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Abstract

We study the effect of a trade induced competitive shock given by rising import competition from China on Chilean manufacturing plants. For identification, we exploit the fact that, during 1995-2006, China import penetration (CIP) increased sharply in Chile, but this increment was quite different across manufacturing industries. We use Chinese export growth in high-income industry-country pairs as instrument for CIP. Our results suggest that plants in more exposed industries exhibit relative declines in revenue, employment and physical capital, and face a higher probability of exiting the panel than comparable plants in less exposed industries. All these effects are concentrated among establishments with low initial levels of productivity.

JEL Classification: F14, D22.

Keywords: Trade Shock, China Import Penetration, Manufacturing Plants, Chile, Productivity.

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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 sectors and to more productive firms within narrowly defined industries, increase the consumer surplus by means of pro-competitive gains and greater number of available varieties, and ease the access to foreign intermediate inputs, capital goods, and new technologies. We also know that reallocation is likely to create short- and medium-term losses that tend to be unevenly distributed across regions, industries, firms, and workers. 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, labor force characteristics, and the nature of institutions such as protection networks, labor market flexibility, and policy responses.

In this paper, we empirically characterize short-term plant- and industry-level responses to a trade induced competitive shock given by rising import competition from China. The remarkable 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's growth was driven by massive migration from rural to urban regions, strong investments in infrastructure, genuine increases in total factor productivity, and an export-oriented strategy that placed China as one of the world's leading producer of manufactures.[1] For identification, we exploit the fact that, during 1995-2006, China import penetration (measured as the total value of imports from China relative to domestic absorption) increased sharply in Chile, from 1.5% in 1995 to 9.9% in 2006, but this increment was quite different across manufacturing industries. For instance, sectors such as textiles, toys, and machines/electrical, present the highest rates of exposure to Chinese import competition, while sectors like food, paper, and chemicals remain barely exposed (see Figure 1).

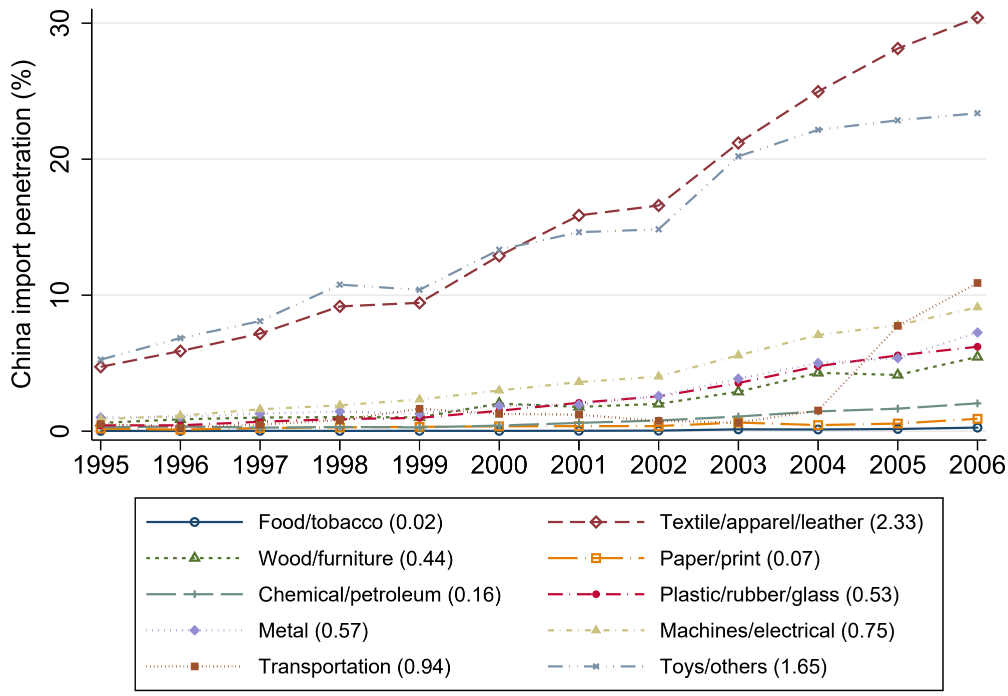
During the studied period, Chilean manufacturing employment decreased until 2001 and fully recovered by 2006 (see Figure 2). Notably, growth patterns across industries differ substantially, being those more exposed to Chinese import competition the ones that contracted the most and recovered the least.[2] Industries with low-exposure were 18.2% bigger in terms of employment in 1995, but this gap increased to 96% in 2006. While many potential factors may explain these divergent patterns, our estimates predict that the trade induced competitive shock given by rising import competition from China explains around one third of the relative employment contraction in exposed industries. Importantly, exploiting CIP variation across industries only delivers relative and not aggregate effects. Plants in non-exposed industries could also be affected by the China shock if there are

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

[2]We see a similar pattern if we plot the evolution of revenue, physical capital, and number plants with 10 or more employees, instead of employment. Thus, industries more exposed to growing CIP end up being smaller in terms of all these outcomes.

spillovers across plants, or other general equilibrium effects (e.g. reallocation of productive factors and aggregate demand multiplier effects).[3]

Figure 1
Evolution of China import penetration by sector



Notes. China import penetration measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. Manufacturing industries are defined at 4-digit International Standard Industrial Classification (ISIC) Rev. 3, and grouped into 10 broad sectors. Each sector includes a set of similar industries. Sector average annual change in China import penetration in brackets. Sources. INE-ENIA and UN-COMTRADE.

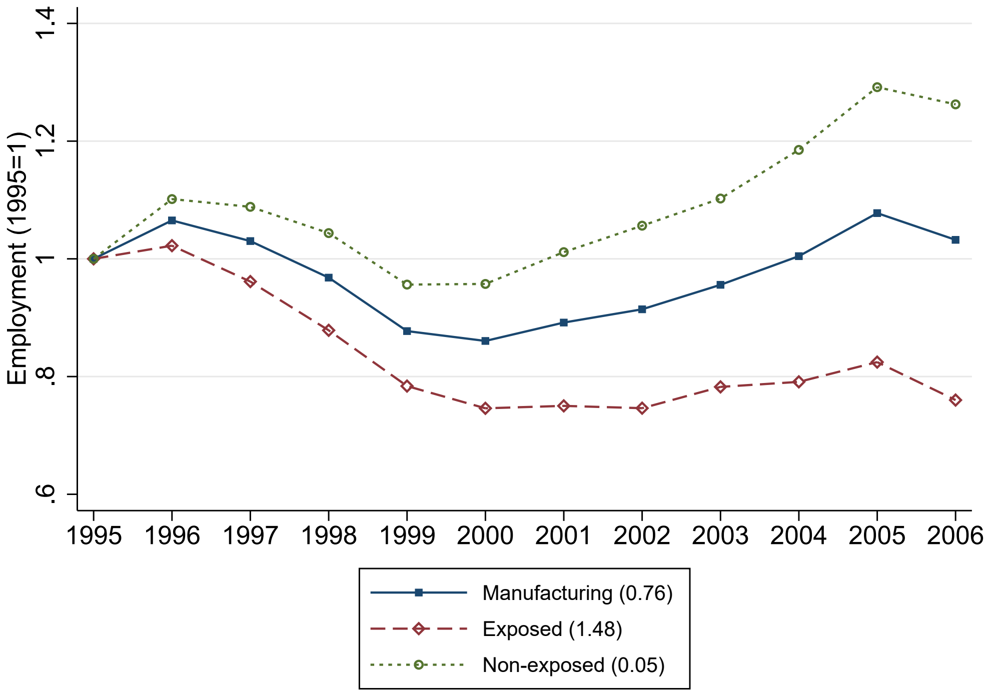
We use microdata on the universe of Chilean manufacturing plants during 1995-2006, obtained from the *Encuesta Nacional Industrial Anual (ENIA)*, collected annually by the Chilean *Instituto Nacional de Estadísticas (INE)*. The main module of the survey includes information on plant characteristics that allow us to estimate total factor productivity (TFP) at the plant-level, following the method proposed by Ackerberg, Caves, and Frazer (2015). This enables us to evaluate the hypothesis that Chinese import competition may have different effects across plants depending on their initial productivity levels. Our main outcomes of interest are revenue, employment, physical capital, and exit probability.[4] The panel structure of the data enables us to control for many unobserved potential confounders. To account for the endogenous nature of trade, we apply an instrumental variable strategy that has also been used by other papers in the literature (Autor, Dorn,

[3]In this line, we study one source of indirect effects using industry input-output linkages exploiting information from 1996 Chilean input-output tables (as studied by Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Pierce and Schott (2016) for the U.S.).

[4]Exiting plants are the ones leaving the sample, including both true plant closures and plant contractions below ten employees (given the ENIA survey design). Nevertheless, it is worth mentioning that the distribution of employment in the last year we observe plants has a mean of 52.5, median of 22, and standard deviation of 97.4.

and Hanson (2013), Autor, Dorn, Hanson, and Song (2014), and Acemoglu et al. (2016)).

Figure 2
Evolution of manufacturing employment



Notes. Exposed (non-exposed) industries are those above (below) percentile 50th of the average annual growth in China import penetration (CIP) during 1995-2006, which equals 0.2%. CIP measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. Average annual growth in CIP across industries of each group in brackets. Manufacturing industries defined at 4-digit ISIC Rev. 3. Sources. INE-ENIA and UN-COMTRADE.

We employ a secondary publicly available dataset from the United Nations Commodity Trade Statistics Database (UN-COMTRADE). It contains annual information on import/export values, quantities, partners, and product codes (at 6-digit Harmonized System international classification) reported by statistical authorities of close to 200 countries and regions. By merging this dataset with the Chilean plant-level data, we construct a measure of China import penetration (CIP), which varies at 4-digit industry-year level (International Standard Industrial Classification, Rev. 3). CIP is measured as the total value of imports from China divided by domestic absorption (production minus net exports).

Since CIP is endogenous because industry shocks affecting the outcome variables could be correlated with demand for imports, we instrument CIP with Chinese export growth in high-income industry-country pairs (as in Bernard, Jensen, and Schott (2006) and Autor et al. (2013, 2014)). This identification strategy aims to capture supply-driven shocks that made China gain market share across these economies over time.[5] First-stage

[5]The identifying assumptions are that: (i) Chinese export growth is exogenous (driven by TFP, infrastructure, migration, etc.), and (ii) industry import demand shocks are uncorrelated between Chile and high-income countries.

regressions show a strong predictive power of the instrument, with a coefficient of 1.95 (0.34) and R-squared of 0.68. We follow a similar strategy for industry-level regressions. Aggregating across plants within an industry avoids confounding aggregate effects with within industry reallocation of productive factors (e.g. workers that exit declining plants and get jobs in other establishments of the same industry). These regressions also capture the net effect of growing CIP on the studied outcomes because of both the variation at the plant-level (intensive margin) and the entry/exit of plants from the panel (extensive margin).

Our main results suggest that plants in industries more exposed to growing CIP exhibit relative declines in revenue, employment and physical capital, and face a higher probability of exiting the panel than comparable plants in less exposed industries. Specifically, a 1 p.p. increase in CIP reduces plant revenue by 0.70%, employment by 0.68%, and physical capital by 1.24%, and increases plant's probability of leaving the panel by 0.50 p.p, *ceteris paribus*, relative to comparable plants in less exposed industries. Our estimates indicate that the impact of CIP on these outcomes increases in magnitude for plants with low initial levels of productivity. For instance, the marginal effect of CIP on revenue for a plant located at the 10th percentile of within sector TFP distribution is 1.39 times bigger than the marginal effect for a plant situated at the 50th percentile. This ratio is equal to 1.60, 1.64, and 1.46, when comparing the marginal effect of CIP on employment, capital, and exit, respectively, across these plants. Moreover, these effects are not statistically significant for plants located in the highest quantiles of TFP distribution.

Recent papers have shown the relevance of studying both supply- and demand-side effects of the China shock (Costa, Garred, and Pessoa (2016), Artuc, Lederman, and Rojas (2015)). Our findings suggest that Chinese demand shock does not seem to have affected Chilean manufacturing plants neither directly or indirectly through manufacturing-primary sectoral-linkages. An underlying concern of neglecting China's demand is the potential overestimation of the effect of CIP on domestic plants if less exposed industries are experimenting greater demand from China. To account for this issue, we present two exercises to test the robustness of our results when excluding industries or plants that are benefiting directly from increasing demand from China, and all estimated coefficients remain virtually unchanged. Our results are also robust to account for pre-existing trends, exclude outliers, use alternative instrumental variables, employ different measures of plant's productivity, or expand the studied period, among others.[6]

This work is connected to the literature studying the effects of Chinese import competition on domestic firms, workers, and markets (Autor et al. (2013, 2014), Bloom, Draca, and Van Reenen (2015), Acemoglu et al. (2016), Pierce and Schott (2018)).[7] For instance, Autor et al. (2013) find that rising imports from China in the U.S between 1990 and 2007 caused higher unemployment, lower labor force participation, and lower wages

[6] We present these robustness exercises in the Appendix.

