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Respuestas Heterogéneas ante un Shock Competitivo: Evidencia a Nivel Firma para Chile

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Heterogeneous Responses to Competitive Shocks: Firm-level Evidence from Chile*

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Abstract

This paper empirically characterizes firm-level responses to a competitive shock given by rising import competition from China. We use microdata on the universe of Chile's manufacturing firms during 1995-2006. For identification we exploit the fact that Chinese import penetration (CIP) increased differently over time across manufacturing industries. We use Chinese export growth in high-income industry-country pairs as instruments for CIP. Average CIP across industries increased from 1.5% in 1995 to 10.1% in 2006. Our results suggest that firms in industries more exposed to rising CIP dismiss more workers, reduce their sales and face a higher probability of exiting the market relative to comparable firms in less exposed industries. All these effects are less pronounced for more productive firms.

JEL Classification: F14, F16, D24.

Keywords: Manufacturing, China Import Penetration, Firm Adjustment, TFP, Chile.

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I Introduction

There is consensus in mainstream economics that globalization and trade liberalization tend to improve long-term welfare by allowing the economy to reallocate resources towards comparative advantage industries and to more productive firms even within narrowly defined industries. We also know that this reallocation process is likely to create short- and medium-term losses that are unevenly distributed across regions, industries, firms and workers. A growing body of theoretical and empirical literature studies the impact of trade liberalization on labor market outcomes, such as rising unemployment, worsening income distribution and more recently, regional labor market effects[1].

The overcoming of the adjustment costs and the materialization of long-term benefits will depend ultimately on the speed of the adjustment process, which might be related to each economy's productive structure, the characteristics of its labor force and the nature of its institutions (e.g. protection networks, labor market flexibility and policy responses). As globalization continues and deepens, the tension between workers concerned with short-term outcomes and policy makers focused on long-term welfare will enhance. In this context, understand which firms and industries are more sensitive to foreign competition is important to measure the potential effects of globalization on labor market results, evaluate the reallocation possibilities and design cost-effective policy responses to speed up the adjustment process or compensate displaced workers. Furthermore, the existing evidence in developing countries is quite scant and far from being conclusive.

The endogeneous nature of trade make it difficult to asses the causal impact of trade liberalization on firms and workers. The main challenges faced by this literature are (i) the endogeneity of trade policy and (ii) the need for measures of actual trade restrictiveness beyond traditional tariffs. Non-tariff barriers are widely used by developing countries and (when measured) remain barely comparable across countries/industries and over time. Recent contributions have partially adressed these drawbacks by focusing instead on ex-post measures of trade such as the import penetration ratio from low-wage countries (e.g. Bernard, Jensen and Schott 2006,

[1]For evidence on trade and local labor markets see Chiquiar 2008 (Mexico), Topalova 2010 (India), Autor, Dorn and Hanson 2013 (U.S.), Kovak 2013 and Dix-Carneiro and Kovak 2017 (Brazil). For industry-level evidence see Goldberg and Pavcnik 2005 (Colombia), Bernard, Jensen and Schott 2006 (U.S.) and Artuç, Chaudhuri and McLaren 2010 (U.S.). Firm-level evidence is presented in Amiti and Davis 2011 (Indonesia), Hummels, Jørgensen, Munch and Xiang 2014 (Denmark) and Bloom, Draca and Van Reenen 2015 (Europe), among others.

Khandelwal 2010).

The espectacular growth of China in the last decades provides a unique opportunity to measure the causal effect of trade on relevant economic outcomes. Much of China growth was driven by massive migration from rural to urban regions, strong investments in infraestructure, genuine increases in total factor productivity and an export-oriented strategy that placed China as one of the world's leading producer of manufactures[2]. The export growth explained by these and many other factors inherent to Chinese economic forces and institutions provides a potencial exogenous shock to the competitiveness of firms and workers from all over the world.

In this paper we empirically characterize firm- and industry-level responses to a competitive shock given by rising import competition from China. To account for the endogenous nature of trade we apply an instrumental variable strategy that have also been used by other recent papers in the literature (e.g. Autor et al. 2013, Autor, Dorn, Hanson and Song 2014, Bloom et al. 2015 and Acemoglu et al. 2016). We use microdata on the universe of Chile's manufacturing firms during 1995-2006. The panel structure of the data enable us to control for many unobserved potencial confounders. For identification we exploit the fact that Chinese import penetration (CIP) increased differently over time across manufacturing industries (see Figure I). Average CIP across industries increased from 1.5% in 1995 to 10.1% in 2006. Textiles, toys and machines/electrical sectors present the highest rates of exposure to Chinese competition, while sectors like food, paper and chemicals remain barely exposed (see Figure II).

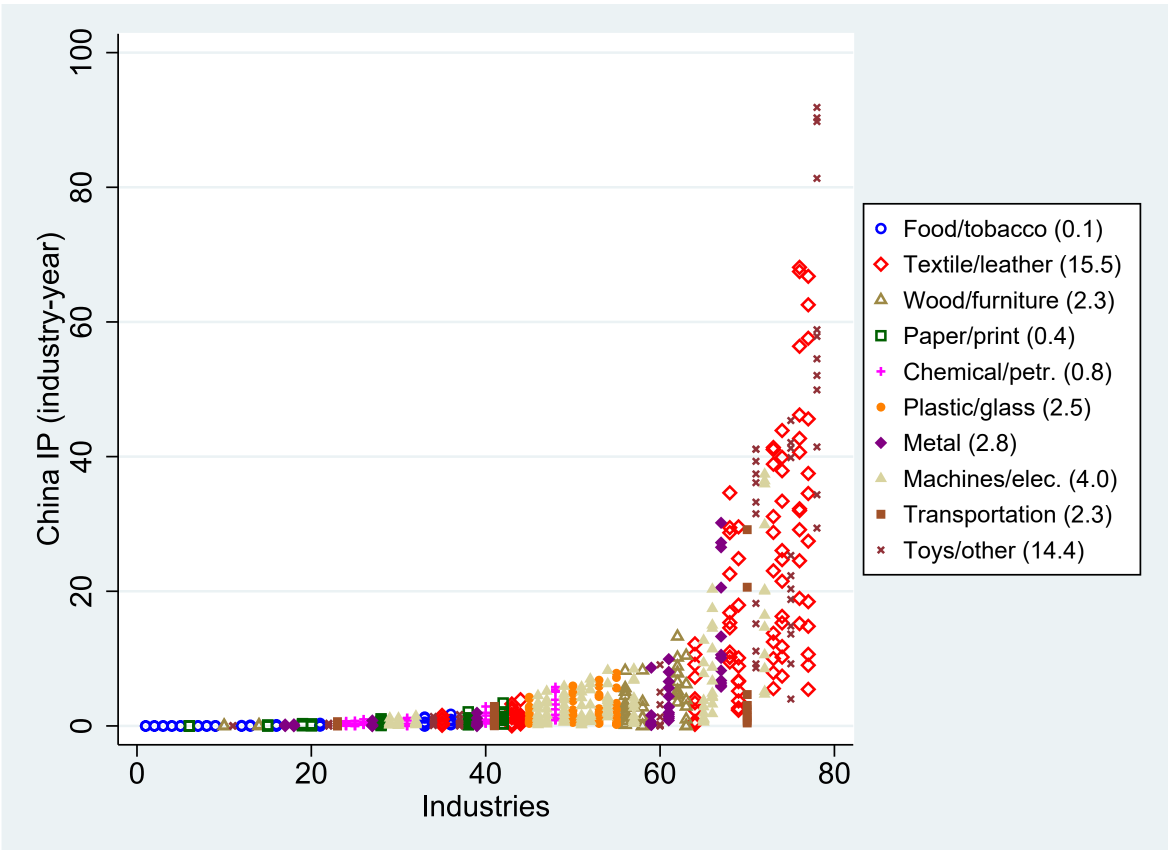
During the studied period, the total number of workers employed in manufacturing decreased until 2001 and fully recovered in 2006. Although, growth patterns across industries differ substantially, being those more exposed to China competition the ones that contracted the more and recovered the less. Industries with low-exposure were 18% bigger in terms of total employment in 1995, while this gap increased to 96% in 2006[3] (see Figure III). While many potential factors could explain this divergent patterns,

[2]Many of these factors arised from market-oriented reforms that began in the 1980s. For evidence on China's economic transition see Naughton (1996), Hsieh and Klenow (2009), Brandt et al. (2012) and Hsieh and Ossa (2016), among others.

[3]Our sample works with 78 out of 111 industries, but results are robust to work with the entire dataset (see Section II for data cleaning and Section V for robustness). Exposed (non-exposed) industries are those above (below) median Chinese import penetration (CIP), which is equal to 0.42%. Exposed (non-exposed) industries had 132,415 (156,508) employees in 1995 and ended up with 100,581 (197,139) in 2006. Overall, 14% of the labor force was employed in manufacturing in 1995 and this fraction reduced to 12.7% in 2006.

our estimates predict that the trade-induced competive shock given by rising import competition from China explains 34.37% of the employment contraction in exposed industries.

