

$$D^2_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } q^{25}_{\ln \hat{X}^t_{ps}} < \ln \hat{X}^t_{ps} \leq q^{50}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{3.7}$$

$$D^3_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } q^{50}_{\ln \hat{X}^t_{ps}} < \ln \hat{X}^t_{ps} \leq q^{75}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

$$D^4_{\ln \hat{X}^t_{ps}} = \begin{cases} 1 & \text{if } \ln \hat{X}^t_{ps} > q^{75}_{\ln \hat{X}^t_{ps}} \\ 0 & \text{otherwise.} \end{cases} \tag{3.9}$$

Consequently, our set of instruments is given by $\{D^2_{\ln \hat{X}^{t-1}_{ps}}, D^3_{\ln \hat{X}^{t-1}_{ps}}, D^4_{\ln \hat{X}^{t-1}_{ps}}\}$, where we exclude the dummy for the first quartile.

To further understand our instrument, consider the case of two firms i and i' that are equal in all respects except for being located in two different provinces, A and B. Assume also that back in 1995 the two provinces were serving two different markets of the same size that hereafter experienced different growth rates $g_A \geq g_B$. Our instrument, which is a measure of export market size, will be larger for the market that experienced the larger growth $\hat{X}^A \geq \hat{X}^B$. Assuming that firm exports to a market destination are persistent over time, our instrument predicts that firm export levels will become $X_i \geq X_{i'}$. Interestingly, our instrument can be constructed using widely available firm-level information (such as firm location or export-market destination) and aggregate trade flows.

3.4 Firm-Level Data

For the empirical analysis, we merge the firm-level data of the "Indagine sulle imprese industriali e dei servizi" (Inquiry on industrial and service firms; henceforth Invind), a survey administrated annually since 1982 by the Bank of Italy, and PATSTAT, a commercial database compiled by the European Patent Office (EPO).

Invind is a widely used survey[9] of about 4,000 industrial and service firms

[9]Papers based on SIM data include Guiso and Parigi (1999) and Iranzo, Schivardi and Tosetti (2008). Data are available upon request through the BIRD system http://www.bancaditalia.it/statistiche/indcamp/sondaggio/bird

with at least 20 employees.[10] Invind collects a wide range of information on nationality, location, age, sector of activity, ownership structure, employment (annual average), investment (realized and planned), sales (domestic and foreign), capacity utilization rate, and indebtedness. The PATSTAT database contains information on firms' patent applications to the European Patent Office. For each patent application, external researchers can access the name and address of the applicant and the priority date of the application. Our PATSTAT data cover the period 1975—2011.

Merging the Invind and PATSTAT data is not easy.[11] We use the matching procedure developed for Italian firms by Marin (2011), who follows the NBER routine (NBER Patent Data Project) by harmonizing names and then match applicants' names recorded in PATSTAT with the names of Italian firms from the AIDA-*Bureau van Dijk* database. The last step consists of matching Invind and AIDA-Patstat using the tax codes as firm identifiers. Combining Patstat data up to 2008 with Invind for manufacturing firms with more than 20 employees,[12] we end up with an open panel of 3,085 firms over the period 2001—05, because our patent data are reliable up to 2009.

We use the Baci-Cepii dataset on world trade flows by sector and country and Italian trade statistics collected by the Italian statistical agency (Istat) to construct our IV. The Baci dataset builds on UN Comtrade but harmonizes the data to reconcile flows reported by importing and exporting countries.[13] Istat's trade data are detailed by sector, 95 provinces, and all countries of origin/destination of trade flows.

Table 3.1 reports basic descriptive statistics of our firm-level database. Mean employment is 319 employees, with a median of 103. Approximately 84% of firms export, and the share of exports over total sales is 33%.

Table 3.1 shows the differences in patent propensity within our dataset.[14] Patentees are about four times larger than firms that have never received a

[10]Invind's data start in 1984. Before 2001 the survey was focused on industrial firms with at least 50 employees. In 2001 it expanded to smaller firms (between 20 and 49 employees) to better represent the Italian production system, which includes vast majority of small- and medium-sized firms. In 2002 Invind additionally began collecting information on private nonfinancial services.