[7] This literature is also related to previous contributions studying the effect of rising imports from low wage countries on firm- and industry-level outcomes (Bernard et al. (2006) and Khandelwal (2010)).

in more exposed local labor markets. Relatedly, Autor et al. (2014) find that individuals who initially worked in manufacturing industries that experienced increasing Chinese import competition garnered lower cumulative earnings and spent less time working for their initial employers, among other negative effects, which were more pronounced for vulnerable workers. Bloom et al. (2015) show that European low-tech firms more affected by exogenous reductions in barriers to Chinese imports reduced employment and faced lower survival probabilities, while high-tech firms created more patents and raised their IT intensity, contributing to faster technical change and productivity growth. Meanwhile, Pierce and Schott (2018) find that U.S. manufacturing industries more exposed to the increase in Chinese import competition exhibited relative declines in investment, which were concentrated among establishments with low initial levels of productivity.

Our paper is perhaps most closely related to Alvarez and Claro (2009). Using Chilean plant-level data from 1990 to 2000, the authors show that imports from China have negatively affected employment growth on surviving plants, and increased the probability of shutting down. Relative to that paper, our contribution is threefold. First, we extend the analysis to focus on a more dramatic period of Chinese productivity growth (post-2000's). Second, we adopt the identification strategy originally proposed by Autor et al. (2013). Finally, we estimate plant-level TFP and document heterogeneous effects of Chinese competition on several outcomes. Also related to our work, Alvarez and Opazo (2011) study the impact of Chinese import penetration on relative wages in Chilean manufacturing plants during 1996-2005. They find a significant reduction in relative wages for those five sectors that experienced the largest increases in Chinese imports, and show that the effect was concentrated among small firms. We also differ from that paper in terms of identification strategy and outcome variables. Moreover, while these authors study differential effects by plants' size, we focus on plant's productivity. In a related paper for Mexico, Iacovone, Rauch, and Winters (2013) study the effect of increasing Chinese competition on selection and reallocation both at firm- and product-level, and document negative effects for small plants and non-core products. In a recent study, Medina (2018) finds that increasing Chinese competition in the Peruvian apparel industry induced firms to improve product quality, with this channel having positive effects on sales and employment. In this line, Fernandes and Paunov (2013) find that increasing import competition led Chilean manufacturing plants to increase unit values, and present complementary evidence suggesting that this price increase indeed capture product quality upgrading.

More generally, our work is also related to a growing body of literature studying the effects of trade on firm-level outcomes (Verhoogen (2008), Lileeva and Trefler (2010), Amiti and Davis (2011), Brambilla, Lederman, and Porto (2012), Caliendo, Mion, Opromolla, and Rossi-Hansberg (2017), Bastos, Silva, and Verhoogen (2018), Garcia-Marin and Voigtländer (2019)), and to recent papers for Latin American countries examining labor market adjustment to trade liberalization (Paz (2014), Cruces, Porto, and Viollaz (2018), Dix-Carneiro and Kovak (2017, 2019)).

The rest of the paper is organized as follows. Section II presents a brief historical background of Chile and China, and argues why Chinese imports represent a real competitive shock for Chilean manufacturing plants. We present the data and descriptive statistics in Section III. Section IV discusses the estimation strategy. We analyze the main empirical findings in Section V. We finish with some concluding remarks in Section VI, and present additional results in the Appendix.

II Background

II.1 Chile

After a period of state intervention and the 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 reforms throughout 1974-1979. As part of the trade liberalization program, Chile eliminated most non-tariff barriers (NTBs) and reduced tariffs significantly.[8] All these reforms positioned Chile as one of the most trade oriented economies of Latin America in the beginning of the 1990s. For instance, trade to GDP ratio for Chile was 61.8% in 1990 compared to an average ratio of 33% across Latin American countries.[9]

Another aspect of reforms focused on labor market regulations. The government banned unions and replaced collective bargaining with a wage setting plan.[10] 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. A few modifications in the Labor Code were introduced in 1991. 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. The new changes in labor laws were implemented in December 2001. While this reform increased the rights to collective bargaining, it also extended some margins of flexibility related to hiring practices and apprenticeships, part-time jobs, and temporal contracts. Besides some changes in the compensation scheme, these reforms still remain in practice.

Overall, we see Chile as a small open economy with a relatively flexible labor market. The Chilean case provides a nice scenario to study the causal impact of a trade induced competitive shock on plant-level outcomes, exploiting the growing import penetration from one of the most competitive countries in the world.

[8] While some tariffs exceeded 100% in 1974, five years later they were reduced to a uniform ad-valorem tariff of 10%. 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. NTBs were not applied during this transitory period (see Levinsohn (1999) and Pavcnik (2002)).

[9] According to World Development Indicators from The World Bank.

[10] 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".

II.2 Chinese import competition

Beginning in the 1980s, China conducted a broad set of structural 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)). Alongside these reforms that promoted growth and trade, there was the country's accession to the World Trade Organization on December 2001, which gave China the permanent status of most-favored nation among the WTO members. According to World Development Indicators from The World Bank, China's exports to GDP ratio increased from 5.9% in 1980 to a peak of 36% in 2006.

Much of China's growth was driven by massive migration from rural to urban regions, strong investments in infrastructure, 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 et al. (2012), China had an average annual growth in manufacturing TFP of 8% over the period 1998-2007.

The export growth explained by the aforementioned factors, inherent to Chinese economic forces and institutions, provides a potential exogenous shock for firms and workers from all over the world. Particularly, given that China is characterized by exporting labor-intensive low-price consumption products, rising imports from China actually represents increasing competitive pressure for domestic manufacturing plants. Besides this point, one might argue that the increase in Chinese imports should not represent a competitive shock to domestic firms if they are substituting expensive intermediate inputs with cheaper inputs imported from China. Although this hypothesis might hold for some firms, Table 1 suggests that, on average, this effect should be dominated by the direct effect of competitive pressure. The table shows that Chilean imports from China are biased towards final consumption goods relative to imports from the rest of the world, which have a larger share of intermediate and capital goods.

It is worth mentioning that we work just with China instead of all low wage countries mainly for two reasons. First, China is by far the main country of origin within the list of low wage countries, representing on average more than 90% of total imports from these countries during the sample period. In dynamic terms, China became the second source of Chilean manufacturing imports in the year 2006 (reaching 14%), after United States (18.8%). In the first year of our sample, China was in the seventh position (3% of total imports), and gained participation mainly at the expense of United States, which went from 27% in 1995 to 18.8% in 2006 (see Table 2). Second, China exports manufacturing products at significant lower prices than other low wage countries.

Table 1
Composition of Chilean imports by origin

	Capital	Intermediate	Consumption	Other goods
U.S.	37.9	49.7	10.5	1.8
China	**10.5**	**19.8**	**69.7**	**0.1**
Brazil	30.1	49.6	16.3	4.0
Argentina	6.8	59.0	31.6	2.6
Germany	35.8	51.7	8.6	3.8
Spain	24.9	49.5	22.4	3.2
Italy	37.1	41.4	20.1	1.4
Low-wage	5.3	41.0	46.9	7.4
Rest	26.5	44.6	19.1	9.8
Weighted average	27.2	45.5	22.1	5.2

Notes. Average composition of Chilean imports during 1995-2006 by origin. To classify products we use the Broad Economic Categories. Low-wage are countries with less than 5% GDP per capita relative to U.S. during 1972-2001 (Bernard, Jensen, and Schott (2006)). Source. COMTRADE-UN.

Table 2
Evolution of Chilean import composition by origin

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
U.S.	27.1	26.8	25.9	25.6	24.1	23.3	21.7	19.0	16.6	17.0	18.7	18.8
China	**3.0**	**3.6**	**4.2**	**5.0**	**5.7**	**7.0**	**7.5**	**8.6**	**10.3**	**12.2**	**12.0**	**14.0**
Brazil	9.0	7.2	7.8	7.1	8.2	9.6	10.3	11.5	12.1	12.0	12.1	9.6
Argentina	6.3	6.3	6.3	6.9	7.9	8.6	8.9	10.5	10.6	10.5	9.7	9.1
Germany	6.0	5.0	5.3	5.3	5.2	4.4	5.1	5.5	4.3	4.2	4.5	4.0
Spain	3.5	3.7	4.0	4.4	3.5	3.1	3.4	3.2	2.7	2.6	2.3	2.3
Italy	3.9	3.8	4.4	4.5	4.4	3.1	3.2	2.7	2.4	2.2	1.9	2.0
Low-wage	0.3	0.4	0.5	0.5	0.9	1.0	1.0	1.0	0.9	0.8	0.7	0.8
Rest	40.9	43.1	41.6	40.8	40.2	39.9	38.9	37.9	40.2	38.5	37.9	39.3
Total	100	100	100	100	100	100	100	100	100	100	100	100

Notes. Evolution of the share of Chilean imports during 1995-2006 by origin. Low-wage are countries with less than 5% GDP per capita relative to U.S. during 1972-2001 (Bernard, Jensen, and Schott (2006)). Source. UN-COMTRADE.

III Data

The plant-level panel dataset is obtained from the *Encuesta Nacional Industrial Anual-ENIA* (Annual National Industrial Survey) collected annually by the Chilean *Instituto Nacional de Estadísticas- INE* (National Institute of Statistics).[11] ENIA covers the

[11] This dataset has also been used by other papers such as Levinsohn (1999), Pavcnik (2002), Levinsohn and Petrin (2003), Alvarez and Claro (2009), Brambilla, Lederman, and Porto (2017) and Garcia-Marin and Voigtländer (2019).

universe of manufacturing plants with 10 or more employees. We follow plants from 1995 to 2006, including plants that enter and exit the sample during this period. After 2007, the INE interrupted the panel structure of the data, alleging confidentiality issues regarding plant's identifiers, so we can not perform a plant-level analysis thereafter. Despite this issue, we can still perform industry-level regressions including more recent years in the sample period.[12]

The main module of the survey includes information on plant characteristics such as revenue, employment, spending on intermediate inputs and raw materials, wage bill, stock value of physical capital, import/export status, industry affiliation, and region of activity. The main outcomes of interest for our analysis are: value of products sold (revenue), number of employees, stock value of physical capital,[13] and plant's probability of exiting the panel. Note that exiting plants are the ones leaving the sample, including both true plant closures and plant contractions below ten employees (given the ENIA design). Nevertheless, the distribution of employment in the last year we observe plants has a mean of 52.5, median of 22, and standard deviation of 97.4. Importantly, these data allow us to estimate total factor productivity (TFP) at the plant-level, following the method proposed by Ackerberg et al. (2015). We present the production function estimates in section A.2 of the Appendix. This enables us to evaluate the hypothesis that Chinese import competition may have different effects across plants depending on their initial productivity levels.

The trade dataset is the United Nations Commodity Trade Statistics Database (UN-COMTRADE).[14] It contains information on import/export dollar-values, quantities, partners, and product codes (at 6-digit of the Harmonized System international classification) reported by statistical authorities of close to 200 countries and regions. By merging these data with the plant-level Chilean information we are able to construct a measure of China import penetration (CIP), which varies at the industry-year level (4-digit International Standard Industrial Classification, Rev. 3). CIP is measured as the total value of imports 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

[12]Results at the industry-level are robust to extending the sample period to 1995-2012 (see section A.4 of the Appendix). Although we could extend the analysis back to 1992 (which is the first year we count on COMTRADE data) we decided not to work with these three years mainly for three reasons. First, there were some methodological changes in the survey in 1995, like the change in plant's identifiers and in the revision of industrial classification (from ISIC Rev.2 to ISIC Rev. 3). Particularly, INE releases these data only since 1995. Second, INE has published industry-specific deflators for intermediate inputs, capital, and revenue for 1995-2009. Finally, CIP did not grow considerably between 1992 and 1994.

[13]Capital is the stock value of physical capital (discounted accumulated depreciation), and includes land, buildings, machinery, equipment, tools, and vehicles.

[14]This information is publicly available at https://comtrade.un.org/, and has also been used by many other papers such as Autor et al. (2013, 2014), Amiti and Khandelwal (2013), and Acemoglu et al. (2016).

industry j in year t, respectively.[15]

Additionally, we use this dataset to construct instrumental variables for CIP_{jt} as the simple average of China's industry import share across c different countries:

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

where M_{jct}^{China} is the total industry-year value of the imports from China in country c, while M_{jct}^{World} is the total value of imports in industry j in year t in country c. We calculate this industry-year index for high-income countries using the definition conducted by The World Bank.[16] Intuitively, this variable serves as an instrument for Chilean CIP if it is capable of capturing Chinese supply-driven shocks that made China gain market share across high-income countries.