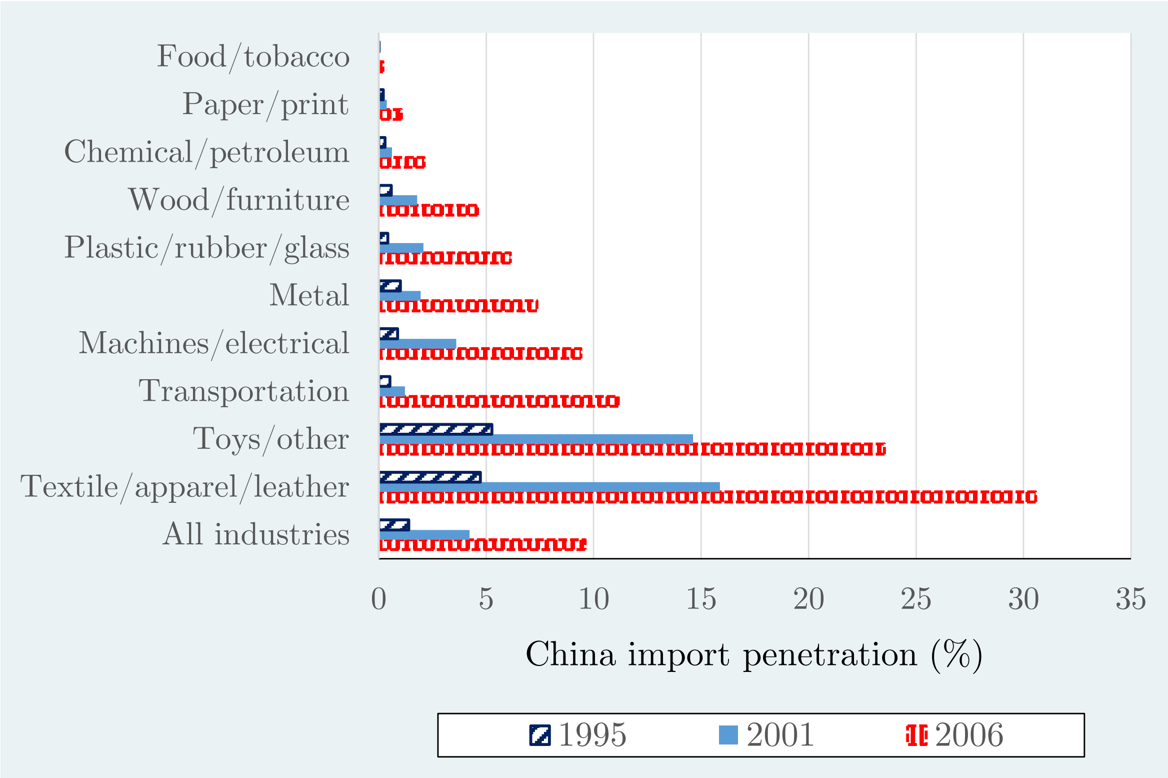
FIGURE I
Evolution of Chinese Import Penetration



Notes. Each point represents an industry-year combination. Industries are defined at 4 digits of the ISIC Rev. 3. Chinese import penetration (CIP) measured as total value of imports divided by domestic absorption (production minus net exports) and varies at industry-year level. Industries are grouped into 10 broad manufacturing sectors and ordered from lowest to highest exposure to CIP. Each symbol represents a different sector. Sector average CIP across industries over time in parenthesis. Sources: INE-ENIA and UN-COMTRADE.

FIGURE II

EVOLUTION OF CHINESE IMPORT PENETRATION BY BROAD SECTORS

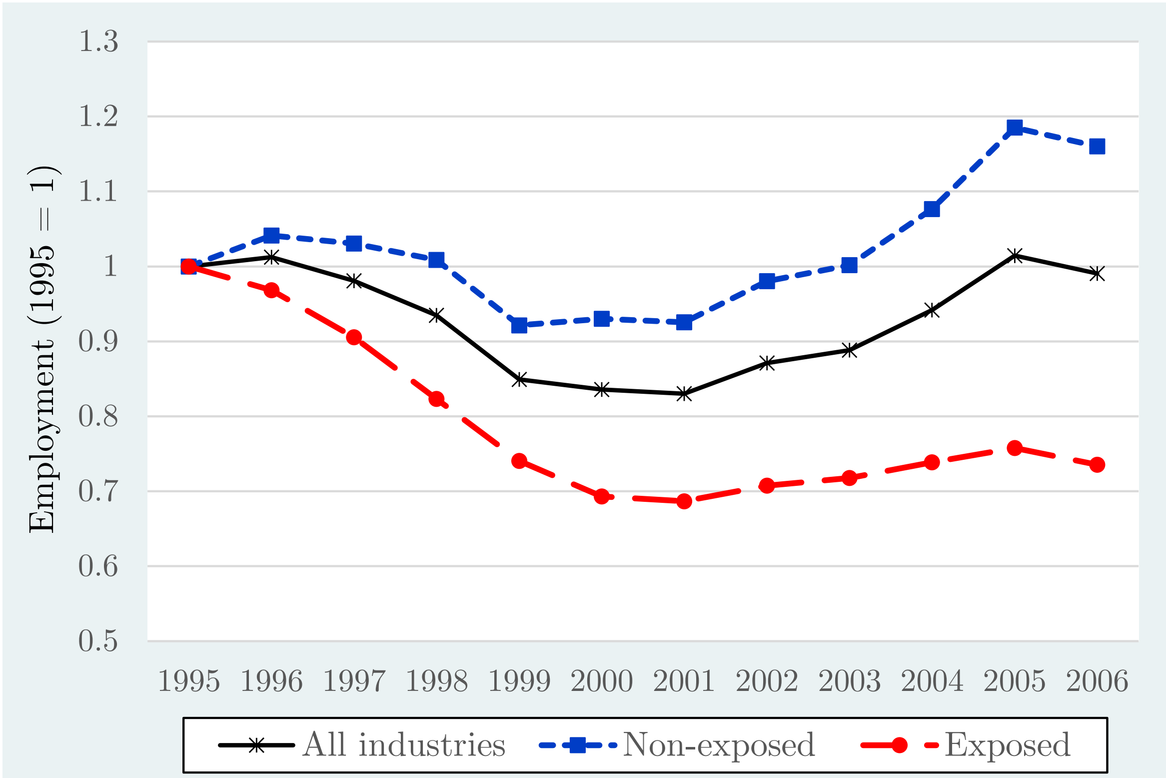


Notes. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. Manufacturing industries classified by ISIC Rev. 3 are grouped into 10 broad sectors. Each sector includes a set of similar manufacturing industries (number of industries within each sector are in brackets): Food/tobacco (14), Textile/apparel/leather (10), Wood/furniture (6), Paper/print (7), Chemical/petroleum (6), Plastic/rubber/glass (4), Metal (7), Machines/electrical (13), Transportation (3), Toys/other (8). Sources: INE-ENIA and UN-COMTRADE.

An easy way of thinking why trade could be associated with labor market adjustments is to reason in a Heckscher-Ohlin framework. Countries have different proportions of productive factors, and so do the goods that each country produces and exports. If this is true, then China's opening to trade represents an increase in labor supply in the world economy and we would expect labor-intensive industries to contract as Chinese import penetration grows. If we think in terms of recent models of trade, the impact of globalization could be heterogeneous across firms even if they belong to the same narrowly defined industry. Melitz (2003) model shows how exposure to trade will induce only the more productive firms to enter the export market and will simultaneously induce the less productive to exit. Conversely, we would expect import penetration to affect more the less productive domestic firms that compete in relatively similar market segments.

FIGURE III

Evolution of Manufacturing Employment, 1995-2006



Notes. Exposed (non-exposed) industries are those above (below) percentile 50th of average Chinese import penetration (CIP), which equals 0.4%. CIP measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. Industries defined at 4 digits ISIC Rev. 3. Sources: Encuesta Nacional Industrial Anual (ENIA) from Chile's National Institute of Statistics (INE) and Commodity Trade Statistics Database (COMTRADE) from United Nations (UN).

The main dataset used throughout this paper is the Annual National Industrial Survey (ENIA) realized by the Chile's National Institute of Statistics (INE). It consists on census yearly panel data on the universe of manufacturing firms with ten or more employees. We count on this dataset from 1995 onwards and we chose to stop the selected sample in 2006 in order to avoid potential counfunding effects arising from the beggining of the global financial crisis in 2007, which severely affected global trade patterns. The main module of the survey includes information on firm characteristics such as total employment, revenue, investment, intermediate inputs, industry affiliation and so on. We use this data in two ways. First, we construct the main economic outcomes of interest for our analysis: employment, revenue and exit rates. Second, we employ it to estimate total factor productivity (TFP) at firm-level, following the method proposed by Ackerberg, Caves and Frazer (2015). This allows us to evaluate the hypothesis that competitive shocks may have different effects across firms depending on their initial productivity levels.