[11]The main difficulty lies in that the name of the patent applicant can be recorded in different ways across years (uppercase vs. lowercase letters, complete vs. abbreviated names, different ways of abbreviating the same name, etc.), sometimes depending on the patent office where the application is filed.

[12]Both exports and product innovation are less relevant activities for most of services firms.

[13]For further details see http://www.cepii.fr/anglaisgraph/bdd/baci.htm

[14]We allocate a firm to the "No patent" column only for the years before its first patent application, if any.

patent in terms of both employment and revenues; they also have a large exporting propensity (+16%) and export share (+50%). These differences are smaller than the ones documented on U.S. census data (Balasubramanian and Sivadasan, 2011), likely because our data set contains only firms with more than 20 employees.

Table 3.2 shows how patenting differs across sectors. Pooling our data over the sample years, we see that patentees account for 19 percent of the total number of firms and 45 percent of total employment and revenues. These average figures indicates a lot of heterogeneity across manufacturing sectors. The share of patentees over the total number of firms ranges from 2 percent in the apparel sector to 42 percent in the machinery industry. Correspondingly, patentees account for 10–15 percent in terms of employment and revenues in the apparel sector verus more than 70 percent in machinery. Not surprisingly, patentees are relatively more likely in high-tech and high-skill intensive sectors.

Table 3.3, columns (1) and (2) show the share of firms that apply for a patent in a given year t and the share of firms that apply for a patent in the subsequent four years, respectively. On average the share of patenting firms doubles from 7% to 14% between columns 1 and 2. Column (3) reports the total number of patent applications in our sample and the distribution across sectors. Finally, we compute a measure of patent stock, which proxies for firms' preexisting knowledge. Column (4) reports an average depreciated patent stock of 1.41, with lot of variability across sectors from 0 patent in the Tobacco sector to 93 patents in the Computer sector.

3.5 Results

We first examin the relation between exporting and patenting using simple descriptive statistics. Table 3.4 reports the probability of patenting for firms with different export levels, conditional on a firm stock of patents. More precisely, we divide firms according to the quintiles of the within-sector distribution of export levels and in five categories in terms of patent stock. Category 1 comprises firms with no patent, and then we divide all the other firms by quartile of the within-industry distribution of patent stock. The probability of applying for a patent is increasing in export level. Firms in the fifth quintile of the export distribution exhibit a probability of applying for a patent that is twice as large as that of the fourth quintile (27.6% vs. 16.8%) and almost 25 percentage points larger than the first quintile. Table 3.4 shows that not only exporting and patenting are strongly correlated activities but also a firm's historical patenting record is a strong determinant of future patenting. For example, the probability that a firm applies for its first patent in a given year is 4 percent. Among firms in the upper quartile of the distribution in terms of the stock of past patents, the probability of applying for a patent is almost 90 percent. Interestingly, the link between future patenting and exporting remains even when we focus on firms with similar past patenting activity. Among first-time patenters, the probability of patenting moves from less than 1 percent of firms in the first quintile of the export distribution to 8 percent for firms in the fifth quintile.

Panel A of Figure 3.3 illustrates the link between exporting and patenting, with the probability of patenting plotted by deciles of the level of exports within each sector (at any decile, each dot is associated with a specific sector). We see a clear linear positive relationship between the level of exports and the probability of patenting. Panel B is similar, but instead of export levels we here use employment levels. Again, we see a positive relationship, with patenting more likely among larger firms. Based on these results, we use employment as one of our control variables.

We next estimate equation (3.4). The baseline results are displayed in Table 3.5. Column (1) is a very parsimonious OLS specification in which we control only for year, sector, and province dummies. The probability of applying for a patent between t and $t+4$ is positively correlated with a firm's level of exports at time t. Given the endogeneity issues discussed earlier, we employ our IV estimation technique. The column (2) IV estimates, which are derived from the model in column (1), confirm the positive and significant effect of exports on patent propensity, and the coefficient of interest is larger than in the OLS. We thus infer a downward bias in the OLS estimation that could stem either from a classical measurement error or from reverse causality. The coefficients of the first stage regression have the expected signs. The first stage F-statistics, reported in the lower part of the Table 3.5, are greater than 10, which is safely above the threshold for weak instruments (Bound et al., 1995).