In order to increase the quality of the data and avoid inconsistencies, we trim the sample in some dimensions. First, we eliminate those plants that do not report information on some input (labor, physical capital, intermediate goods) or the value of production. Second, we drop those plants that are present just in a single year or present gaps in reporting.[17] Finally, we work with industries having at least ten different plants over the sample period in order to avoid any bias resulting from industries that are not representative of the Chilean manufacturing sector.[18]

Table 3 presents the mean and standard deviation of the main variables of interest for all plants in the sample, and separately for plants in different quintiles of within sector TFP distribution. The table shows a positive association between plant's productivity and number of workers, physical capital, and trade participation, in line with previous findings in the literature (e.g. Bernard, Jensen, Redding, and Schott (2007)).[19] The first four rows of this table present statistics for the outcome variables and exhibit substantial variation both within plants of the same quintile and across plants belonging to different quintiles of within sector TFP distribution.

On average, every year 7.5% of plants fall below the threshold of 10 employees and, given the ENIA design, exit our panel. As we would expect, exit rates decrease with plant-level productivity. While 10.49% of plants in the first quintile exit the sample every year, this fraction diminishes to 5.48% for those plants in the fifth quintile. The average number of workers at the plant-level is 76. On average, plants in the fifth quintile are

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

[16] We also test the robustness of our results to alternative groups of countries (subset of high-income countries (Autor et al. (2013, 2014)), Middle-income (World Bank), and all countries in the World.

[17] We need continuous information about production and inputs because the estimation of TFP relies on the use of lagged variables as instruments (for details see Ackerberg et al. (2015)).

[18] These industries represent 1% of total employment and 0,25% of total value of production. Our results remain virtually unchanged if we include them in the analysis.

[19] The only exception is that physical capital is not increasing between quintiles one and two. This is mainly due to differences in machines and buildings. In the rest of variables these plants are relatively similar.

almost ten times larger in terms of employment and have a stock value of physical capital almost fifty times bigger than plants in the first quintile (215 vs. 22, and 9,152 vs. 195 constant 1995 U.S.$, respectively). Only 5.76% (8.95%) of plants in the least productive quintile export (import), while this fraction increases to 50.52% (48.35%) for plants in the most productive quintile.

Table 4 presents some descriptive statistics for the distribution of the independent variable (China IP) and the instrumental variable (China's import share across high-income countries). CIP has a mean of 4.89, a standard deviation of 11.76, and takes a value close to 0 for about a quarter of industries. A zero means that an industry presents no exposure to Chinese imports in that year, and this happens mainly in the food and tobacco sector. China's import share has a mean of 6.43 and a standard deviation of 6.77. Both variables grew significantly over the studied period. For instance, average CIP increased by a factor of 6.6, going from 1.5 in 1995 to 9.9 in 2006.

Table 3
Summary statistics of Chilean manufacturing plants by quintile of TFP

	Q1	Q2	Q3	Q4	Q5	Mean
Revenue	164	330	669	2,222	16,930	4,062
	(251)	(502)	(1,095)	(7,040)	(76,332)	(34,883)
Employment	21.91	27.06	38.41	77.72	215.32	76.07
	(29.85)	(30.66)	(38.4)	(137.22)	(273.73)	(156.95)
Physical capital	195	170	315	1,192	9,152	2,204
	(1,775)	(551)	(1,038)	(5,640)	(73,849)	(33,311)
Plant's exit (%)	10.49	7.71	6.98	6.83	5.48	7.50
	(30.64)	(26.67)	(25.48)	(25.23)	(22.77)	(26.33)
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)
Share exporting (%)	5.76	7.53	16.12	28.98	50.52	21.78
	(23.29)	(26.39)	(36.77)	(45.37)	(50.)	(41.28)
Share importing (%)	8.95	11.88	19.03	26.71	48.35	22.98
	(28.55)	(32.36)	(39.25)	(44.25)	(49.98)	(42.07)
N	8,859	8,873	8,871	8,873	8,864	44,340

Notes. Standard deviation in parenthesis. TFP calculated by the method proposed by Ackerberg, Caves and Frazer (2015) and normalized by average sector-year TFP. Quintiles constructed within 2-digit ISIC Rev. 3 industries. Exit =0 in active years, and =1 one year before a plant leaves the panel. Revenue, capital, and wage measured in millons of 1995 Chilean pesos. Importing (exporting) is a binary variable equal to 1 if the plant exports (imports) in the corresponding year. Average 1995 exchange rate: 396.8 pesos/U.S.$1. Sources. INE-ENIA and UN-COMTRADE.

Table 4
Summary statistics of Chinese imports

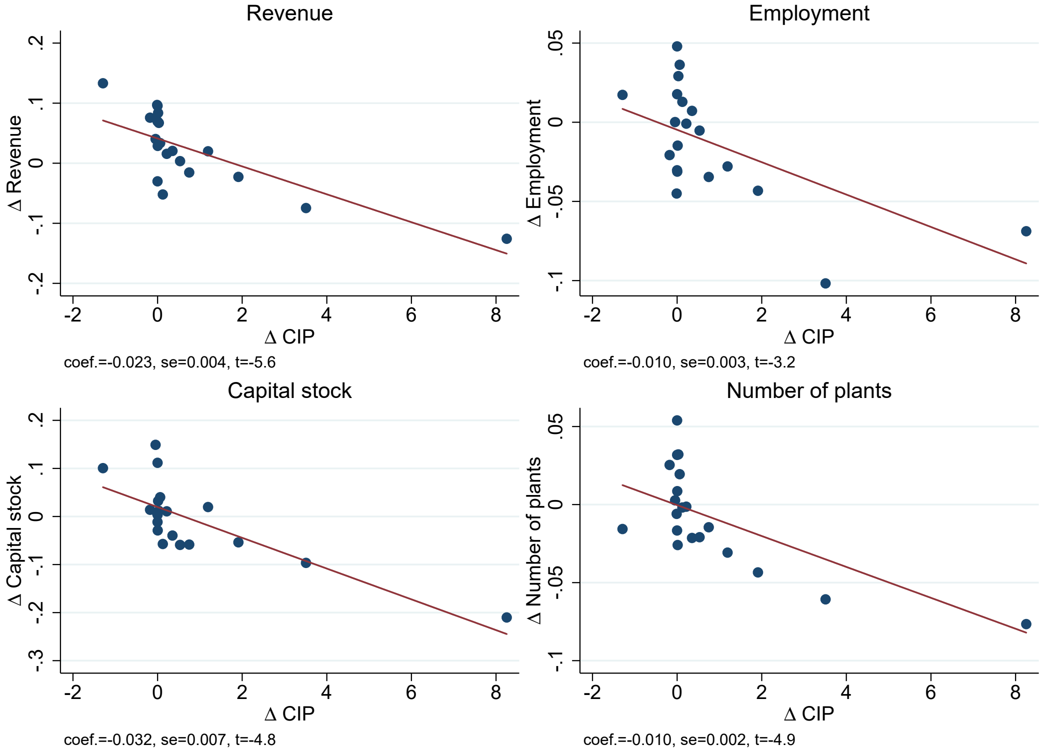
	China import penetration	China's import share in high-income countries
Mean	4.89	6.43
Standard deviation	11.76	6.77
Percentil 25	0.02	2.17
Percentil 50	0.42	3.65
Percentil 75	3.19	7.34
Minimum	0	0.09
Maximum	91.86	40.99

Notes. Descriptive statistics for a sample of 78 industries across 12 years (N=936). Industries defined at 4-digit ISIC Rev. 3. China import penetration (CIP) measured as total value of imports from China divided by domestic absorption (production minus net exports). China's import share is the average China's participation in total imports across high-income countries (defined using the classification conducted by The World Bank). Sources. INE-ENIA and UN-COMTRADE.

Before explaining the empirical strategy, we present a motivational figure that provides a non-parametric way of visualizing the relationship between increasing CIP and the main outcome variables, and allows to preview some of the main findings of the paper. Specifically, Figure 3 plots the unconditional correlation between the annual change in CIP and the log annual change in revenue, employment, physical capital, and number of plants with 10 or more employees at the 4-digit industry-level. In line with the motivation provided in Figure 2, this graph shows that increasing Chinese competition is negatively correlated with industry revenue, employment, physical capital, and number of active plants.[20] While this analysis is still merely descriptive, it provides a strong motivation to further investigate the existence of causal effects and measure the economic magnitude of the potential negative responses associated with the China shock.

[20]This exercise is robust to excluding the 10% upper tail of the CIP annual change distribution, which are the two "outliers" in the right-side of each plot. Note that each point represents 43 industry-year combinations. After excluding these observations, all coefficients remain statistically significant and the magnitude increases compared to Figure 3.

Figure 3
China import penetration and industry outcomes



Notes. Industry-year observations are grouped into 20 segments of the same size according to the variable in the horizontal axis, which is the average annual change in China import penetration (N=858). Each point represents the conditional expectation of each outcome variable for each segment. Outcome variables in the vertical axis are the average log annual change in industry revenue/employment/capital/number of active plants. The red line represents the linear prediction. Sources. ENIA-INE and COMTRADE-UN.

IV Empirical strategy

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

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

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

The main outcome variables Y_{ijt} are revenue, employment, physical capital, and plant's probability of exiting the panel. In the latter case, an observation takes the value 1 in the year t if the plant leaves the sample in the following year $t+1$, and 0 otherwise. The main variable of interest is China import penetration (CIP_{jt}), which varies at 4-digit industry-year level. We also include region-year fixed effects to control for time-varying shocks affecting differently geographically distant regions.[21] Additionally, the preferred

[21] Additionally, we present a robustness exercise including sector-year fixed effects to control for time-varying shocks affecting differently broad manufacturing sectors (see discussion in Section A.4 of

specification controls for pre-existing trends in industry-outcomes.[22]

CIP_{jt} is potentially endogenous because industry demand shocks affecting plant-level outcomes could be correlated with demand for imports. To account for this endogeneity concern, we apply an instrumental variable strategy that has also been used by other papers in the literature (e.g. Autor et al. (2013, 2014) and Acemoglu et al. (2016)). We instrument CIP_{jt} with the simple average of China's industry import share across high-income countries using the definition conducted by The World Bank.[23] Again, this variable aims to capture supply-driven shocks inherent to Chinese economy, that allowed the country to gain market share across some of the most competitive industrial countries of the world, within specific industries over time. Then, we use this variable to predict China import penetration in Chilean manufacturing industries.

First-stage unconditional correlation shows a strong predictive power of the instrument, with a coefficient of 1.37 (0.17) and R-squared of 0.75 (see Figure 4). Then, we estimate equation (3) by Two-Stages Least Squares (2SLS). The first-stage for the main specification includes plant and region-year fixed effects, and controls for pre-existing trends in industry-level outcomes (see Table 5). The table presents the first-stage of the baseline case without interaction (column 1), and the first-stage of the specification with heterogeneous effects (cols. 2 and 3), which we explain below. In the former case, the estimated coefficient for the IV (1.95) is precisely estimated (with a standard error of 0.34) and the R-squared of this regression is 0.68. In the latter case, the relevant coefficients are also statistically significant.