We employ a secondary publicly available dataset from the United Nations Commodity Trade Statistics Database (UN-COMTRADE). It contains yearly information on import/export dollar-values, quantities, partners and product codes (at 6 digits of the Harmonized System international classification) reported by statistical authorities of close to 200 countries and regions. By merging this dataset with the firm-level Chilean information we are able to construct a measure of Chinese import penetration (CIP) which varies by 4 digits industry-year level (International Standard Industry Classification, Rev. 3). CIP is measured as the total value of imports coming from China divided by domestic absorption (production minus net exports). Importantly, we use this dataset to construct an instrumental variable for CIP given by the average import industry shares across a subset of high-income countries (as in Bernard et al. 2006, Autor et al. 2013 2014 and Bloom et al. 2015). This dataset is also useful to describe the degree of competitive presure caused by Chinese import penetration, as given by the average price differences of the products exported from China and their pairs from the rest of the world.

We perform firm- and industry-level regressions. The baseline estimation equation at firm-level regresses the three main outcome variables (firm total employment, firm total revenue and firm's exit rate) on CIP, including an extensive set of firm-level control variables (e.g. TFP, K/L ratio, import/export status) plus year, firm, region-year and sector-year fixed effects. The inclusion of these fixed effects enables us to control for many unobserved time-invariant potential confounders (such as the ability of firms' managers) and also for time-varying shocks affecting differently geographically distant regions within the country or specific manufacturing sectors. Since CIP is endogenous because industry shocks affecting the outcome variables could be correlated with demand for imports, we instrument this variable with the average China's industry import shares across a sample of high income countries. This variable is aimed to capture supply-driven shocks that made China gain market share across this economies over time (e.g. increases in TFP). First-stage regression shows a strong predictive power of the instrument, with a coefficient of 0.96 (0.13) and R-squared of 0.70. The identifying assumptions are that: (i) China export growth is exogeneous (driven by TFP, infraestructure, migration, etc.) and (ii) industry import demand shocks are uncorrelated between Chile and this group of countries. We follow a similar strategy for industry-level regressions. This specification will capture the net effect of growing CIP on employment because of both the variation of firm-level employment (intensive margin) and the open/closure of new/existing firms (extensive margin)[4]. These regressions are run mainly to motivate the discussion by showing more rigorously the idea that Figure III roughly described: industries more exposed to growing CIP end up being smaller in terms of total employment, revenue and number of active firms[5].

The second set of firm-level regressions are aimed to capture the existence of heterogenous effects of CIP on the aforementioned outcomes as a function of firm total factor productivity (TFP), which is unobserved and presents two main estimation challenges. First, input choices are correlated with firm-level productivity (not observed by the econometrician) and will generate an endogeneity problem (simultaneity bias) when using the classic OLS estimator. Second, firm-level datasets usually have a considerable level of attrition, since firm exit is likely to be correlated with firm productivity if firms have some knowledge of their future productivity prior to exiting (selection bias)[6]. To estimate TFP we follow recent advances in the literature given by the method proposed by Ackerberg, Caves and Frazer (2015). We use the estimated firm-level TFP in two types of regressions. Initially, adding firms initial TFP interacted with CIP in the main specifications. And then, estimating the baseline specification separately for firms of different quintiles of the TFP sector distribution.

Our main results suggest that firms in industries more exposed to growing CIP dismiss more workers, reduce their sales and face a higher probability of exiting the market relative to comparable firms in less exposed industries. Specifically, an increase in 1 p.p. of CIP reduces firm employment by 0.89%, reduces firm sales by 1.87% and increases the firm's probability of shut down by 0.65 p.p. Our estimates indicate that the impact of CIP on employment, revenues and exit decrease in magnitude as firms initial TFP is higher. The marginal effect of CIP on employment/revenue/exit for a firm located at the 25th percentile of its sector TFP distribution is 2.69/1.66/2.12 times bigger than this marginal effect for a firm situated at the 75th percentile. Even more, when we perform separate regressions for each quintile of the firm-level TFP

[4]We cannot account for general equilibrium effects with this identification strategy. We are unable to capture indirect employment effects via input-output linkages between upstream/downstream industries. Additionally, we would expect displaced workers of exposed industries to look for employment in non-exposed industries (positive reallocation effects) and presume that other sectors might also be influenced by a potentially negative Keynesian aggregate demand multiplier effect. Recent papers focused on local labor markets explore these and other related questions (see for example Autor et al. 2013, Acemoglu et al. 2016 and Dix-Carneiro and Kovak 2017).

[5]The same pattern noted in Figure III is seen if we graph total revenue and total number of firms instead of total employment.

[6]For an excellent exposition on these topics we recommend the chapter of Ackerberg, Benkard, Berry and Pakes (2007) in the Handkook of Econometrics, and the seminal papers of Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2015).

distribution, we find the same pattern that we noted with the interaction regressions: effects decrease for firms that are more initially productive in their sectors of activity. Even more, effects of CIP on firm employment and revenue are not statistically significant for firms located in the highest quintile of within sector TFP distribution.

These results point out considerable heterogeneity across firms in the adjustment costs to Chinese import competition. Firms with higher initial productivity levels were better able to withstand this competitive shock. This is consistent with the idea that more productive firms can escape competition from low-wage countries because they produce higher quality products that do not compete directly with products imported from these countries.

Our main contribution to the existing literature is empirical. Evidence for developing countries is quite scant and far from being conclusive. Much of the evidence for developed nations is not entirely transferable to small developing countries like Chile. The relatively small size of the Chilean economy and its great trade openness given her early liberalization episodes during the late 1970s and early 1980s augment the credibility of our identification strategy. Much of the evidence for U.S. does not complete isolate the fact that industry demand shocks might be correlated with industry trade exposure given that U.S. demand represents and important share of Chinese exports (20% on average during this period). Another contribution of this paper is to reinforce the idea that competitive shocks may have heterogeneous effects on firms according to their initial productivity levels. Our findings are especially relevant for developing countries with visible problems of unemployment or missalocation of productive factors, where an important share of the labor force is employed in low-competitive sectors characterized by relatively high presence of low-productivity firms.

The rest of the paper is oganized as follows. Section II presents the data and discuss some descriptive statistics. We present a brief historical background of Chile and China in Section III. Section IV discusses the estimation strategy. We analyze all the empirical findings of the paper in Section V. We finish with some concluding remarks in Section VI. Additional figures and tables are included in the Appendix.

II Data and Descriptive Statistics

In this section we explain the main characteristics of the two datasets we combine and the criteria used to clean the data. We then present some descriptive statistics which may be important to consider when interpreting the main findings of the paper.

II.I Data

The firm-level panel data we use consists on the manufacturing yearly census (Annual National Industrial Survey, ENIA) realized by the Chile's National Institute of Statistics (INE). It covers the universe of Chilean firms with ten or more employees. We count on this dataset from 1995 onwards. We decided to stop the sample period in 2006 in order to avoid potential counfunding effects arising from the beggining of the global financial crisis, which severely affected global trade patterns[7]. This dataset have also been used by other papers such as Levinsohn (1999), Pavcnik (2002), Levinsohn and Petrin (2003), among others.

The main module of the survey includes information on firm characteristics such as the number of employees, expenditure on labor compensation, investment, intermediate inputs, revenue, gross value of production, industry affiliation, region of activity and so on. The main outcomes of interest for our analysis are employment, value of products sold (revenue) and firm's exit rate. Importantly, the information available enable us to estimate total factor productivity (TFP) at firm-level following one of the most recent advances in the literature of production function's estimation. We follow the method proposed by Ackerberg, Caves and Frazer (2015).

The international trade dataset is the United Nations Commodity Trade Statistics Database (UN-COMTRADE)[8]. It contains information on import/export dollar-values, quantities, partners and product codes (at 6 digits of the Harmonized System international classification) reported by statistical authorities of close to 200 countries and regions. This dataset have also been used by many other related papers (e.g. Autor et al. 2013 2014, Acemoglu et al. 2016, Amiti and Khandelwal 2013 and Hummels et al. 2014). By merging this data with the firm-level Chilean information we are able to construct a measure of Chinese import penetration (CIP) which varies by 4 digits industry-year level (International Standard Industry Classification, Rev. 3). CIP

[7]Unfortunately, we can not perform the analysis thereafter because the panel structure was discontinued by the INE in the year 2008, alleging confidentiality issues regarding firms' identifiers.
[8]This information is publicly available at https://comtrade.un.org/.

is measured as the total value of imports coming from China divided by domestic absorption:

$$CIP_{jt} = \frac{M_{jt}^{China}}{[Q_{jt} + M_{jt} - X_{jt}]} \tag{1}$$

where Q_{jt}, M_{jt} and X_{jt} are the value of production, imports and exports for industry j in year t, respectively[9].