To control for the fact that larger firms have a higher propensity to both patent and export and that current patenting is strongly correlated with the stock of patents, in column (3) we add lagged $(t-4)$ employment and a set of dummies measuring the existing stock of patents at $t-4$. We take lags of these variables because we want to be sure that the controls are not influenced by exports at time t (Angrist and Pischke, 2009). As expected, previous patenting activity is a significant determinant of future patenting, greatly improving the fit of the regression and reducing the size of the IV coefficient of exports, although it remains statistically significant. Past employment has a positive but statistically insignificant coefficient. This specification, which is our preferred one, confirms that the level of exports has a sizable causal impact on patenting propensity: indeed, passing from the 25th to the 75th percentile of the export distribution increases the probability of patenting by 15%, which is half of a standard deviation.

We check the robustness of our estimates in three ways. First, to address the concern that very large Italian exporters might influence world trade in a certain industry, thereby invalidating the exclusion restrictions, in column (4) we run the baseline regression excluding provinces with a Balassa index in a given sector larger than 10.[15] Previous results hold by and large.

In column (5) we restrict our sample further. In theory, we would like to identify the effect of an increase in the intensive margin of exports on the extensive margin of patenting. To maximize the number of observations, we have so far estimated equation (3.4) on all firms and controlled for the past stock of patents. A neater specification would restrict the sample to firms with zero patents before $t-4$ so that the identification of the causal impact of exports relies only on truly new patenters. When we restrict the sample in this way, we still find that the level of exports has a positive and significant effect on patenting propensity; the estimated coefficient is smaller but now surprising, because the propensity to patent among firms with zero patents is lower due to the high fixed costs of innovation and patenting.

As a final robustness check, we remove observations with zero exports to more precisely identify a foreign market size channel. We find that not only do the main result holds, but the magnitude of the estimated effect doubles and the F-statistics of the first stage improves significantly (column (6)).

3.5.1 Heterogeneity

Our simple theoretical model suggests that the effect of a trade expansion on the probability of filling a patent application differs based on the productivity distribution of firms. Specifically, innovation should be driven by larger and more productive firms.

We test this idea in Table 3.6. Columns (1) and (2) split the sample between smaller (below the median) and larger (above the median) firms based on the number of employees. Results show that the positive effect estimated in Table 3.5 is entirely driven by larger firms. We get a similar result when we split the sample based on the level of labor productivity (columns (3) and (4)): again only more productive firms increase their patent propensity when facing a foreign market expansion.

The results for the first-stage estimation, reported at the bottom of table

[15]The Balassa index is computed by dividing the share of world trade of a province in a certain sector by the share of the same province in all the sectors.

3.6, give additional support to the theoretical predictions and instrumental variable. The F-statistics of the first stage for smaller and less productive firms is quite low. This result implies that when hit by a trade shock, this group is not likely to change its exporting behavior (i.e., they are *never takers*), because they are too far from the exporting threshold. For larger and more productive firms, instead, the first stage is above the threshold of 10, implying that an increase in international demand is likely to expand the exports for a sizable number of firms (the so-called *compliers*) due to their proximity to the exporting threshold.

3.6 Concluding remarks

This paper examines the effect of an increase in exports on the propensity to innovate at the firm level. We first present a simple theoretical model with heterogeneous firms in which we show how an increase of foreign demand could increase firms' incentives to innovate. As the model shows, this effect is asymmetric because it is mainly driven by more productive firms.

Our empirical evidence supports these theoretical predictions. Using an IV approach that exploits sectoral world demand as an exogenous variation in firm-level exports, we find that one standard deviation increase in foreign sales raises the probability of apply for a patent by half of one standard deviation (15%). This result is stronger for larger and more productive firms, and it is robust to confounding factors like past innovative activities and previous export experience. These results are compatible with the complementarity hypothesis between market size and innovation, as expected future profits due to an expansion of foreign demand are a relevant driver that induces firms to bear the fixed costs of innovation. Our results also suggest that policies aimed at supporting firms' internationalization can also have beneficial effects in terms of innovation.