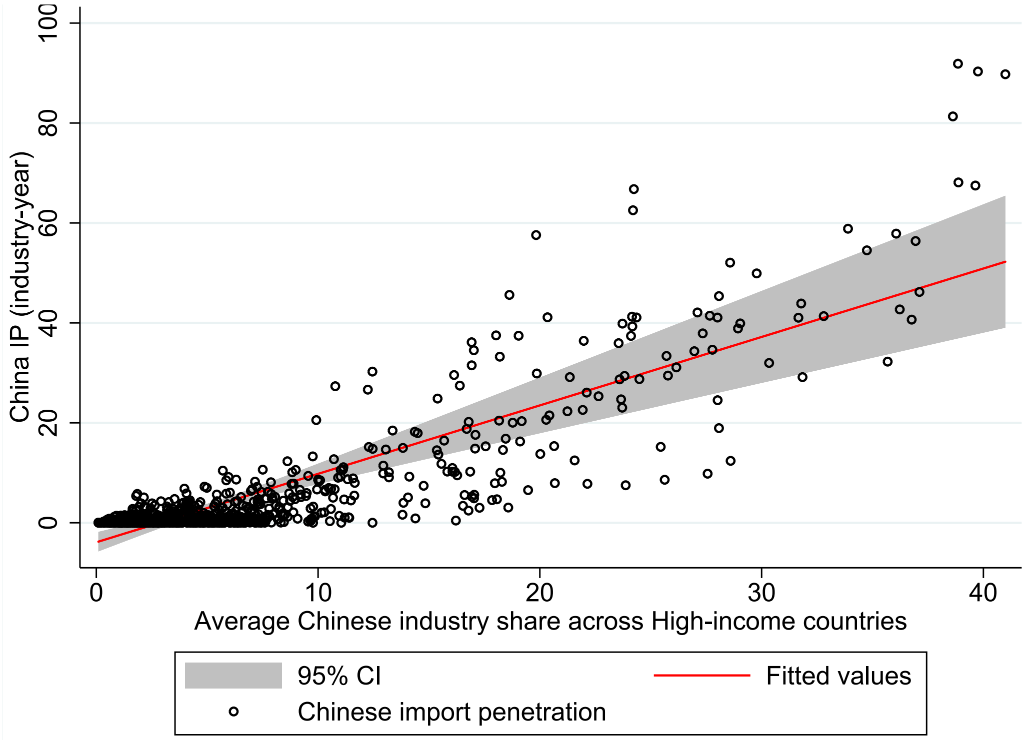
In all cases, first-stage regressions satisfy by large the F test of excluded instruments. The identifying assumptions are that: (i) China's export growth is exogenous (driven by TFP, infrastructure, migration, etc.), and (ii) industry demand shocks affecting product demand are uncorrelated between Chile and high-income countries. A potential threat to this identification strategy arises if Chile's industry demand shocks are correlated with high-incomes' ones. The specifications including sector-year fixed effects, presented as a robustness check in the Appendix, will account for any contemporaneous shock affecting both Chile and this group of countries' specific sectors (e.g. automation, changes in preferences, etc.). The only potential concern is the existence of industry shocks that are unevenly distributed across sectors, and are common between Chile and high-income countries. Overall, we think that the probability of industry-level common shocks is quite small.

the Appendix).

[22] Industry outcome pre-existing trend corresponds to the 5-year change (1989-1994) in each's dependent variable interacted with year fixed effects.

[23] We also test the robustness of our results to alternative groups of countries (subset of high-income countries (Autor et al. (2013, 2014)), Middle-income (World Bank), and all countries in the World.

Figure 4
First-stage correlation



Notes. Each point represents an industry-year combination. High-income countries defined using the classification conducted by The World Bank . The 95% confidence interval is based on standard errors clustered by 2-digit industries (ISIC Rev. 3). The slope coefficient is 1.37, standard error is 0.17, and the regression has an R-squared of 0.75. Sources. INE-ENIA and UN-COMTRADE.

The second set of plant-level regressions is aimed to capture the existence of heterogeneous effects of CIP on the outcome variables, as a function of plant's initial level of total factor productivity (TFP). To estimate TFP, we follow the method proposed by Ackerberg et al. (2015).[24] We present different estimates of the production function in Section A.2 of the Appendix.[25] Then, we run the following regression, including plant's initial level of TFP interacted with CIP:

$$Y_{ijt} = \beta_0 + \beta_1 CIP_{jt} + \beta_2 CIP_{jt} * TFP_{i0} + \alpha_i + \delta_t + \varepsilon_{ijt} \tag{4}$$

Where TFP_{i0} is the initial level of plant's TFP, and the remaining terms are the same as in equation (3). Estimated TFP is normalized by 2-digit industry-year averages.[26]

[24]Note that TFP 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). For an excellent exposition on these topics see the chapter of Ackerberg, Benkard, Berry, and Pakes (2007) in the Handbook of Econometrics, and the papers of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015).

[25]Results are robust to the use of different measures of TFP, and also to the use of a simple measure of labor productivity (sales per worker).

[26]This normalization allows us to take into account relative differences in TFP for plants in the same industry-year combination. Although, our results remain virtually unchanged without this normalization.

The inclusion of plant's initial level of TFP interacted with CIP is key to capture the heterogeneous effect of Chinese import competition on plant-level outcomes. We fix productivity at the initial level to avoid potential confounding impacts of CIP on TFP.

Table 5
First-stage regressions

	Main	Heterogeneous	
	Dep. Variable China IP	Dep. Variable China IP	Dep. Variable China IP*TFP_0
	(1)	(2)	(3)
China's import share in	1.9518***	1.9568***	-0.0317
high-income countries	(0.3410)	(0.3444)	(0.0341)
China's import share in		-0.0830	1.7244***
high-income countries*TFP_0		(0.0997)	(0.2966)
R-squared	0.6754	0.6757	0.6308
N	44,340	44,340	44,340
Plants	6,680	6,680	6,680
Weak IV F-stat	32.23	16.01	

Notes. China IP measured as total value of imports from China divided by domestic absorption. China's import share is the average China's participation in total imports across high-income countries (using the classification conducted by The World Bank). Both vary at industry-year level. Industries defined at 4-digit ISIC Rev. 3. Regressions include plant- and region-year fixed effects, and control for industry-level pre-existing trends. These trends are constructed using the past 5-year change (during 1989-1994) in industry revenue interacted with year fixed effects. TFP measured following Ackerberg, Caves and Frazer (2015). Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We follow a similar strategy for industry-level regressions. Aggregating across plants within an industry avoids confounding aggregate effects with within industry reallocation of productive factors (e.g. workers leaving declining plants to take new jobs in other establishments of the same industry; or within industry capital absorption from exiting to surviving plants). These regressions also capture the net effect of growing CIP on industry outcomes because of both the variation of plant-level outcomes (intensive margin) and the entry/exit of plants from the panel (extensive margin). We estimate the following regression equation:

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

Where j and t index industries and time, respectively; α_j is an industry-level 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, again, revenue, employment, physical capital, and number of active plants, but aggregated at the 4-digit industry-year level. Regressions also control for pre-existing trends in the corresponding industry outcome.

V Results

V.1 Baseline estimates

Table 6 presents the baseline plant-level estimates of equation (3) for the log of total revenue (Panel A), log of total employment (Panel B), log of the stock value of physical capital (Panel C), and plant's exit probability (Panel D). Column (1) presents the OLS estimator including plant- and year- fixed effects. Column (2) presents the same specification but estimated by 2SLS. The 2SLS coefficients on CIP increase in magnitude compared to OLS coefficients, which is consistent with the existence of a positive correlation between Chile's industry import demand shocks and Chile's industry revenue/labor/capital demand shocks, that biases OLS estimates towards zero. Column (3) incorporates region-year fixed effects. Column (4) incorporates the corresponding industry outcome pre-existing trend, that is constructed as the interaction between the past five year industry-level change (during 1989-1994) of each dependent variable and year fixed effects.[27]

Results in Table 6 suggest that plants in industries more exposed to increasing CIP exhibit relative declines in revenue, physical capital and employment, and face a higher probability of exiting the sample than comparable plants in less exposed industries. Specifically, the preferred specification (column (4)) suggests that a 1 p.p. increase in CIP reduces plant revenue by 0.70%, employment by 0.68%, and physical capital by 1.24%, and increases plant's probability of exiting the panel by 0.50 p.p, *ceteris paribus*, relative to comparable plants in less exposed industries.[28] It is worth noting that the number of observations is different in Panel D because these regressions are run for the period 1996-2005. This happens for two reasons. First, we do not work with plants observed just in a single year, making the exit rate artificially zero in 1995. Second, given that exit takes the value 1 if a plant leaves the sample in the following year, we can not construct this variable for 2006.[29]

[27] In Section A.4 of the Appendix, we present a robustness exercise including sector-year fixed effects (see Table A12). Although all results remain statistically significant, the inclusion of these fixed effects increases the magnitude of the standard errors considerably. This is mainly explained by the fact that most CIP occurs at the level of broad manufacturing sectors (a simple descriptive regression of CIP on sector-year dummies has an R-squared of 0.67). Nevertheless, the remaining within sector variation across industries over time is enough to capture a significant causal effect of the competitive shock on domestic plants' outcomes.

[28] To increase the confidence in our estimates we present in an Online Appendix two types of falsification tests to verify that future increases in Chinese competition are not correlated with past changes in industry outcomes. In the first test, we regress the (log) change in each dependent variable during 1984-1994 (or 1989-1994) in the change in industry CIP during 1995-2005 (or 1995-2000). In the second test, we conduct similar regressions but separating plants according to their size, in order to verify that future Chinese competition is not related to past changes in industry outcomes for different type of plants. In both cases we find no correlation, supporting the idea that our identification strategy isolates industry-level shocks caused by rising CIP instead of other confounds.

[29] As a robustness exercise, Table A13 in the Appendix presents our preferred specifications for log-revenue,

We present the results for industry-level regressions in Table 7. The first column presents the OLS estimator including industry- and year- fixed effects. The second column shows the same specification but estimated by 2SLS. Column (3) controls for pre-existing trends in the dependent variable at the industry-level, that are constructed analogously to those included in column (4) of Table 6. In line with the plant-level results, Table 7 suggests that industries more exposed to growing Chinese import competition present relative declines in revenue, employment, physical capital, and number of plants with 10 or more employees, with respect to less exposed industries.

Compared to plant-level regressions, industry estimates suggest a larger impact of CIP on the studied outcomes. This is consistent with within-industry reallocation of productive factors, which attenuates estimated coefficients at the plant-level. Moreover, given the negative effect of CIP on plant's probability of surviving, plant-level estimates might also be attenuated in this context. These results are also in line with previous findings in Autor et al. (2014), and also with the heterogeneous effects we find in this paper. For more discussion, see Section A.1 of the Appendix.

log-employment and log-capital for two different subsamples: (i) excluding entrant plants, and (ii) excluding entrant and exiting plants (balanced sample). All estimated coefficients present the same sign and, with the only exception of the revenue coefficient in the balanced sample, are statistically significant.

Table 6
Plant-level effects of China import penetration

	OLS	2SLS		
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0073***	-0.0084**	-0.0076**	-0.0070**
	(0.0021)	(0.0035)	(0.0032)	(0.0031)
Weak IV F-stat	-	34.50	32.50	32.23
Panel B. Employment				
China import pen.	-0.0070***	-0.0078***	-0.0068***	-0.0068***
	(0.0011)	(0.0019)	(0.0017)	(0.0016)
Weak IV F-stat	-	34.50	32.50	34.01
Panel C. Capital				
China import pen.	-0.0136***	-0.0208***	-0.0126***	-0.0124***
	(0.0026)	(0.0048)	(0.0034)	(0.0035)
Weak IV F-stat	-	34.50	32.50	32.57
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0029***	0.0040***	0.0052***	0.0050***
	(0.0006)	(0.0007)	(0.0008)	(0.0007)
Weak IV F-stat	-	30.35	28.60	35.96
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Region x Year FE	-	-	Yes	Yes
Industry PT x Year FE	-	-	-	Yes

Notes. Revenue is the log of plant's total sales of manufactured products. Employment is the log of plant's total number of workers. Capital is the log of plant's stock value of physical capital (discounted depreciation), and includes land, buildings, machinery, equipment, tools, and vehicles. Revenue and capital are deflated using specific 4-digit industry deflators obtained from INE. Exit=0 in active years, and =1 one year before a plant leaves the panel. China import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at 4-digit industry-year level. This variable is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Industries defined at 4-digit ISIC Rev. 3. Regions correspond to country's first-level administrative division. Industry pre-existing trend defined as the 5-year past change (1989-1994) in the corresponding dependent variable interacted with year fixed effects. In the case of plant's exit (Panel D) the pre-trend variable is the past change in the number of plants. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7
Industry-level effects of China import penetration

	OLS	2SLS	
	(1)	(2)	(3)
Panel A. Revenue			
China import pen.	-0.028***	-0.016**	-0.016**
	(0.006)	(0.007)	(0.007)
Weak IV F-stat	-	53.68	48.46
Panel B. Employment			
China import pen.	-0.021***	-0.017***	-0.016***
	(0.005)	(0.005)	(0.005)
Weak IV F-stat	-	53.68	49.51
Panel C. Capital			
China import pen.	-0.034***	-0.027***	-0.027***
	(0.007)	(0.006)	(0.006)
Weak IV F-stat	-	53.68	53.61
Panel D. Number of plants			
China import pen.	-0.017***	-0.016***	-0.015***
	(0.003)	(0.004)	(0.005)
Weak IV F-stat	-	53.68	53.00
N	936	936	936
Industries	78	78	78
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry outcome pre-trend	-	-	Yes

Notes. Revenue and capital are deflated using specific 4-digit industry deflators obtained from Chilean Institute of Statistics- INE. China import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports). This variable is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Industries defined at 4-digit ISIC Rev. 3. Industry outcome pre-existing trend corresponds to 5-year change (1989-1994) in dependent variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

V.2 Heterogeneous effects

Table 8 presents results for the estimates of equation (4), which include an interaction term between CIP and plant's initial level of TFP. Dependent variables are, again, the log of total revenue (Panel A), log of total employment (Panel B), log of physical capital (Panel C), and plant's probability of leaving the panel (Panel D). Columns present different specifications that follow the same structure as Table 6.