Additionally, we use this dataset in two ways. First, we construct instrumental variables for CIP_{jt} as the simple average of China's industry import shares across c different countries with available product data in COMTRADE:

$$Sh_{jt}^{China} = \frac{1}{c}\sum_{c}\frac{M_{jct}^{China}}{M_{jct}^{World}} \tag{2}$$

where M_{jct}^{China} is the total industry-year value of the imports coming from China in country c, while M_{jct}^{World} is the total value of imports in industry j in year t in country c. In order to capture supply-driven shocks inherent to the Chinese economy, we calculate this industry-year index for a group of highly competitive industrial economies, as given by the following high-income countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland[10].

Importantly, we also use this data to capture the degree of competitive presure caused by Chinese import penetration, given by the average price differences across industries of the hs6-products imported from China and their hs6-pairs imported from the rest of the world. Following standard practices in trade literature we use unit values as proxy for prices.

In order to increase the quality of the data and avoid inconsistencies, we trim the sample in some dimensions. First, we eliminate those firms that do not report complete information about its input usage (labor, capital, intermediate inputs) and the value of production. Second, we drop those firms that are present just in a single year or have

[9] M_{jt} and X_{jt} are obtained by aggregating product-level information from UN-COMTRADE data, while Q_{jt} is measured by adding up firm-level information from INE-ENIA.

[10] This group of high-income countries is the same used by Autor et al. 2014 and Acemoglu et al. 2016. We test the robustness of our results to the use of alternative groups of countries (G7, OECD, Latin America and Mercosur) and results do not change significantly.

gaps in reporting. We need continuos information about production and inputs because the estimation of TFP relies on the use of lagged variables as instruments (for details see Ackerberg, Caves and Frazer 2015). Finally, we choose to work with industries having at least ten different firms over the sample period in order to avoid any bias resulting from industries that are not representative of the Chilean manufacturing sector[11]. Overall, the final sample represents two thirds of total manufacturing employment and two thirds of total value of production.

II.II Descriptive Statistics

We present the two basic descriptive statistics (mean and standard deviation) for the main variables of interest in our study in Table I. We present this statistics for all the firms in the sample and separetely for firms that are in different quintiles of their sector TFP distribution. The table shows a positive correlation between firm productivity and number of workers, capital intensity and international trade participation, as we would expect given previous findings in the literature (e.g. Bernard, Jensen, Redding and Schott 2007 and Verhoogen 2008)[12]. The first three rows of this table show considerable variation in our main outcome variables within firms of the same quintile and across firms over different quintiles of sector TFP distribution.

On average, 7.5% of the firms shut down every year. As we would expect, exit rates decrease with firm-level TFP. While 10.47% of the firms in the first quintile close during an average year, this fraction diminishes to 5.47% for those firms in the fifth quintile of sector TFP distribution. The average number of workers at firm-level is 76. On average, firms in the fifth quintile are almost ten times bigger in terms of total workers and have more than five times capital per worker than firms in the first quintile (215 vs. 22 and 34,630 vs. 6,860 U.S.$, respectively). Only 5.79% (9.05%) of the least productive firms exports (imports), while this fraction increases to 50.5% (48.3%) in the most productive quintile.

[11]They represent 1% of total employment and 0,25% of total value of production. Our results remain virtually unchanged if we include these industries in the analysis. For more details, see robustness Section.

[12]The only exception is that K/L ratio is not increasing between quintiles one and two. Specifically, this is due mainly to differences in machines and buildings. In the rest of variablese these firms are relatively similar.

TABLE I

Summary Statistics by Quintil of TFP

	Q1	Q2	Q3	Q4	Q5	All
Firm's exit rate (%)	10.47	7.71	6.99	6.85	5.47	7.50
	(30.62)	(26.67)	(25.5)	(25.26)	(22.74)	(26.34)
Revenues	164	331	668	2,221	16,928	4,061
	(253)	(502)	(1,095)	(7,039)	(76,324)	(34,881)
Employment	21.96	27.05	38.40	77.63	215.36	76.07
	(29.9)	(30.65)	(38.41)	(137.12)	(273.73)	(156.94)
Average wage	1.78	2.05	2.38	3.10	4.23	2.71
	(1.29)	(1.52)	(1.5)	(4.04)	(3.78)	(2.85)
K/L ratio	6.86	5.35	7.29	11.28	34.63	13.08
	(42.42)	(14.11)	(43.58)	(28.47)	(168.85)	(82.22)
Share exporting (%)	5.79	7.53	16.10	28.98	50.50	21.78
	(23.36)	(26.39)	(36.75)	(45.37)	(50.)	(41.27)
Share importing (%)	9.05	11.81	19.03	26.80	48.29	22.99
	(28.69)	(32.27)	(39.25)	(44.29)	(49.97)	(42.08)
N	8,860	8,874	8,872	8,874	8,866	44,346

Notes. Standard deviations in parenthesis. TFP is calculated by the method proposed by Ackerberg, Caves and Frazer (2015) and normalized by average year-sector TFP. Quintiles constructed within 2 digits ISIC Rev. 3 industries. Exit =0 in active years and =1 one year before a firm leaves the panel. Revenues, wages and K/L ratio measured in millons of chilean pesos of 1995. Exporting (importing) means exports (imports) >0. Average 1995 exchange rate: 396.8 pesos/U.S.$1. Sources. INE-ENIA and UN-COMTRADE.

III Historical Background

III.I Chile

After a period of state intervention and implementation of an import-substitution policy regime during the 1960s and early 1970s, the Chilean military government carried out a large set of market-oriented economic reforms throughout 1974-1979. As part of the trade liberalization program, Chile eliminated most of its non-tariff barriers (NTBs) and reduced significantly its tarrif barriers. While some tariffs exceeded 100% in 1974, they were reduced to an ad valorem tariff of 10% five years later, a rate that was uniform across industries. After some years of increased protection during the recession of 1982-1984, when the uniform tariff increased up to 35%, it declined to 20% in 1985. Even more, NTBs were not applied during this transitory period (see Levinsohn 1999 and Pavcnik 2002). All these reforms positioned Chile as one of the most trade oriented economies of Latin America in the beginning of the 1990s[13].

Another important aspect of the reforms focused on labor market regulations. The government banned unions and replaced collective bargaining with a wage setting plan. Although labor laws did not change, there was considerable *de facto* deregulation with courts favoring firms' dismissals. Since June 1978 firms were legally allowed to dismiss workers for economic needs without any requirement on "just causes". Besides some changes in the compensation scheme, this reform still remains in practice. The new Labor Code approved in 1979 replaced national unions with firm-level ones, workers' rights to strike were curtailed and the costs of hiring/firing decreased significantly.

Chile underwent a new institutional change with the recovery of democracy in 1990. The same political coalition was in power during the period 1990-2010. These governments kept a basic consensus on the critical role of the private sector and markets deregulations to achieve efficiency, while pursuing poverty reduction and the improvement of income distribution. In 1991 some few modifications were introduced in the Labor Code, perhaps the most relevant was the increase in the limit for the wage compensation of fired workers from 5 to 11 months of wage. Between 1998 and 2001 Chile experienced a macroeconomic turndown and there was an intense debate about labor regulations. During this same time there was an increase in the minimum wage of 30%. The new changes in labor laws were implemented in December 2001. While

[13] According to World Development Indicators from the World Bank, trade to GDP ratio for Chile was 61.75% in 1990 compared to an average ratio of 32.99% across Latin American countries.

this reform increased the rights to collective bargaining, it also extended some margins of flexibility related to hiring practices related to apprenticeships, part-time jobs and temporal contracts.

The relatively small size of the Chilean economy, its great trade openness given her early trade liberalization episodes during late 1970s and early 1980s and its flexible labor market provide us with a nice scenario to study the causal impact of a trade competitive shock given by the rising import penetration from one of the most competitive countries in the world on firms behaviour.