Figures and Tables

Figure 3.1: Export and Investment Decision

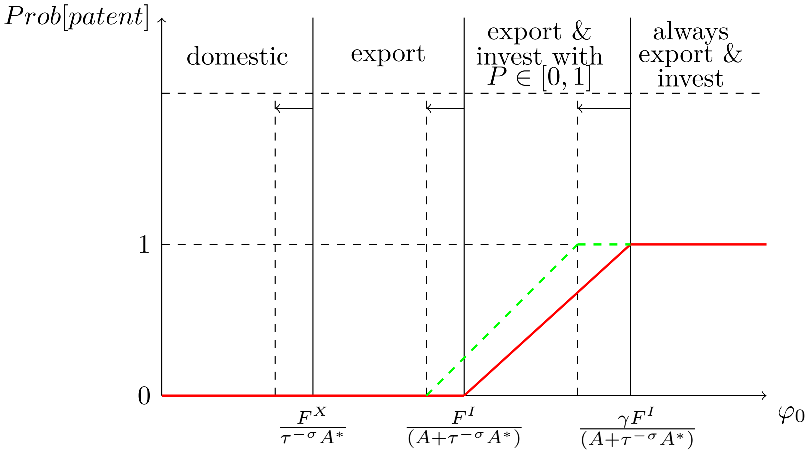
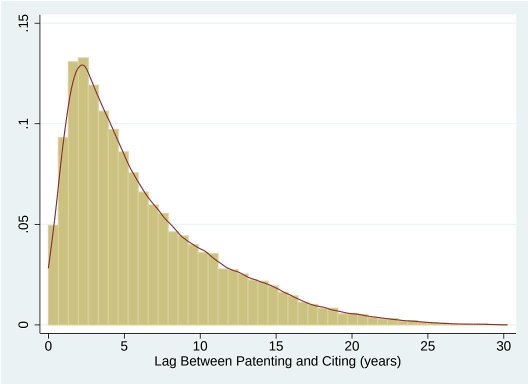
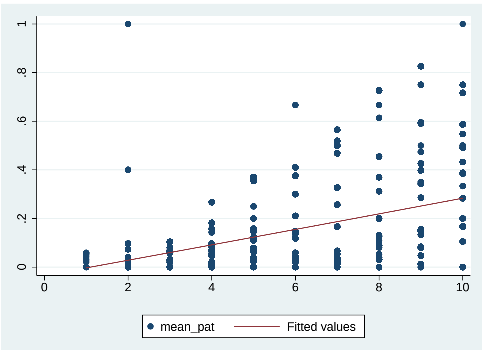
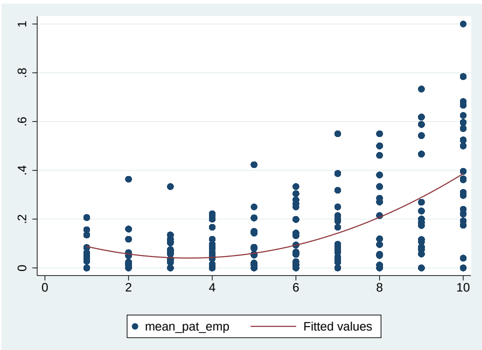


Figure 3.2: Lags Between Patenting and Citing



Notes: Authors' calculation using Patstat and INVIND data. Distribution of the forward citation lags in years in our sample. For each patent granted, we compute the time between the patent being granted and the citation.

Figure 3.3: Distribution of the Probability of Patenting

(a) Export levels	(b) Employment
	

Source: INVIND and Patstat.

Table 3.1: Summary Statistics

	No patent		Patent		Total	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Employment	194	440	793	1958	319	1007
Sales (mil. euros)	60.6	407.8	241.4	923.1	98.1	560.1
Export (mil. euros)	17.6	66.6	105.8	413.8	35.9	200.6
Export dummy	.812	.391	.965	.183	.844	.362
Export share	.293	.296	.461	.281	.328	.300

Notes: Authors' calculation on Invind and PATSTAT data. Averages and standard deviations over the period 2001–2005. Firms belong to the "No patent" column for the years before the first patent application. Afterward, they are included in the "Patent" column. The last column reports the totals across all firms in our sample.