Our estimates indicate that the impact of CIP on revenue, employment, capital, and exit probability decreases in magnitude for plants that were initially more productive. This can be seen by looking at the estimated coefficient of the interaction term, which has the opposite sign than the coefficient for CIP in the four cases. The marginal effect of CIP on revenue, employment, capital, and exit probability, for a plant located at the 10th percentile of initial within sector TFP distribution is 1.39, 1.60, 1.64, and 1.46 times larger (respectively) than the marginal effect for a plant situated at the 50th percentile.[30] For example, a 1 p.p. increase in CIP reduces plant's revenue, employment, and capital in 1.01%, 1.18%, and 2.21%, resp., for a plant located at the 10th percentile, while this effect is 0.73%, 0.73%, and 1.34%, resp., for a plant situated at the 50th percentile.

In Figure 5, using the estimated coefficients from the preferred specification in column (4) of Table 8, we plot the estimated linear predictions of the marginal effect of CIP on each outcome variable plus 95% confidence intervals, for plants located at different percentiles of the initial within sector TFP distribution.[31] These figures show that the marginal effect of CIP on the outcome variables is statistically indistinguishable from zero for those plants that were initially more productive.

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 (Khandelwal (2010)). Relatedly, more productive plants might be more innovative *per se*, so they respond to growing CIP by increasing innovation (Bloom et al. (2015)) or boosting investment in new technologies (Bustos (2011)), switching their product mix (Bernard, Redding, and Schott (2010)), or modifying their hierarchical structure (Caliendo et al. (2017)). However, looking for evidence on the different mechanisms behind these heterogeneous responses is beyond the scope of this paper.

[30] The marginal effect for a plant located at the 25th percentile is 1.60, 2.13, 2.27, and 2.80 times larger, resp., than the marginal effect for a plant situated at the 75th percentile. However, it is worth mentioning that the marginal effect of CIP on revenue is statistically indistinguishable from zero for a plant situated at the 75th percentile.

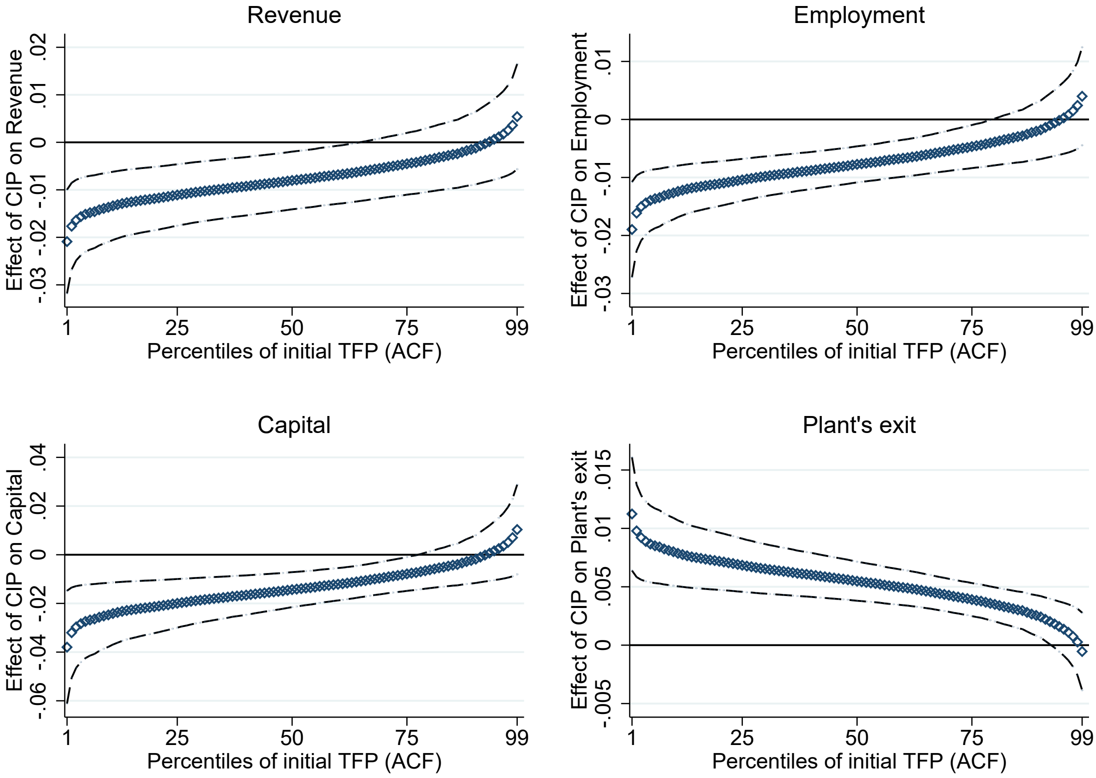
[31] Standard error for each TFP percentile p is constructed as $\sqrt{Var(\hat{\beta}_1 + \hat{\beta}_2 * \overline{TFP_p})}$.

Table 8
Heterogeneous effects of China import penetration

	OLS	2SLS		
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0074***	-0.0086**	-0.0078**	-0.0072**
	(0.0021)	(0.0035)	(0.0032)	(0.0031)
China IP x TFP_0	0.0041*	0.0046*	0.0047	0.0054*
	(0.0023)	(0.0027)	(0.0028)	(0.0028)
Weak IV F-stat	-	16.34	15.97	16.01
Panel B. Employment				
China import pen.	-0.0072***	-0.0081***	-0.0072***	-0.0072***
	(0.0011)	(0.0018)	(0.0017)	(0.0016)
China IP x TFP_0	0.0042	0.0082***	0.0084***	0.0085***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Weak IV F-stat	-	16.34	15.97	16.85
Panel C. Capital				
China import pen.	-0.0138***	-0.0214***	-0.0132***	-0.0131***
	(0.0026)	(0.0048)	(0.0035)	(0.0035)
China IP x TFP_0	0.0067*	0.0133	0.0166**	0.0167**
	(0.0036)	(0.0081)	(0.0080)	(0.0081)
Weak IV F-stat	-	16.34	15.97	16.13
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0030***	0.0042***	0.0053***	0.0052***
	(0.0007)	(0.0008)	(0.0009)	(0.0008)
China IP x TFP_0	-0.0044***	-0.0051***	-0.0047***	-0.0046***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Weak IV F-stat	-	15.12	14.54	18.65
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Region x Year FE	-	-	Yes	Yes
Industry PT x Year FE	-	-	-	Yes

Notes. Revenue is the log of plant's total sales of manufactured products. Employment is the log of plant's total number of workers. Capital is the log of plant's stock value of physical capital (discounted depreciation), and includes land, buildings, machinery, equipment, tools, and vehicles. Revenue and capital are deflated using specific 4-digit industry deflators obtained from INE. Exit=0 in active years, and =1 one year before a plant leaves the panel. China import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at 4-digit industry-year level. TFP measured following Ackerberg, Caves and Frazer (2015). China import penetration and its interaction with initial TFP are instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank) and its interaction with initial TFP. Regions correspond to country's first-level administrative division. Industry pre-existing trend defined as the 5-year past change (1989-1994) in the corresponding dependent variable interacted with year fixed effects. In the case of plant's exit (Panel D) the pre-trend variable is the past change in the number of plants. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Figure 5
Predicted effect of CIP across the TFP distribution



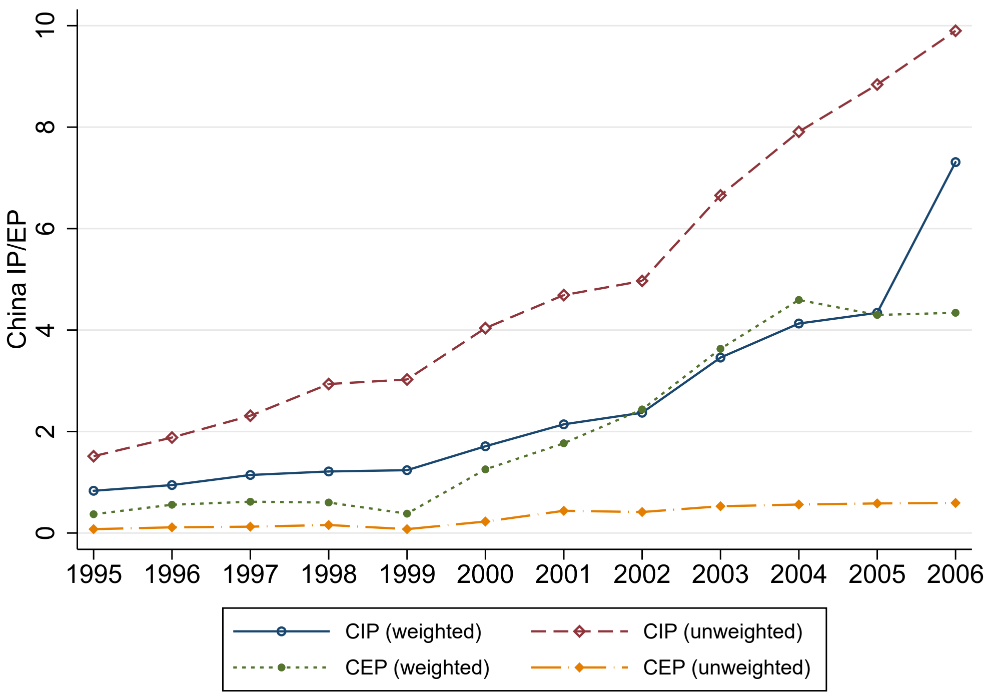
Notes. Linear predictions and 95% confidence intervals of the effect of China IP on revenue, employment, capital, and exit probability, for plants located at different percentiles of the initial within sector TFP distribution (computed using estimated coefficients from the preferred specification in column 4 of Table 8).

V.3 Chinese demand shock

Until now, we have focused only on the supply-side of the China shock. Nevertheless, recent papers have shown the relevance of studying the economic effects of the growing Chinese demand for commodities. For instance, Costa, Garred, and Pessoa (2016) study the heterogeneous effects of both, supply- and demand-side of the China shock on Brazilian local labor markets. Their findings suggest that import-competing regions have suffered from Chinese import competition via slower growth in manufacturing wages, while regions specializing in raw materials have gained from Chinese export demand, through faster wage growth and shifts towards formal jobs. Relatedly, Artuc, Lederman, and Rojas (2015) calibrate a model of labor mobility using surveys of Argentina, Brazil and Mexico, and find that rising trade with China has had negative effects on manufacturing employment and wages, but they were offset by positive effects on agriculture and mining in the cases of Argentina and Brazil but not in Mexico, where total employment reduced in the long run.

In this section we investigate if the increasing Chinese demand for commodities affected Chilean manufacturing plants directly or indirectly through manufacturing-primary sectoral-linkages. An underlying concern of neglecting China's demand shock is that we could be overestimating the effect of CIP on domestic plants if less exposed industries are the ones experimenting greater demand from China. In this context, we incorporate an export demand variable in our analysis. We define China export penetration (CEP) as the industry value of exports to China relative to industry value of production. This variable, like CIP, varies at the 4-digit ISIC Rev. 3 industry-year level. Figure 6 presents the evolution of CIP and CEP for the Chilean manufacturing sector during 1995-2006, distinguishing between weighted and unweighted measures of CIP and CEP.[32] First, we note that the variable capturing Chinese demand shock (CEP) did not increase as much as the measure of Chinese import competition (CIP). The unweighted measures highlight that while CIP increased for most manufacturing industries CEP did not. In particular, the increase in the weighted measure of CEP is driven by three industries (Fish products; Pulp, paper and paperboard; and Basic precious and non-ferrous metals).[33]

Figure 6
Evolution of China import and export penetration



Notes. China import penetration measured as the total value of imports from China divided by domestic absorption (production minus net exports). China export penetration measured as the total value of exports to China divided by domestic production. Both vary at the 4-digit industry-year level (ISIC Rev. 3). Weights are given by the share of each industry in total manufacturing value of production. Sources. INE-ENIA and UN-COMTRADE.

To incorporate the indirect effect of CEP through manufacturing-primary

[32] Weights are given by the share of each industry in total manufacturing value of production. Note that weighted CEP is equal to total manufacturing exports to China divided by total manufacturing value of production.

[33] Below we present a robustness exercise excluding these industries.

sectoral-linkages, that is, the Chinese demand for primary products that propagates upstream to manufacturing suppliers, we calculate the following measure:

$$CEP_{jt}^{U} = \sum_{b} \theta_{bj}^{U} CEP_{bt} \tag{6}$$

which is a weighted average of the China export penetration of all primary industries b that purchase from industry j. The weights θ_{bj}^{U} represent the share of industry j's total sales that are used as inputs by industry b. Thus, when a primary sector b is exposed to Chinese increasing demand for commodities it may propagate "upstream" because industry j will face higher demand for its products, and the effect should be unambiguously positive. Notably, although the average CEP^{U} grew significantly during the studied period, from 0.08 in 1995 to 0.59 in 2006, the level is still very low compared to CIP.