III.II China

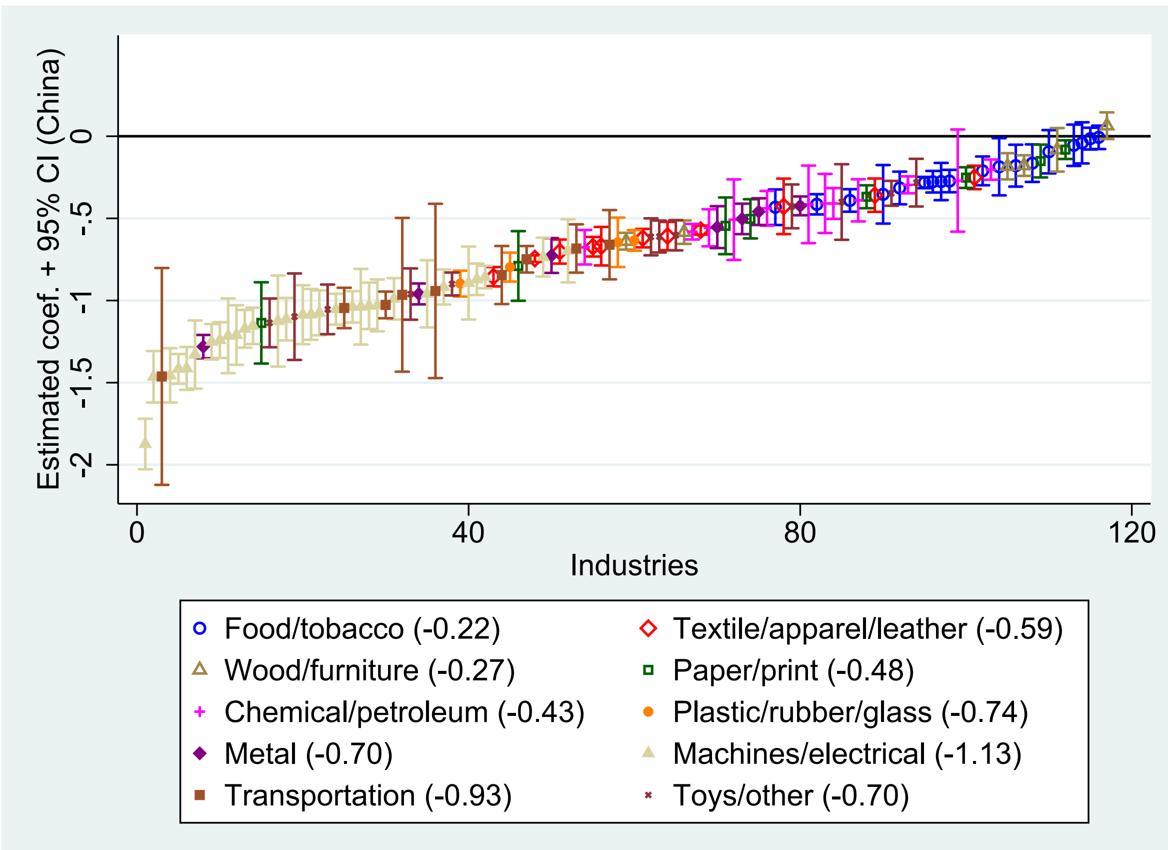
Beginning in the 1980s, China conducted a broad set of structural economic reforms that transformed its agrarian structure into a modern industrialized economy and a world leading producer of manufactures. The main trade reforms pursued a dualistic regime characterized by import-substitution and export promotion policies (Naughton 1996). Not surprisingly, China exports to GDP ratio increased from 5.91% in 1980 to a peak of 37.18% in 2006. The global financial crisis of 2007 severely affected global trade patterns and China exports to GDP ratio experimented a downward reversal thereafter. In order to avoid potential confounding effects arising from the global financial crisis we decided to stop the analysis in 2006.

Much of China growth was driven by massive migration of workers from rural to urban regions, strong investments in infraestructure, Chinese firm's increasing access to foreign technologies, intermediate inputs and capital goods, a massive inflow of foreign direct investment and a stunning increase in total factor productivity. According to Brandt, van Biesebroeck and Zhang (2012), China had an average TFP growth in manufacturing of 8.0% over the period 1998-2007. Along with these internal reforms that promoted growth and trade was the country accession to the World Trade Organization, which gave China the permanent most-favored nation status among the WTO members on December 2001.

The export growth explained by the aforementioned factors inherent to Chinese economic forces and institutions provides a potencial exogenous shock to the competitiveness of firms and workers from all over the world. Particularly, given that China is characterized by exporting labor-intensive low price products, the rising import penetration of Chinese manufactures actually represents a competitive pressure to domestic manufacturing firms. As we can see in Figure IV, products imported from

China are on average cheaper than their pairs from the rest of the world in most of the industries. Particularly, numbers in brackets show that products imported from China are on average significantly cheaper than their pairs imported from the rest of the world for all manufacturing sectors. For example, machines/electrical products exported from China are on average 113% cheaper than their similars exported from all other countries.

FIGURE IV
PRICE DIFFERENCES OF PRODUCTS IMPORTED FROM CHINA



Notes. Estimated coefficients of separate regressions by industry of log price of imported varieties on a China dummy (=1 if a product is imported from China and =0 if it is imported from any other country) controlling for importing country-product-year fixed effects. In brackets we show the average estimated coefficients across industries within broad sectors. Prices measured in constant U.S.$ unit values. A variety is a product-exporting country combination. Products are defined at 6 digits of the Harmonized System international classification. Industries defined at 4 digits ISIC Rev. 3. Sample is restricted to top 50 importing countries in terms of total value of imports per year during the sample period 1995-2006. Robust standard errors clustered by products. Source. UN-COMTRADE.

IV Estimation

We perform firm- and industry-level regressions. The baseline estimation equation at firm-level is the following:

$$Y_{ijt} = \beta_0 + \beta_1 CIP_{jt} + X_{ijt} + \alpha_i + \delta_t + \varepsilon_{ijt} \tag{3}$$

Where i, j and t index firms, industries and time, respectively; α_i is a firm fixed effect; δ_t is a time fixed effect and ε_{ijt} is a mean-zero disturbance.

The main outcome variables Y_{ijt} are firm total employment (number of employees), value of products sold (revenue) and firm's exit rate. In the latter case, an observation takes the value 1 in the year t if the firm shuts down in the following year $t+1$, and 0 otherwise. We include an extensive set of firm-level control variables (TFP, capital intensity, import/export status) and import penetration from other countries different from China (which varies at industry-year level). The main variable of interest is China import penetration CIP_{jt}, which varies by 4 digits industry-year level. In some specificacions we also include region-year and sector-year fixed effects in order to control for time-varying shocks affecting differently specific regions or sectors[14]. These regressions exploit within sector (region) variation in CIP over time.

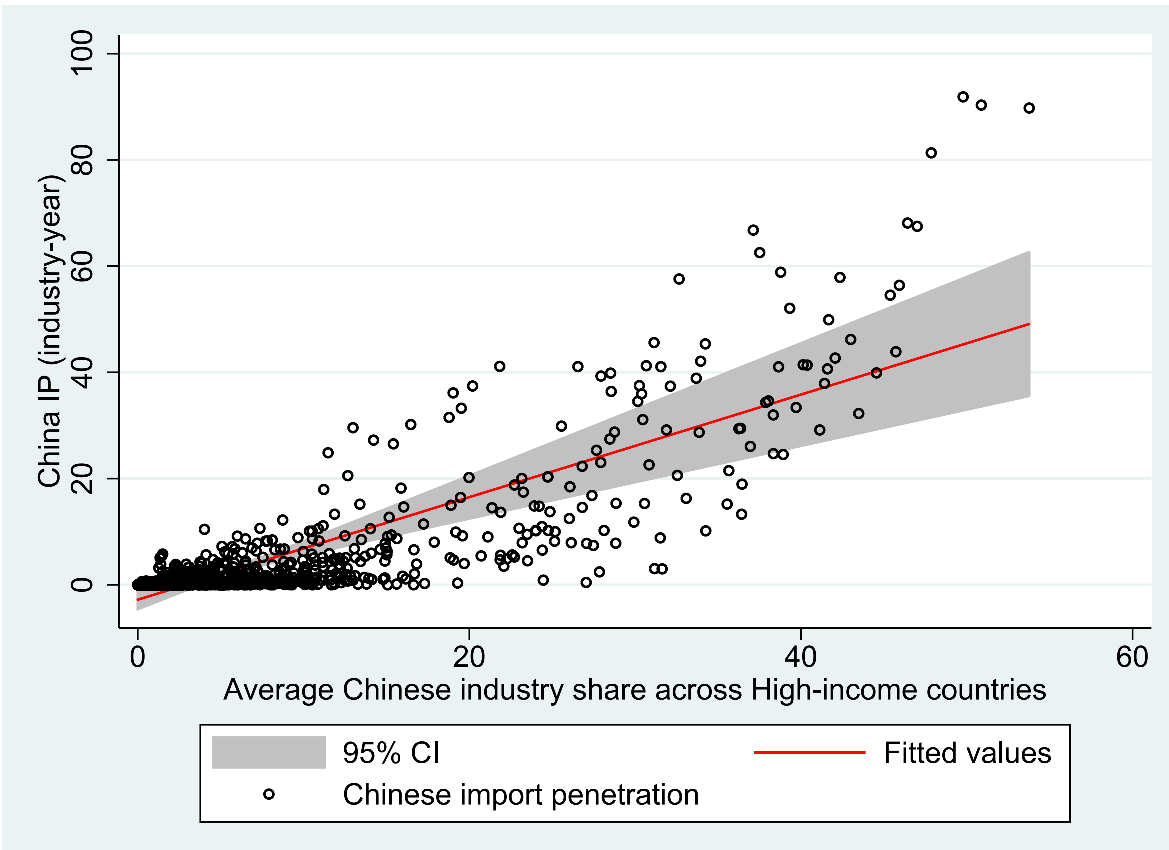
CIP_{jt} is potentially endogenous because industry demand shocks affecting firm and labor market outcomes are potentially correlated with demand for imports. To account for this endogeneity concern we apply an instrumental variable strategy that have also been used by other recent papers in the literature (e.g. Autor et al. 2013 2014, Acemoglu et al. 2016 and Bloom et al. 2015). We instrument CIP_{jt} with the simple average China's industry import shares across a group of high-income countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland[15]. This instrument captures supply-driven shocks inherent to the Chinese economy that allowed China to gain market share in some of the most competitive industrial countries within specific industries over time. Then we estimate equation (3) by Two-Stages

[14]We construct 10 broad sectors, where each sector includes a set of similar manufacturing industries: Food/tobacco (14), Textile/apparel/leather (10), Wood/furniture (6), Paper/print (7), Chemical/petroleum (6), Plastic/rubber/glass (4), Metal (7), Machines/electrical (13), Transportation (3), Toys/other (8).