Table 3.2: Patentees by Sector

Sector description	Number of firms	Share of patentees	Patentees: share of empl.	Patentees: share of revenue
Food and beverages	446	0.0493	0.3198	0.3457
Tobacco	6	0.1667	0.7757	0.9486
Textile	203	0.0542	0.1236	0.1058
Apparel	124	0.0242	0.1182	0.1666
Leather	133	0.0827	0.1208	0.1498
Timber	62	0.0806	0.2476	0.2050
Paper	86	0.1628	0.2175	0.1909
Printing and publishing	53	0.0755	0.5513	0.5571
Petroleum and coke	26	0.0769	0.1393	0.0081
Chemicals	184	0.3641	0.6654	0.6792
Plastic	163	0.2638	0.3276	0.2718
Minerals	226	0.1062	0.3129	0.3125
Metals	126	0.1905	0.6945	0.6611
Metal products	283	0.1908	0.3751	0.3453
Machinery	421	0.4276	0.7220	0.7405
Computer	12	0.2500	0.9377	0.8926
Electrical equipment	115	0.3217	0.6772	0.6526
Telec. equipment	48	0.3333	0.6065	0.7125
Medical and optical instr.	47	0.4043	0.5894	0.6665
Cars and trucks	92	0.2935	0.6995	0.7704
Other automotive	66	0.2424	0.7102	0.7108
Furniture	163	0.0982	0.2267	0.2118
Total	3085	0.1942	0.4559	0.4588

Notes: Authors' calculation Invind and PATSTAT data. The first column reports the number of firms in our final sample, and the second column shows the share of patentees, defined as firms that hold at least one patent. The shares of employment and revenues in the last two columns are calculated as averages over the period 2001–2005.

Table 3.3: Sectoral Measure of Patent Activity

Sector Description	Patent dummy at t	Patent dummy $[t+1, t+4]$	Number patent app.	Stock of patent
Food and beverages	0.0187	0.0424	87	0.21
Tobacco	0.0526	0.2105	2	0.00
Textile	0.0168	0.0643	17	0.03
Apparel	0.0074	0.0198	11	0.13
Leather	0.0289	0.0578	29	0.25
Timber	0.0106	0.0798	3	0.08
Paper	0.0341	0.0922	17	0.18
Printing and publishing	0.0000	0.0000	0	0.02
Petroleum and coke	0.0000	0.0000	0	0.05
Chemicals	0.1431	0.2524	541	3.75
Plastic	0.0584	0.1770	226	0.88
Minerals	0.0253	0.0625	29	0.17
Metals	0.0470	0.0850	31	0.51
Metal products	0.0495	0.1013	76	0.26
Machinery	0.1875	0.3347	1095	3.12
Computer	0.2059	0.1765	829	93.39
Electrical equipment	0.1906	0.3343	225	1.77
Telec. equipment	0.1156	0.1850	136	2.47
Medical and optical instr.	0.2115	0.3269	76	2.03
Cars and trucks	0.1640	0.2540	318	5.03
Other automotive	0.1027	0.1964	144	1.30
Furniture	0.0288	0.0653	23	0.32
Total	0.0736	0.1417	3915	1.41

Notes: Authors' calculation using Invind and Patstat data. The first column shows the share of firms that apply for a patent in a given year. The second column gives the share of firms that apply for a patent in the following four years, which is our main variable of interest in the empirical analysis. The third column reports the total number of applications. The last column reports the stock of depreciated patents calculated using the perpetual inventory method with an annual depreciation rate of 15%.

Table 3.4: Relation Between Stock of Patents and Exports

Stock of Patents	Export Quintiles 1	2	3	4	5	Total
Zero	0.008	0.025	0.039	0.063	0.078	0.039
1st quartile	0.143	0.148	0.194	0.319	0.214	0.221
2nd quartile	0.088	0.238	0.333	0.433	0.390	0.343
3th quartile	0.400	0.488	0.607	0.556	0.633	0.591
4th quartile	0.900	0.889	0.783	0.853	0.936	0.908
Total	0.015	0.044	0.091	0.168	0.276	0.119

Notes: Authors' calculation on Invind and PATSTAT data. For each sector, we divide firms into quartiles based on their stock of depreciated patents calculated using perpetual inventory method with an annual depreciation rate of 15%. In the first row we include all firms with zero patents, i.e., those that have never applied for a patent. Firms are divided into quintiles based the employment distribution within sector (displayed by column). Each cell reports the probability that a firm applied for a patent in the subsequent four years. The Table displays averages over the period 2001–2005.