Now we estimate equation (3) incorporating CEP and CEP^{U}. Note that both variables are subject to similar endogeneity concerns than CIP. To capture the Chinese demand shock we instrument CEP with the share of China in the exports of all countries in the world (with available COMTRADE data), excluding Chile. We present the results in Table 9. Column (1) presents our baseline estimates for CIP (specification in column 4 of Table 6). Column (2) estimates the same specification but using CEP instead of CIP as the main regressor. Unlike the instrument for CIP, which works quite well explaining Chinese import competition in Chile with the share of China in the imports of high-income countries, the instrument for CEP presents a weak first-stage (note that the Weak IV F-stat in column (2) is very small).[34] The inclusion of CEP^{U} in column (3) does not improve the first-stage. Finally, in column (4) we include CIP, CEP and CEP^{U}. While the first-stage is still weak, the coefficients for CIP are very similar to baseline estimates when including CIP as the sole explanatory variable.

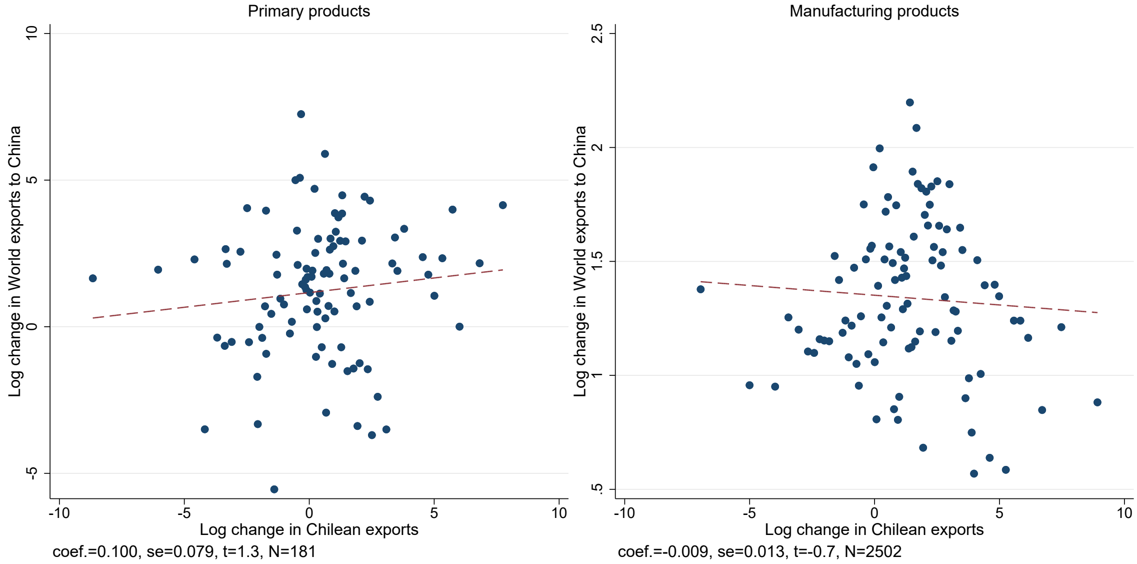
To address potential concerns about the IV we follow the identification strategy proposed by Costa et al. (2016). The idea is to clean out potential correlated world level shocks by running an auxiliary regression to obtain China-specific dummies that measure the deviation in Chinese industry export share as compared to the cross-country average. As in the case of the raw IV measure, the first-stage is weak, and estimated coefficients for CIP do not change significantly (see columns 5 to 7).

The main reason behind the poor performance of these instruments is perhaps the fact that we work with manufacturing plants only, which are not directly exposed to the commodity boom. Moreover, we find that Chile did not increase its exports in those products that were more demanded by China at the world-level. To provide a simple graphical visualization, Figure 7 shows a scatter plot at the 6-digit product-level relating the log change of China imports from the World and the log change of Chilean exports

[34] We also constructed similar IVs using exports to China from high-income, middle-income, or latin american countries, and also obtained weak first-stages in all these cases.

during the studied period. We present separate plots for primary (left) and manufacturing products (right). Although the slope of the linear prediction for primary products is slightly positive, the correlation is not statistically significant, which may partially explain why the IV strategy does not work either when we include the indirect effects of CEP.

Figure 7
Chilean exports versus China imports from the World



Notes. Products are grouped into 100 segments of the same size according to the variable in the horizontal axis, which is the log change in Chilean exports between 1995 and 2006. Each point represents the conditional expectation of the outcome variable for each segment. Outcome variable in the vertical axis is the log change of China imports from the World between the same years. The left panel includes primary products and the right panel contains manufacturing. The red line represents the linear prediction. Slope coefficient, standard error, and t-statistic presented below each sub-graph. Source. UN-COMTRADE.

Given that this identification strategy does not perform as expected, we present two additional exercises to test the robustness of estimated coefficients for CIP when excluding industries or plants that benefit directly from increasing demand from China. First, we exclude from the analysis the three industries that experienced a disproportionately large increase in CEP. Panel A of Table 10 presents the results. All coefficients remain virtually unchanged. Then, we implement a second robustness check based on the exclusion of manufacturing plants exporting to China, using plant-product-destination administrative customs records on Chilean exports, available during 2001-2005.[35] We present the results in Panels B and C of Table 10. First, it is worth noticing that all our results are robust to limit the analysis to this 5-year period (Panel B).[36] Estimated coefficients for exit are bigger than in baseline by an order of magnitude, which might be rationalized by the fact that this period captures a more dramatic increase in Chinese import competition, after China joined the WTO in 2001.[37] Results remain robust to the exclusion of plants exporting to China at least one year during 2001-2005 (Panel C).

[35]The fraction of plant-years exporting to China is 5,1% and, among these plants, the average participation of China in total plant's exports is 2,1%.

[36]The only exemption is revenue, which presents a p-value of 1.19.

[37]While the estimated coefficients for capital and revenue change very little compared to our baseline estimates, coefficient for employment reduces around 30%.

Table 9

Robustness to Chinese demand shock

	Baseline	IV (Export share)			IV (China dummy)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Revenue							
China import pen.	-0.0070**			-0.0068*			-0.0067*
	(0.0031)			(0.0037)			(0.0038)
China export pen.		-0.0479	-0.0484	0.0161	-0.0575	-0.0598	0.0182
		(0.1136)	(0.1144)	(0.0860)	(0.1279)	(0.1324)	(0.0967)
China export pen. (PL)			0.0028	-0.0983		0.0091	-0.0990
			(0.1904)	(0.1904)		(0.1983)	(0.1924)
Weak IV F-stat	32.23	3.504	1.439	1.158	3.270	1.205	1.037
Panel B. Employment							
China import pen.	-0.0068***			-0.0064***			-0.0064***
	(0.0016)			(0.0018)			(0.0018)
China export pen.		-0.0293	-0.0400	0.0239	-0.0385	-0.0555	0.0234
		(0.0614)	(0.0777)	(0.0459)	(0.0707)	(0.0977)	(0.0530)
China export pen. (PL)			0.0547	-0.0559		0.0680	-0.0556
			(0.1665)	(0.1162)		(0.1831)	(0.1207)
Weak IV F-stat	34.01	3.680	1.328	1.092	3.464	1.049	0.932
Panel C. Capital							
China import pen.	-0.0124***			-0.0128***			-0.0129***
	(0.0035)			(0.0047)			(0.0049)
China export pen.		-0.1095	-0.1283	-0.0074	-0.1337	-0.1638	-0.0135
		(0.1622)	(0.1804)	(0.1010)	(0.1878)	(0.2190)	(0.1123)
China export pen. (PL)			0.1034	-0.0886		0.1245	-0.0863
			(0.2387)	(0.1628)		(0.2563)	(0.1651)
Weak IV F-stat	32.57	3.515	1.555	1.267	3.272	1.332	1.164
N	44,340	44,340	44,340	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680	6,680	6,680	6,680
Panel D. Plant's exit							
China import pen.	0.0050***			0.0051***			0.0051***
	(0.0007)			(0.0012)			(0.0013)
China export pen.		0.0540	0.0722	0.0010	0.0619	0.0879	-0.0017
		(0.0448)	(0.0723)	(0.0383)	(0.0515)	(0.1005)	(0.0465)
China export pen. (PL)			-0.0470	0.0506		-0.0534	0.0509
			(0.1315)	(0.0696)		(0.1579)	(0.0708)
Weak IV F-stat	35.96	3.186	0.540	0.462	2.951	0.373	0.359
N	36,761	36,761	36,761	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012	6,012	6,012	6,012

Notes. China export penetration (CEP) defined as the ratio of exports to China over sales and varies at 4-digit industry-year level. China export pen. (PL) includes indirect exports to China given by manufacturing sales to primary activities exporting to China (calculated as the interaction of the China's share in Chilean exports of primary sectors and the share of manufacturing sales to each primary sector using Leontieff coefficients from 1996 Chilean Input-Output table). Column (1) presents the baseline estimates. In columns (2) to (4) CEP is instrumented with the average Chinese industry export share across all countries. In columns (3) to (7) CEP is instrumented with China-specific dummies (from an auxiliar regression) representing the deviation in Chinese industry export share as compared to the cross-country average (following Costa, Garred, and Pessoa (2016)). All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table 10
Robustness to excluding industries or plants exporting to China

	Revenue (1)	Employment (2)	Capital (3)	Plant's exit (4)
Panel A. Excluding industries exporting to China (1995-2006)				
China import pen.	-0.0072**	-0.0070***	-0.0123***	0.0050***
	(0.0033)	(0.0017)	(0.0035)	(0.0007)
Weak IV F-stat	32.26	34.34	32.58	36.69
N	42,241	42,241	42,241	35,066
Plants	6,332	6,332	6,332	5,714
Panel B1. All plants (2001-2005)				
China import pen.	-0.0074	-0.0046*	-0.0145***	0.0101***
	(0.0062)	(0.0025)	(0.0047)	(0.0020)
Weak IV F-stat	10.91	11.83	10.75	14.12
N	18,081	18,081	18,081	18,081
Plants	4,451	4,451	4,451	4,451
Panel B2. Excluding plants exporting to China (2001-2005)				
China import pen.	-0.0071	-0.0046*	-0.0136***	0.0099***
	(0.0063)	(0.0025)	(0.0047)	(0.0020)
Weak IV F-stat	10.75	11.64	10.54	13.89
N	17,153	17,153	17,153	17,153
Plants	4,224	4,224	4,224	4,224

Notes. Panel A presents estimated coefficients from baseline regressions excluding the three industries that experience a disproportionately large growth in China export penetration. Panel B1 shows estimated coefficients from baseline regressions run for the period 2001-2005. Panel B2 excludes plants exporting to China at least one year during 2001-2005. All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

V.4 Input-output linkages

As we previously acknowledged, exploiting CIP variation across industries only delivers relative and not aggregate effects. Plants in non-exposed industries could also be affected by the China shock if there are spillovers across plants, or other general equilibrium effects (e.g. reallocation of production factors and aggregate demand multiplier effects). In this section, we bring into the analysis one source of indirect propagation of the shock, using industry input-output linkages.[38] These links may have both positive and negative effects

[38] This channel, among others, has also been studied by Acemoglu et al. (2016) and Pierce and Schott (2016) for the U.S. For instance, Acemoglu, Autor, Dorn, Hanson, and Price (2016) study the effects of rising Chinese competition over 1999–2011 in U.S. manufacturing, including input-output linkages and other general equilibrium channels, and their estimates suggest job losses in the range of 2.0–2.4 million. Relatedly, Caliendo, Dvorkin, and Parro (2018) develop a dynamic trade model incorporating many of

in plants' outcomes, thus generating an ambiguous net effect. The effect of CIP that propagates "upstream" from customers to suppliers should be unambiguously negative because customers exposed to Chinese import competition may reduce its demand for intermediate inputs. On the other side, the effect of CIP that propagates "downstream" from suppliers to customers is theoretically ambiguous because while some buyers clearly benefit from cheaper inputs imported from China, other might lose because they use highly customized inputs that are no longer provided by (directly exposed) domestic suppliers.

The framework to study these indirect effects is based on the recent contribution of Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012). The idea is that each industry uses (with different intensities) the output of other industries as inputs. To quantify these links, we employ data from the Chilean input-output table for 1996.[39] It is worth mentioning that we can not account for the indirect effects that propagate to non-manufacturing activities because we are working with manufacturing data.