[15]This is the same group of countries used by Autor et al. (2013 2014). Although, we also tested the robustness of our results to alternative groups of countries such as G7, OECD, Latin America and Mercosur countries.

Least Squares (2SLS). First-stage regression shows a strong predictive power of the instrument, with a coefficient of 0.96 (0.13) and R-squared of 0.70 (see Figure V). The identifying assumptions are that: (i) China export growth is exogeneous (driven by TFP, infraestructure, migration, etc.), and (ii) industry demand shocks affecting product demand are uncorrelated between Chile and this group of high-income countries.

FIGURE V
FIRST-STAGE REGRESSION



Notes. Each point represents an industry-year combination. The high-income countries used to construct the average Chinese industry share are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland, which are the same group used by Autor et al. 2014. The 95% confidence interval is based on std. errors clustered by two-digit industries (ISIC Rev. 3). The slope coefficient is .96 with std. error .13, and the regression has an R-squared of .70. Sources: INE-ENIA and UN-COMTRADE.

A potential threat to this identification strategy could arise if Chile's industry demand shocks are correlated with high-incomes' ones. Given that Chile is very different to these industrialized economies we expect this situation to be very unlikely. Furthermore, the specifications that include sector-year fixed effects turn this situation even more unlikely because these regressions would control for any contemporaneous import demand shock affecting both Chile and this group of countries' specific sectors.

One may think a situation where an income shock to consumers from all these countries affects demand for Chinese imports. Time fixed effects will capture any shock evenly distributed across industries. Even more, sector-year fixed effects will capture any shock evenly distributed across industries within sectors. The only potential concern is the existence of shocks unevenly distributed across specific industries within sectors that are common to Chilean consumers and those in high-income countries. For example, a common positive shock that increase demand in the textile sector will not be a problem. Instead, if the common shock affects handbags and footwear differently there will be a violation of our identifying assumption. Once again, we think the probability of shocks correlated between Chile and high-income countries in very specific industries is quite small.

The second set of firm-level regressions are aimed to capture the existence of heterogenous effects of CIP on the main outcomes of interest, as a function of initial firm total factor productivity (TFP), which is unobserved and presents two main estimation challenges. First, input choices are correlated with firm level productivity (not observed by the econometrician) and will generate an endogeneity problem (simultaneity bias) when using the classic OLS estimator. Second, firm-level datasets usually have a considerable level of attrition, since firm exit is likely to be correlated with firm productivity if firms have some knowledge of their future productivity prior to exiting (selection bias). To estimate TFP we follow recent advances in the literature given by the method proposed by Ackerberg, Caves and Frazer (2015).

We use the estimated firm-level TFP in two types of regressions. First, in the main equation regression we add firm initial TFP interacted with CIP:

$$Y_{ijt} = \beta_0 + \beta_1 CIP_{jt} + \beta_2 CIP_{jt} * TFP_{ij0} + X_{ijt} + \alpha_i + \delta_t + \varepsilon_{ijt} \tag{4}$$

Where TFP_{ij0} refers to firm's estimated TFP in the first year we observe each firm, and the rest of the equation is the same as in (1). Estimated TFP is normalized by 2 digits industry-year averages[16]. The inclusion of initial TFP interaction with CIP is key to capture heterogeneous firm-level response to the competitive shock. We decided to fix TFP at firm initial level in order to avoid a potential confounding impact of CIP on TFP. Another potential bias arise from new firms that begin to operate after the

[16]This normalization allows us to take into account relative differences in TFP for firms in the same industry-year combination. Our results remain virtually unchanged without this normalization.

initial year 1995. The entry rate in our sample is on average 8.3% per year. All our results are robust to drop this subset of firms or use current instead of initial TFP.

Then we construct quintiles of the normalized TFP distribution and estimate the baseline specification of equation (3) separately for each quintile. We construct quintiles of firm-level average TFP over time within each 2 digits industries given that we want to evaluate the existence of heterogeneous effects of CIP on firms belonging to narrowly defined industries. Results are robust to construct quintiles that vary by year so firms can scale up or down in the TFP distribution and to build quintiles within broad sectors or with overall TFP distribution.

We follow a similar strategy for industry-level regressions. This regressions are run just with motivational purposes, given that we can not control for the many unobserved potencial confounders that we do with firm-level regressions. We estimate the following regression equation:

$$Y_{jt} = \beta_0 + \beta_1 CIP_{jt} + \overline{X}_{jt} + \alpha_j + \delta_t + \varepsilon_{jt} \tag{5}$$

Where j and t index industries and time, respectively; α_j is an industry fixed effect, δ_t is a time fixed effect and ε_{jt} is a mean-zero disturbance. In this case, the main outcome variables Y_{jt} are total number of employees, total revenue and total number of firms within each industry j over time t. We include industry-year controls (average TFP, average capital intensity, share of firms importing/exporting). If we think in terms of total employment, this specification will capture the net effect of growing CIP on industry employment because of both the variation of firm-level employment (intensive margin) and the open/closure of new/existing firms (extensive margin).

We cannot account for general equilibrium effects with this identification strategy. For example, imagine a firm providing some service to a directly exposed manufacturing firm. We would expect that part of the China shock also affects this firm's demand for services indirectly. Although, we are unable to capture indirect revenue/employment effects via input-output linkages across upstream/downstream industries. Additionally, we would expect displaced workers of exposed industries to look for employment in non-exposed industries (positive reallocation effects) and presume that other sectors might also be influenced by a potentially negative Keynesian aggregate demand multiplier effect. Some recent papers find evidence in favor of this local labor market effects (e.g. Autor et al. 2013, Acemoglu et al. 2016 and Dix-Carneiro and Kovak

2017).

V Results

V.I Baseline Estimates

Tables II, III and IV present baseline estimates of equation (3) for log total employment, log total revenue and firm's exit rate. In column (1) of each table we present the OLS estimator with firm fixed effects, year fixed effects and a control variable for import penetration from other countries different from China[17]. Then, in column (2) we present the same specification but estimated by 2SLS. The 2SLS estimate for CIP increases its magnitude in the three tables, which is consistent with the existence of a positive correlation between Chile's industry import demand shocks and Chile's industry labor demand and firm sales that biases the OLS estimate toward zero. Columns (3) to (5) include firm-level control variables subsequently (TFP, K/L ratio and importing/exporting status). All these control variables have the expected signs. There is a correlation between the increase in firm's TFP and: (i) rising demand for workers (ii) increasing revenues (iii) lower probability of exit the market. The same is valid for the importing and exporting conditions. Firms with increasing K/L ratios have increasing revenues, decreasing demand for workers (by construction) and a higher chance of exit the market. Given that we are including firm-level fixed effects, these regressions capture correlations within firms over time. In this context, given that employment is more mobile than capital we expect exiting firms to contract in terms of workers before they leave the market.

Columns (6) and (7) include region-year fixed effects and sector-year fixed effects to control for potential unobserved time-varying shocks affecting specific regions or sectors. These regressions exploit within sector (region) variation in CIP over time. The inclusion of sector-year fixed effects in column (7) increases significantly the magnitude of the standard errors. This is explained for the fact that most CIP occurred at the level of broad manufacturing sectors[18]. Although, the remaining variation across industries over time within sectors is enough to capture the causal effect of the competitive shock on firms' responses.

All these additional controls in columns (3) through (7) do not affect either the significance or the sign of the estimated CIP coefficient. Furthermore, the magnitude

[17]This variable varies at 4-digit ISIC Rev. 3 industry-year level and is constructed analogously to Chinese import penetration described in Section II.

[18]A simple descriptive regression of CIP on sector-year dummies has an R-squared of 0.67.

of the estimated coefficient presents little variation across 2SLS specifications[19].