Table 3.5: Main Results: OLS and IV Regressions

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
log(export)	0.020***	0.0320***	0.0209*	0.0243**	0.0187*	0.0394*
	[0.001]	[0.0097]	[0.0110]	[0.0124]	[0.0105]	[0.0227]
1st quartile			0.1781***	0.1566***		0.1882***
			[0.0391]	[0.0389]		[0.0405]
2nd quartile			0.2143***	0.1969***		0.2217***
			[0.0310]	[0.0319]		[0.0316]
3rd quartile			0.4031***	0.3994***		0.3993***
			[0.0376]	[0.0392]		[0.0377]
4th quartile			0.6436***	0.6415***		0.6309***
			[0.0332]	[0.0378]		[0.0338]
employment$_{t-4}$			0.0095	0.0037	0.0084	-0.0055
			[0.0140]	[0.0153]	[0.0133]	[0.0251]
R^2	0.042					
F-statistic		21.06	12.85	10.45	10.13	15.26
$D^2_{\ln \hat{X}^t_{ps}}$		0.7726***	0.6211***	0.5561**	0.5969***	0.3061**
		[0.1781]	[0.1653]	[0.1717]	[0.1784]	[0.0967]
$D^3_{\ln \hat{X}^t_{ps}}$		1.1545***	0.9467***	0.8421***	0.9131***	0.5825***
		[0.1987]	[0.1780]	[0.1863]	[0.1975]	[0.1014]
$D^4_{\ln \hat{X}^t_{ps}}$		1.6977***	1.1461***	1.1434***	1.1064***	0.6822***
		[0.2148]	[0.1921]	[0.2084]	[0.2097]	[0.1096]
Observations	10235	10215	10215	8942	8536	8630

Notes: Authors' calculations using Invind and PATSTAT data. The dependent variable is a dummy equal to one if a firm applies for a patent in the following four years and zero otherwise. The variables 1st–4th quartiles refer to the within-industry distribution of the stock of depreciated patents calculated using the perpetual inventory method with an annual depreciation rate of 15%. Each regression includes year, province, and 2-digit sector fixed effects. Column (1) presents the baseline OLS and columns (2)–(6) the IV regressions. In column (2) we include in the regression only the log of exports and the main fixed effects. In column (3) we include controls for lagged employment and the stock of depreciated patents. Column (4) excludes sector-provinces with a Balassa index ≥ 10. Column (5) restricts the sample to firms whose stock of patent = 0, i.e., firms that have never applied for a patent. Finally, the sample in column (6) includes only firms with log(export) > 0. The F-statistic of the first stage is reported for each IV regression. The bottom panel reports the first stage coefficients of our instruments. Robust standard errors clustered at the firm level are in brackets. Significance: * 10%, ** 5%, *** 1%.

Table 3.6: Heterogeneity

	Employment		Labor Productivity	
	below the median	above the median	below the median	above the median
log(export)	0.0170	0.0200**	0.0110	0.0219**
	[0.0354]	[0.0090]	[0.0143]	[0.0099]
Firm Controls	Y	Y	Y	Y
Year Dummies	Y	Y	Y	Y
Sector Dummies	Y	Y	Y	Y
Provinces Dummies	Y	Y	Y	Y
F-statistic	0.86	14.89	3.57	17.31
Observations	4236	4272	3916	3912

Notes: Authors' calculations using Invind and PATSTAT data. The dependent variable is a dummy equal one if a firm applies for a patent in the following four years and zero otherwise. Each regression includes firms controls (lagged employment and dummies for the stock of depreciated patents) and year, province, and 2-digit sector fix effects. In columns (1) and (2), firms are divided within each sector above and below the median employment level. In columns (3) and (4), firms are divided above and below the median value of value added per worker (labor productivity) within each sector. Robust standard errors clustered at the firm level are in brackets. Significance: * 10%, ** 5%, *** 1%.

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