The upstream effect, that is, the CIP exposure that propagates upstream from an industry's buyers, is calculated as:

$$CIP_{jt}^{U} = \sum_{b} \theta_{bj}^{U} CIP_{bt} \tag{7}$$

which is a weighted average of the China import penetration of all industries b that purchase from industry j. The weights θ_{bj}^{U} represent the share of industry j's total sales that are used as inputs by industry b. Thus, CIP_{jt}^{U} is a weighted average of the trade shocks faced by the buyers of j's output. When an industry b is exposed to Chinese competition it may propagate "upstream" because industry j will face lower demand for its products, and the effect should be unambiguously negative.

The downstream effect, that is, the CIP exposure that propagates downstream from an industry's suppliers, is calculated as:

$$CIP_{jt}^{D} = \sum_{s} \theta_{sj}^{D} CIP_{st} \tag{8}$$

which is a weighted average of the China import penetration of all industries s that supply to industry j. The weights θ_{sj}^{D} represent the share of industry s's total sales that are used as inputs by industry j. Thus, CIP_{jt}^{D} is a weighted average of the trade shocks faced by the suppliers of j's inputs. Given that some buyers could benefit from cheaper inputs imported from China, while others might lose because they use highly customized

these channels and find that the China shock resulted in a loss of 0.8 millon jobs (25% of the observed decline in manufacturing employment between 2000 and 2007) but increasing aggregate U.S. welfare by 0.35%, with significant heterogeneous effects across local labor markets due to trade and migration frictions.

[39] Coefficients from this table should not be contaminated by the large increase in CIP that took place especially in the 2000s, while being representative of sectoral-linkages during the studied period. The information can be found at https://si3.bcentral.cl/estadisticas/Principal1/Excel/CCNN/cdr/excel.html.

inputs that are no longer provided by domestic suppliers, the "downstream" effect of CIP is *a priori* ambiguous.

To take into account not only the direct first-order effect but the full chain of linked downstream and upstream effects, θ_{sj} coefficients are augmented by higher-order linkages given by the Leontief inverse matrix (as in Acemoglu et al. (2016)).[40] These higher-order interconnections capture the possibility of "cascade effects" whereby competitive shocks to a sector could propagate not only to its intermediate downstream (upstream) customers (buyers) but also to the rest of the economy (Acemoglu et al. (2012)).

To formally incorporate these indirect propagation channels in our analysis, we estimate our baseline regression equation adding up the downstream and upstream effects sequentially. Particularly, we estimate the following regressions:

$$Y_{ijt} = \beta_0 + \beta_1 CIP_{jt} + \beta_2 CIP^X_{jt} + \alpha_i + \delta_t + \varepsilon_{ijt} \tag{9}$$

Where CIP^X_{jt} represents CIP^U_{jt} or CIP^D_{jt}. We instrument both the upstream and downstream effects analogously to CIP: exploiting temporal variation in the average Chinese industry import share across high-income countries. Concretely, we construct these instruments by replacing the terms CIP_{bt} and CIP_{st} in equations (7) and (8) with Sh^{China}_{bt} and Sh^{China}_{st} while retaining the same weights.

Table 11 presents the results. The first column shows the estimated coefficients of the preferred specification of equation (3) (column 4 of Table 6).[41] Columns (2) and (3) present the results when we include downstream and upstream effects, separately. In column (4) we include both variables simultaneously.[42] In all cases, the estimated coefficients associated to indirect effects of CIP are statistically indistinguishable from zero. Importantly, the estimated coefficients for direct CIP change very little and remain statistically significant.

[40] For instance, in the case of the upstream effect, the weights represent the direct and indirect requirements of inputs of industry j for each monetary unit of modification of the final demand of industry b.

[41] Remember that this specification includes plant-level and region-year fixed effects, and controls for pre-existing trends in the corresponding industry-level outcome variable.

[42] It is worth mentioning that CIP^U and CIP^D are highly correlated between them (the Pearson correlation coefficient is 0.94) but not so much with CIP (0.32 and 0.44, respectively). Given this multicollinearity concern, estimates in column 4 should be interpreted with caution.

Table 11
Direct and indirect effects of CIP

	Baseline	Baseline plus indirect effects		
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China IP (Direct)	-0.0070**	-0.0077**	-0.0083*	-0.0081*
	(0.0031)	(0.0033)	(0.0047)	(0.0046)
China IP (Upstream)		0.0050		0.0049
		(0.0091)		(0.0086)
China IP (Downstream)			0.0044	0.0013
			(0.0168)	(0.0142)
Weak IV F-Stat	32.23	13.63	7.595	5.341
Panel B. Employment				
China IP (Direct)	-0.0068***	-0.0069***	-0.0081***	-0.0081***
	(0.0016)	(0.0018)	(0.0028)	(0.0028)
China IP (Upstream)		0.0007		0.0003
		(0.0032)		(0.0032)
China IP (Downstream)			0.0046	0.0044
			(0.0075)	(0.0074)
Weak IV F-Stat	34.01	14.20	7.667	5.373
Panel C. Capital				
China IP (Direct)	-0.0124***	-0.0122***	-0.0147***	-0.0144***
	(0.0035)	(0.0025)	(0.0049)	(0.0048)
China IP (Upstream)		0.0076		0.0071
		(0.0060)		(0.0064)
China IP (Downstream)			0.0123	0.0081
			(0.0121)	(0.0108)
Weak IV F-Stat	32.57	13.36	7.643	5.324
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China IP (Direct)	0.0050***	0.0046***	0.0044***	0.0044***
	(0.0007)	(0.0006)	(0.0011)	(0.0011)
China IP (Upstream)		-0.0010		-0.0011
		(0.0017)		(0.0016)
China IP (Downstream)			0.0002	0.0009
			(0.0040)	(0.0039)
Weak IV F-Stat	35.96	15.09	6.504	4.417
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012

Notes. First column presents the baseline estimates (preferred specification in column 4 of Table 6). The second (third) column includes the upstream (downstream) effect of CIP. Column (4) includes both indirect effects. In all cases, CIP is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

VI Conclusion

In this paper we presented evidence on the short-term effects of Chinese import competition on Chilean manufacturing plants. We have found that the adjustment costs are unevenly distributed across plants, being the least productive the ones that suffered the most.

Using a panel of Chilean manufacturing plants for the period 1995-2006, we found that plants belonging to industries more exposed to growing China import penetration exhibited relative declines in revenue, employment and physical capital, and faced a higher probability of exiting the market than comparable plants in less exposed industries. Plants with higher levels of initial productivity were better able to withstand this competitive shock. Our findings suggest that Chinese demand shock does not seem to have affected Chilean manufacturing plants neither directly or indirectly through manufacturing-primary sectoral-linkages.

Our results are consistent with related literature showing 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. Also, more productive plants might be more innovative *per se*, so they respond to growing CIP by increasing innovation or boosting investment in new technologies, switching their product mix, or modifying their hierarchical structure.

Overall, we believe that these findings are especially relevant for developing countries with visible problems of unemployment or misallocation of productive factors, where a significant share of workers are employed in low-competitive sectors or low-productivity firms.

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A Appendix

A.1 Economic magnitude

To evaluate the economic magnitude of these estimates, we perform a simple "back-of-the-envelope calculation". We compare the observed plant-level revenue, employment, and capital, with the counterfactuals that would have occurred in the absence of increasing CIP. Importantly, this exercise assumes that Chinese competition affects the absolute level of each manufacturing outcome, instead of the relative effects across plants in different industries. Using equation (3), we write the counterfactual level of each dependent variable Y_{ijt}^{sim} as the difference between the actual level of each variable and the predicted effect of CIP:

$$Y_{ijt}^{sim} = Y_{ijt} - Y_{ijt}e^{(\hat{\beta}_1 * \Delta CIP_{jt} - 1)} \tag{A.1}$$

Where $\hat{\beta}_1$ is the 2SLS estimated coefficient for CIP from equation (3) and ΔCIP_{jt} is the industry annual change in CIP. We use estimated coefficients from the preferred specification of plant-level estimates reported in column 4 of Table 6 (which includes plant- and region-year fixed effects, plus industry-level pre-trends in outcome variables). Additionally, following Autor et al. (2013) and Acemoglu et al. (2016), we present a more conservative estimation by multiplying the observed CIP with the partial R-squared from the first-stage regression of CIP on the instrument, which has a value of 0.81 in our baseline specification of the plant-level regression (column 4 of Table 6), and 0.64 in the industry-level regression (column 3 of Table 7). If the instrument is valid and presents no measurement error, the adjusted partial R-squared variable is a consistent estimate of the contribution of Chinese import supply shocks to changes in CIP.

Table A1 presents the results of these simulations. Column (1) presents plant average exposure to CIP across sectors during the studied period. Columns (2), (5), and (8) present the observed change in sector revenue, employment, and capital, respectively, between 1995 and 2006. Columns (3), (6), and (9) report the counterfactual change in sector revenue, employment, and capital, resp., that would have occurred if CIP had not grown over this period (calculated using equation (A.1)). Columns (4), (7), and (10) report the corresponding counterfactual changes using a more conservative approach (adjusting estimated coefficient with the partial R-squared from the first-stage regression). For instance, comparing the observed and simulated changes in employment, our estimates suggest that if CIP had remained constant over this period, total manufacturing employment would have grown by 3.0 or 4.4 p.p. more than the observed growth during 1995-2006 (6.2% or 7.6% versus 3.2%, respectively), depending on the counterfactual adopted (adjusted or raw/unadjusted). Our estimates can account for a significant fraction of the relative contraction of more exposed sectors. For instance, in the textile sector, employment contracted by 43.7% during the studied period, and Chinese competition explains 23.5% or 34.3% of this variation. Relatedly, going back to Figure 2, which defines exposed (non-exposed) industries as the ones above (below) the average annual growth in CIP, this counterfactual analysis predicts that had CIP not grown over this period, overall employment contraction in exposed industries would have been 26.7% or 40.0% lower than the observed one.

Table A2 presents analogous simulations but using the estimated coefficients for CIP of the industry-level regressions. Note that this table incorporates a simulation for the number of active plants with 10 or more employees, presented in columns (11), (12), and (13). In this case, estimates suggest that if CIP had remained constant at the initial level, the total number of active plants would have grown by 1.9% or 6% instead of contracting by 5.6%, depending on the simulation adopted (adjusted or raw/unadjusted). This simulation suggests a larger impact of CIP on industry employment compared to counterfactuals at the plant-level. Note that, if CIP had remained constant over 1995-2006, manufacturing employment would have grown by 6.6 or 10.2 p.p. more than the observed growth during 1995-2006. Aggregating across plants within an industry avoids confounding aggregate effects with within-industry reallocation of productive factors, which occurs as some workers exit declining plants and get jobs in other establishments of the same industry, thus attenuating the estimated coefficients in the plant-level regressions. This is consistent with the results in Autor et al. (2014), and also with the heterogeneous effects we find in this paper. These regressions also capture the net effect of growing CIP on industry outcomes because of both the variation of plant-level outcomes (intensive margin) and the entry/exit of plants from the panel (extensive margin). Given the negative effect of CIP on plant's probability of exiting the sample, plant-level estimates might also be attenuated in this context.

Table A1

Simulated changes using plant-level estimates

	Annual change CIP (%)	1995-2006 change (%)								
		Revenue			Employment			Capital		
		Obs.	Raw sim.	Adj. sim.	Obs.	Raw sim.	Adj. sim.	Obs.	Raw sim.	Adj. sim.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Food/tobacco	0.01	65.6	65.7	65.7	18.5	18.7	18.6	12.1	12.3	12.3
Textile/apparel/leather	3.10	-26.5	-9.2	-14.7	-43.7	-28.7	-33.5	-45.4	-19.9	-27.9
Wood/furniture	0.34	204.6	206.7	206.1	29.8	31.8	31.1	33.7	36.3	35.5
Paper/print	0.08	100.6	100.9	100.8	-5.3	-5.0	-5.1	10.6	10.9	10.8
Chemical/petroleum	0.16	181.3	182.8	182.3	10.9	12.3	11.8	116.6	119.0	118.2
Plastic/rubber/glass	0.50	84.1	90.5	88.5	4.9	8.6	7.4	36.1	46.8	43.3
Metal	0.47	430.9	434.5	433.4	47.9	51.0	50.1	290.4	294.4	293.2
Machines/electrical	0.75	21.4	30.1	27.4	-18.7	-12.8	-14.7	-19.9	-3.7	-8.8
Transportation	0.69	-39.2	-38.4	-38.6	-30.7	-28.4	-29.1	-25.1	-20.7	-22.1
Toys/other	1.06	106.9	111.1	109.8	-27.0	-20.2	-22.3	-7.2	-2.0	-3.6
Total manufacturing	0.70	135.5	138.6	137.6	3.2	7.6	6.2	76.7	81.2	79.8

Notes. First column reports the average annual change in China import penetration across plants of each sector. Columns (2)/(5)/(8) present the observed change in sector revenue/employment/capital between 1995 and 2006. Columns (3)/(6)/(9) report the corresponding counterfactual changes that would have occurred if we assume that China import penetration remains constant at the 1995 level. Columns (4)/(7)/(10) adjust counterfactuals with the partial R-squared from the first-stage regression of CIP on the instrument. We use estimated coefficients from the preferred specification of plant-level estimates reported in column 6 of Table 6 (which includes plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Last row reports these numbers for all manufacturing industries (full sample).