Our estimates indicate that an increase of 1 p.p. in Chinese import penetration decreases firm total employment by 0.89%, reduces firm total revenue by 1.87% and increases probability of firm's exit by 0.65 p.p. To evaluate the economic magnitude of these estimates we compare the observed firm-level employment with the counterfactuals that would have ocurred in the absence of increasing CIP. The counterfactual employment L_{ijt}^{sim} is given by:

$$L_{ijt}^{sim} = L_{ijt}[1 + (1 - \exp(\hat{\beta}_L * \Delta CIP_{jt} * R_{IV}^2))] \tag{6}$$

Where $\hat{\beta}_L$ is the 2SLS coefficient estimate for CIP from equation (3) and ΔCIP_{jt} is within industry change in CIP over time adjusted by the partial R-squared from the first-stage regression in order to capture the fraction of increasing CIP explained by Chinese supply shock (as in Autor et al. 2013 and Acemoglu et al. 2016). In our sample, exposed (non-exposed) industries had 132,415 (156,508) employees in 1995 and ended up with 100,581 (197,139) in 2006[20]. While many potential factors could explain this divergent pattern, this counterfactual analysis predicts that had CIP not grown over this period, overall employment contraction in exposed industries would have been 34.4% lower than the observed one. It is worth noting that this counterfactual is a *ceteris paribus* partial-equilibrium analysis.

[19]The only exception is column (7) of table II. In this case, the magnitude of CIP estimate doubles when we include sector-year fixed effects. This is consistent with time-varying sector shocks that are positively correlated with firms' revenues.

[20]These industries are the same group we used in Figure III of Section I.

TABLE II

ESTIMATES FOR EMPLOYMENT, 1995-2006

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
China import pen.	-0.0071***	-0.0091***	-0.0091***	-0.0104***	-0.0101***	-0.0084***	-0.0089**
	(0.0012)	(0.0022)	(0.0022)	(0.0024)	(0.0024)	(0.0021)	(0.0042)
Other import pen.	-0.0005	-0.0005	-0.0002	-0.0002	-0.0001	0.0002	0.0001
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0004)
TFP			0.1333***	0.0867***	0.0837***	0.0839***	0.0852***
			(0.0162)	(0.0156)	(0.0157)	(0.0155)	(0.0151)
Log(K/L ratio)				-0.0782***	-0.0789***	-0.0844***	-0.0840***
				(0.0101)	(0.0102)	(0.0107)	(0.0107)
Importing					0.0449***	0.0431***	0.0416***
					(0.0126)	(0.0123)	(0.0118)
Exporting					0.0865***	0.0844***	0.0857***
					(0.0131)	(0.0136)	(0.0136)
N	44,346	44,346	44,346	44,346	44,346	44,346	44,346
Firms	6,681	6,681	6,681	6,681	6,681	6,681	6,681
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Region x Year FE	-	-	-	-	-	YES	YES
Sector x Year FE	-	-	-	-	-	-	YES

Notes. Employment is the log of total workers. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

TABLE III

ESTIMATES FOR REVENUE, 1995-2006

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
China import pen.	-0.0094***	-0.0115***	-0.0113***	-0.0097***	-0.0093***	-0.0087***	-0.0187**
	(0.0022)	(0.0042)	(0.0036)	(0.0034)	(0.0034)	(0.0028)	(0.0083)
Other import pen.	-0.0023**	-0.0023**	-0.0001	-0.0002	-0.0002	-0.0000	0.0001
	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0008)
TFP			0.9832***	1.0404***	1.0358***	1.0350***	1.0432***
			(0.0242)	(0.0270)	(0.0271)	(0.0266)	(0.0260)
Log(K/L ratio)				0.0960***	0.0950***	0.0944***	0.0969***
				(0.0058)	(0.0059)	(0.0059)	(0.0055)
Importing					0.0901***	0.0890***	0.0878***
					(0.0107)	(0.0108)	(0.0107)
Exporting					0.1001***	0.0968***	0.0896***
					(0.0150)	(0.0149)	(0.0149)
N	44,346	44,346	44,346	44,346	44,346	44,346	44,346
Firms	6,681	6,681	6,681	6,681	6,681	6,681	6,681
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Region x Year FE	-	-	-	-	-	YES	YES
Sector x Year FE	-	-	-	-	-	-	YES

Notes. Revenue is the log of total sales of manufactured products deflated using a 4 digit industry deflator obtained from Chile's Institute of Statistics. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

TABLE IV

ESTIMATES FOR FIRM'S EXIT RATE, 1996-2005

	OLS	2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
China import pen.	0.0029***	0.0043***	0.0043***	0.0045***	0.0044***	0.0056***	0.0065***
	(0.0006)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0016)
Other import pen.	-0.0005***	-0.0005***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
TFP			-0.0671***	-0.0610***	-0.0602***	-0.0585***	-0.0586***
			(0.0077)	(0.0077)	(0.0076)	(0.0075)	(0.0073)
Log(K/L ratio)				0.0101***	0.0103***	0.0069**	0.0069**
				(0.0034)	(0.0034)	(0.0030)	(0.0031)
Importing					-0.0175**	-0.0186***	-0.0188***
					(0.0072)	(0.0071)	(0.0070)
Exporting					-0.0206***	-0.0212***	-0.0233***
					(0.0073)	(0.0069)	(0.0067)
N	36,766	36,766	36,766	36,766	36,766	36,766	36,766
Firms	6,013	6,013	6,013	6,013	6,013	6,013	6,013
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Region x Year FE	-	-	-	-	-	YES	YES
Sector x Year FE	-	-	-	-	-	-	YES

Notes. Exit=0 in active years and =1 one year before a firm leaves the panel. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

V.II Heterogeneous Effects

Table V presents 2SLS estimates of equation (4) for log total employment (cols. 1-2), log total revenue (cols. 3-4) and firm's exit rate (5-6). Control variables are the same described in the previous subsection. The difference between even and uneven columns is that the formers include region-year and sector-year fixed effects. In order to test the existence of heterogeneous effects of CIP on our variables of interest equation (4) includes an interaction term of CIP with firm level initial TFP. We decided to fix TFP at firm initial level in order to avoid a potential confounding impact of CIP on TFP.

Our estimates indicate that the impact of CIP on employment, revenues and exit decreases in magnitude as firms initial TFP is higher. This can be seen by looking at the estimated coefficient of the interaction term which has the opposite sign than the main effect in all three cases. The marginal effect of CIP on employment/revenue/exit for a firm located at the 25th percentile of its sector TFP distribution is 2.69/1.66/2.12 times bigger than this marginal effect for a firm situated at the 75th percentile. For example, an increase in 1 p.p. of CIP reduces firm employment in 1.33% for a firm located at the 25th percentile, while this effect is 0.47% for a firm situated at the 75th percentile.

In Figures VI to VIII we show the CIP coefficient estimates from our baseline regression equation (3) (specification in cols. 7 with full controls) when we run it separately for each quintile of sector TFP distribution. These estimates show the same pattern that we noted with the interaction regressions: effects decrease for firms that are more productive in their sectors of activity. Even more, effects of CIP on firm employment and revenue are not statistically significant for firms located in the highest quintile of within sector TFP distribution.

We can interpret these results in a similar way as we did with interaction regressions. The estimated coefficient of CIP on employment/revenue/exit for a firm in the first quintile of its sector TFP distribution is 1.78/1.44/1.72 times bigger than the estimated coefficient for a firm in the fourth quintile[21]. For example, an increase in 1 p.p. of CIP reduces firm employment in 1.21% for a firm in the first quintile, while the effect is 0.68% for a firm in the fourth quintile.

[21] We use the fourth instead of the fifth quintile because estimated coefficients are not statistically different from zero for employment and revenue.

TABLE V

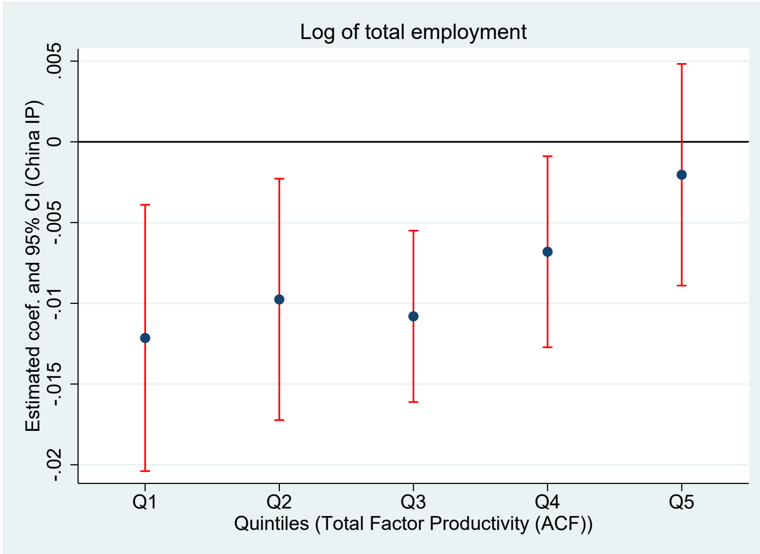
Estimates With TFP Interactions (2SLS)

	Log total employment		Log total revenue		Firm's exit rate	
	(1)	(2)	(3)	(4)	(5)	(6)
China import pen.	-0.010***	-0.0090**	-0.010***	-0.0189**	0.0045***	0.0065***
	(0.002)	(0.0042)	(0.003)	(0.0083)	(0.0010)	(0.0016)
China IP x TFP_0	0.013***	0.0126***	0.015***	0.0138***	-0.0075***	-0.0069***
	(0.004)	(0.0041)	(0.005)	(0.0046)	(0.0017)	(0.0016)
Other import pen.	-0.000	0.0001	-0.000	0.0001	-0.0006***	-0.0006***
	(0.001)	(0.0004)	(0.001)	(0.0008)	(0.0001)	(0.0002)
TFP	0.087***	0.0889***	1.040***	1.0473***	-0.0619***	-0.0602***
	(0.016)	(0.0154)	(0.027)	(0.0262)	(0.0075)	(0.0072)
Log(K/L ratio)	-0.079***	-0.0842***	0.095***	0.0968***	0.0102***	0.0069**
	(0.010)	(0.0108)	(0.006)	(0.0055)	(0.0035)	(0.0032)
Importing	0.045***	0.0416***	0.090***	0.0878***	-0.0176**	-0.0190***
	(0.013)	(0.0118)	(0.011)	(0.0103)	(0.0072)	(0.0070)
Exporting	0.090***	0.0894***	0.104***	0.0937***	-0.0229***	-0.0255***
	(0.013)	(0.0134)	(0.015)	(0.0146)	(0.0077)	(0.0071)
N	44,346	44,346	44,346	44,346	36,766	36,766
Firms	6,681	6,681	6,681	6,681	6,013	6,013
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Region x Year FE	-	YES	-	YES	-	YES
Sector x Year FE	-	YES	-	YES	-	YES

Notes. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE VI

Estimates by Quantiles of TFP Distribution



Notes. Estimated coefficientes and 95% confidence intervals obtained from five regressions that relate log firm total employment to Chinese import penetration. Quintiles of TFP distribution are constructed separately for each sector. Regressions include firm-level control variables (TFP, K/L ratio, import/export status), time, year, region-year and sector-year fixed effects. The vector of controls is the same used in column (7) of Table I. Robust standard errors clustered by industries.

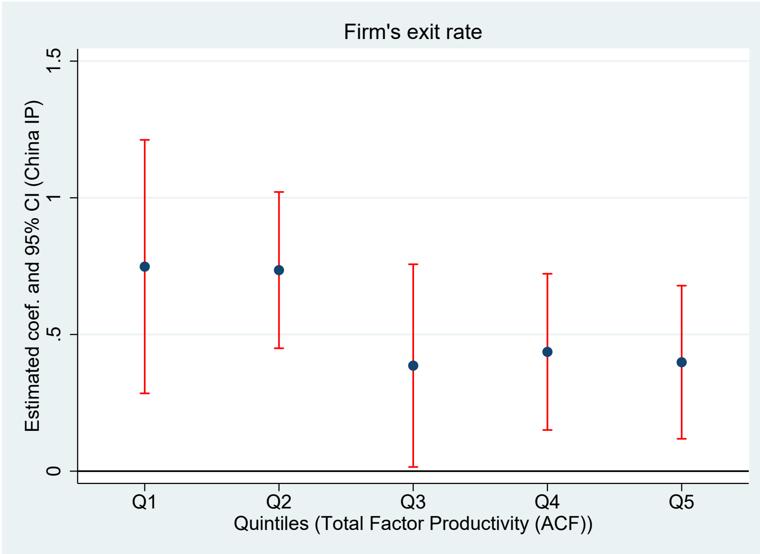
FIGURE VII

Estimates by Quantiles of TFP Distribution

Notes. Estimated coefficientes and 95% confidence intervals obtained from five regressions that relate log firm total revenues to Chinese import penetration. Quintiles of TFP distribution are constructed separately for each sector. Regressions include firm-level control variables (TFP, K/L ratio, import/export status), time, year, region-year and sector-year fixed effects. The vector of controls is the same used in column (7) of Table II. Robust standard errors clustered by industries.

FIGURE VIII

ESTIMATES BY QUANTILES OF TFP DISTRIBUTION



Notes. Estimated coefficientes and 95% confidence intervals obtained from five regressions that relate firm's exit probability to Chinese import penetration. Quintiles of TFP distribution are constructed separately for each sector. Regressions include firm-level control variables (TFP, K/L ratio, import/export status), time, year, region-year and sector-year fixed effects. The vector of controls is the same used in column (7) of Table III. Robust standard errors clustered by industries.

V.III Robustness Checks

We perform robustness exercises in several dimensions to check the sensivity of the results. First, we drop 5% tails of the distribution of CIP, employment, revenue and K/L ratio, separately. Our results are virtually unchanged when we eliminate these outliers from the estimation sample. Second, we construct a similar instrumental variable but considering different set of countries: OECD, G7, Latin America and Mercosur member states. None of our results change when we instrument CIP with the China's average industry imports share for these different groups of countries. Third, results are robust to use a non-normalized firm-level TFP or to normalize TFP with sector averages instead of 2 digit industry averages. Also, results are robust to using labor productivity (revenue per worker) instead of TFP as a measure of firm productivity. Finally, our results also remain virtually unchanged if we estimate them for the full sample. Remember that our sample contains 78 out of 111 industries which represent about two thirds of total manufacturing employment and revenue. Naturally, we can not include some of the key control variables such us capital intensity or TFP, because we lack the key variables for some of these firms.

VI Conclusion

This paper has offered substantial evidence that there are considerable short-term firm-level costs of adjustment in the face of a trade induced competitive shock. Particularly, it has shown robust evidence that these costs are unevenly distributed across firms, being the less productive firms the ones that suffered the most.

Using a panel of Chilean manufacturing firms for the period 1995-2006, we found that firms belonging to industries more exposed to growing Chinese import penetration dismissed more workers, reduced their sales and faced a higher probability of exiting the market than comparable firms in less exposed industries.

There is considerable heterogeneity across firms in the adjustment to Chinese import competition. Firms with higher initial productivity levels were better able to withstand this competitive shock. These results are consistent with the idea that more productive firms can escape competition from low-wage countries because they produce higher quality products that do not compete directly with products imported from these countries.

Our findings are especially relevant for developing countries with visible problems of unemployment or missalocation of productive factors, where an important share of the labor force is employed in low-competitive sectors characterized by relatively high presence of low-productivity firms.

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VII Appendix

TABLE AI
Industry Estimates for Employment, 1996-2005

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
China import pen.	-0.005**	-0.006**	-0.006**	-0.006**	-0.005*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Other import pen.	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg. TFP			0.165**	0.165**	0.097
			(0.065)	(0.065)	(0.069)
Avg. Log(K/L ratio)				0.018	-0.008
				(0.019)	(0.012)
Share importing					0.450***
					(0.121)
Share exporting					0.505***
					(0.166)
N	936	936	936	936	936
Industries	78	78	78	78	78
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Notes. Dependent variable is the log quantity of total workers within an industry. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TABLE AII

Industry Estimates for Revenue, 1996-2005

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
China import pen.	-0.029***	-0.020***	-0.019***	-0.017***	-0.016***
	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)
Other import pen.	-0.010**	-0.010**	-0.007*	-0.008**	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Avg. TFP			0.618***	0.611***	0.570***
			(0.120)	(0.109)	(0.112)
Avg. Log(K/L ratio)				0.218***	0.203***
				(0.065)	(0.063)
Share importing					0.239
					(0.323)
Share exporting					0.331
					(0.210)
N	936	936	936	936	936
Industries	78	78	78	78	78
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Notes. Dependent variable is the log quantity of total workers within an industry. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

TABLE AIII

Industry Estimates for Number of Firms, 1996-2005

	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
China import pen.	-0.017***	-0.016***	-0.016***	-0.017***	-0.016***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Other import pen.	-0.003***	-0.003***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg. TFP			-0.150*	-0.149*	-0.106
			(0.080)	(0.080)	(0.093)
Avg. Log(K/L ratio)				-0.010	0.009
				(0.047)	(0.033)
Share importing					-0.484**
					(0.217)
Share exporting					-0.166
					(0.203)
N	936	936	936	936	936
Industries	78	78	78	78	78
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Notes. Dependent variable is the log quantity of firms within an industry. Chinese import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. This variable is instrumented with the average Chinese industry import shares across a subset of high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). Industries defined at 4 digits ISIC Rev. 3. Other import pen. measured as total value of non-China imports divided by domestic absorption. TFP measured following Ackerberg, Caves and Frazer (2015). Importing (exporting) means exports (imports) >0. Regions are the country's first-level administrative division. Industries are grouped into 10 broad manufacturing sectors. Robust standard errors clustered by industries. *** p$<$0.01, ** p$<$0.05, * p$<$0.1.