Table A2
Simulated changes using industry-level estimates

	Annual change CIP (%)	1995-2006 change (%)											
		Revenue			Employment			Capital			Number of plants		
		Obs.	Raw sim.	Adj. sim.	Obs.	Raw sim.	Adj. sim.	Obs.	Raw sim.	Adj. sim.	Obs.	Raw sim.	Adj. sim.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Food/tobacco	0.02	65.6	65.9	65.8	18.5	18.9	18.8	12.1	12.7	12.5	8.4	8.6	8.6
Textile/apparel/leather	2.33	-26.5	12.0	-1.4	-43.7	-9.3	-21.4	-45.4	8.0	-10.3	-41.6	-1.0	-15.2
Wood/furniture	0.43	204.6	209.2	207.7	29.8	34.3	32.7	33.7	38.9	37.3	-14.4	-9.2	-11.1
Paper/print	0.07	100.6	101.2	101.0	-5.3	-4.7	-4.9	10.6	11.3	11.0	14.0	15.4	14.9
Chemical/petroleum	0.16	181.3	184.7	183.5	10.9	14.2	13.0	116.6	121.7	119.9	1.0	3.9	2.8
Plastic/rubber/glass	0.53	84.1	98.6	93.4	4.9	13.7	10.5	36.1	59.2	50.9	0.0	8.7	5.6
Metal	0.57	430.9	438.9	436.1	47.9	55.1	52.6	290.4	298.9	295.9	8.0	16.5	13.5
Machines/electrical	0.75	21.4	41.1	34.1	-18.7	-5.0	-9.9	-19.9	14.6	2.5	-2.0	11.6	6.8
Transportation	0.94	-39.2	-37.4	-38.0	-30.7	-25.6	-27.3	-25.1	-15.6	-18.9	-25.0	-16.2	-19.2
Toys/other	1.65	106.9	116.2	113.0	-27.0	-11.6	-16.9	-7.2	3.5	-0.1	0.0	16.4	10.7
Total manufacturing	0.76	135.5	142.4	140.0	3.2	13.4	9.8	76.7	86.1	82.9	-5.6	6.0	1.9

Notes. First column reports the average annual change in China import penetration across industries of each sector. Columns (2)/(5)/(8)/(11) present the observed change in sector revenue/employment/capital/number of plants between 1995 and 2006. Columns (3)/(6)/(9)/(12) report the corresponding counterfactual changes that would have occurred if we assume that China import penetration remains constant at the 1995 level. Columns (4)/(7)/(10)/(13) adjust counterfactuals with the partial R-squared from the first-stage regression of CIP on the instrument. We use estimated coefficients from the preferred specification of industry-level estimates reported in column 3 of Table 7 (which includes industry and year fixed effects, plus industry outcome pre-trends. Last row reports these numbers for all manufacturing sectors (full sample).

A.2 Production function estimation

A production function is a relation that specifies how firms transform inputs (e.g. labor, capital) into output. The main econometric challenge to estimate production functions is that firms make decisions about inputs based on determinants of production not observed by the econometrician. This will generate an endogeneity problem (simultaneity bias) when using the classic OLS estimator. For an excellent exposition on these topics we recommend the chapter of Ackerberg, Benkard, Berry, and Pakes (2007) in the Handbook of Econometrics, and the seminal papers of Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), and Ackerberg, Caves, and Frazer (2015) (ACF). To estimate TFP we follow the method proposed by ACF. These authors propose an alternative estimation procedure that uses moment conditions very similar to OP and LP, but that avoid what they call a functional dependence problem. Particularly, while OP and LP invert investment and intermediate inputs demand functions that are unconditional on the labor input, ACF suggest to invert investment or intermediate demand functions that are conditional on the labor input.

To estimate TFP we use information on plant characteristics such as revenue, total number of employees, spending on intermediate inputs and raw materials (electricity and fuels), stock value of physical capital (discounted accumulated depreciation) including land, buildings, machinery, equipment, tools, and vehicles. The measures of revenue, capital, materials, electricity and fuels are deflated using specific 4-digit industry deflators obtained from Chilean Institute of Statistics- INE.

Table A3 presents the estimated coefficients of the production function. In column (1) coefficients are estimated by OLS. Columns (2) to (4) present these estimates using different specifications of the method proposed by ACF.[43] Columns (2) and (3) use as labor input the total number of employees. The difference between these two columns is that in column (2) we invert the demand of intermediate inputs to control for unobserved productivity shocks while in column (3) we invert the demand of raw materials. In column (4) we make an additional adjustment to improve the measure of employment taking into account that workers are heterogeneous in their productivity. Using information about the type of workers employed by each plant and their average compensation, we separate between blue-collar and white-collar workers in order to construct a new measure of labor that takes into account that white-collar workers should be, on average, more productive than blue-collars.[44]

[43] The larger OLS bias on the labor compared to the capital coefficient is consistent with most empirical results and models of inputs choice where labor is more easily adjustable than capital, and thus, highly correlated with productivity shocks (Ackerberg et al. (2007)).

[44] In particular, $L = (wageratio * white + blue)$. The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average.

Table A3
Production function estimates

		ACF		
	OLS	*Proxy=* *Int. Inputs*	*Proxy=* *Raw mat.*	*Labor* *adjusted*
	(1)	(2)	(3)	(4)
Labor	0.181***	0.062***	0.095***	0.135***
	(0.005)	(0.021)	(0.031)	(0.037)
Capital	0.068***	0.111***	0.099***	0.092***
	(0.002)	(0.005)	(0.006)	(0.008)
Iintermediate inputs	0.696***	0.553***	0.583***	0.590***
	(0.004)	(0.016)	(0.022)	(0.026)
Raw materials	0.082***	0.028***	0.032***	0.037***
	(0.003)	(0.004)	(0.005)	(0.004)
R-squared	0.928			
N	44,340	37,657	37,657	37,643
Plants	6,680			

Notes. Revenue is the log of plant's total sales of manufactured products. Employment is the log of plant's total number of employees. Capital is the log of plant's stock value of physical capital (discounted accumulated depreciation), and includes land, buildings, machinery, equipment, tools, and vehicles. Spending on raw materials includes electricity and fuels (also in logs). The measures of revenue, capital, materials, electricity and fuels are deflated using specific 4-digit industry deflators obtained from Chilean Institute of Statistics- INE. In column (1) the production function is estimated by OLS. In columns (2), (3) and (4) following the method proposed by Ackerberg, Caves and Frazer (2015). The second-stage of the ACF method is estimated by GMM instrumenting labor with its lag. In col. (2) we invert the demand of intermediate inputs to control for unobserved productivity shocks, while in col. (3) we invert the demand of raw materials.In col. (4) the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers applying the formula: L=(wageratio*white + blue). The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average. Robust standard errors calculated by bootstrap (n=100). *** p<0.01, ** p<0.05, * p<0.1.

A.3 Productivity changes

Other papers in the literature have found that Chinese import competition triggered productivity improvements within firms (Bloom et al. (2015)). To test this hypothesis, we run the baseline regression using the three different estimates of TFP explained above as dependent variables. Table A4 presents the results. Although positive in columns (4) to (6), estimated coefficients are not statistically significant. This evidence suggests that there is no significant effect of CIP on plant-level productivity. However, it is important to acknowledge that we are not testing alternative hypotheses based on different mechanisms that could also enhance within firm productivity. For instance, firm re-organization through changes in the number of layers (Caliendo et al. (2017)), investment in new technologies (Bustos (2011)), or product quality upgrading (Fernandes and Paunov (2013), Medina (2018)), among others.

Table A4
Plant-level TFP and China import penetration

	OLS	2SLS		
	(1)	(2)	(3)	(4)
Panel A. TFP 1				
China import pen.	-0.0017	-0.0011	-0.0016	-0.0015
	(0.0012)	(0.0019)	(0.0018)	(0.0018)
Weak IV F-stat	-	34.50	32.50	34.82
Panel B. TFP 2				
China import pen.	-0.0014	-0.0007	-0.0011	-0.0010
	(0.0012)	(0.0019)	(0.0018)	(0.0018)
Weak IV F-stat	-	34.50	32.50	34.82
Panel C. TFP 3				
China import pen.	-0.0013	-0.0008	-0.0011	-0.0010
	(0.0012)	(0.0018)	(0.0018)	(0.0018)
Weak IV F-stat	-	34.48	32.49	34.83
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Region x Year FE	-	-	Yes	Yes
Industry PT x Year FE	-	-	-	Yes

Notes. TFP estimated using the method proposed by Ackerberg, Caves and Frazer (2015). The second-stage of the ACF method is estimated by GMM instrumenting labor with its lag. In Panel A we invert the demand of intermediate inputs to control for unobserved productivity shocks, while in Panel B we invert the demand of raw materials. In Panel C the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers applying the formula: L=(wageratio*white + blue). The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average. China import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports) and varies at 4-digit industry-year level. This variable is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Industries defined at 4-digit ISIC Rev. 3. Regions correspond to country's first-level administrative division. Industry pre-existing trend defined as the 5-year past change (1989-1994) in the corresponding dependent variable interacted with year fixed effects. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Although we do not find effects on within plant productivity, we could still find effects on aggregate productivity, which is the weighted average productivity across plants. Empirically, producers present considerable differences in productivity, even within narrowly defined industries, and changes in aggregate productivity over time not only reflect shifts in the distribution of plant's productivity but also compositional changes across plants (including changes in market shares among surviving plants, and also due to the entry and exit of new and old establishments, respectively). Note that results on the heterogeneous effects of CIP, presented in Section V.2, show that the negative effects of the competitive shock were unevenly distributed among plants, being the least productive those that suffered the most.

In order to investigate the effects of CIP on aggregate productivity we follow the method of Melitz and Polanec (2015), who propose an extension of the Olley and Pakes (1996) productivity decomposition that accounts for the contributions of surviving, entering, and exiting firms to aggregate productivity changes. The Olley and Pakes (1996) approach is based on a decomposition of the aggregate productivity level Φ_t in each period. Specifically, this decomposition is:

$$\Phi_t = \bar{\phi_t} + \sum_i (s_{it} - \bar{s_t})(\phi_{it} - \bar{\phi_t}) \tag{A.2}$$

$$\Phi_t = \bar{\phi_t} + cov(s_{it}, \phi_{it}) \tag{A.3}$$

Where $\bar{\phi_t} = \frac{1}{n}\sum_i^n \phi_{it}$ is the unweighted plant-level productivity mean, s_{it} is the market share of plant i at time t, and $\bar{s_t} = \frac{1}{n}$ is the mean market share. Changes in productivity over time $\Delta\Phi$ are then given by the change in the unweighted mean $\Delta\bar{\phi_t}$ and the change in covariance Δcov. This methodology provides a simple way to decompose productivity changes into one component measuring shifts in the productivity distribution (due to the change in the first moment $\Delta\bar{\phi_t}$), and another component capturing market share reallocations via the change in covariance.

Melitz and Polanec (2015) propose an extension of the Olley and Pakes (1996) productivity decomposition that accounts for the contributions of surviving, entering, and exiting firms to aggregate productivity changes. Let $s_{Gt} = \sum_{i\in G} s_{it}$ represent the aggregate market share of a group G of firms and define $\Phi_{Gt} = \sum_{i\in G}(\frac{s_{it}}{s_{Gt}})\phi_{it}$ as that group's aggregate (average) productivity. Then, aggregate productivity in each period can be written as a function of the aggregate share and aggregate productivity of three types of firms (survivors, entrants, and exiters):

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}) \tag{A.4}$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}) \tag{A.5}$$

Where S correspond to survivors, E to entrants, and X to exiters. Thus, the aggregate productivity change ($\Delta\Phi$) can be decomposed into components for the three groups of firms: survivors, entrants, and exiters.

$$\Delta\Phi = (\Phi_{S2} - \Phi_{S1}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{X1} - \Phi_{S1}) \tag{A.6}$$

Applyng the Olley and Pakes (1996) decomposition to the survivers component:

$$\Delta\Phi = \Delta\bar{\phi_S} + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{X1} - \Phi_{S1}) \tag{A.7}$$

The first two terms measure the aggregate productivity change due to the contribution of surviving firms – further separating that component into one induced by a shift in the distribution of firm productivity (the unweighted mean change in the productivity of surviving firms $\Delta\bar{\phi_S}$), and another one induced by market share reallocations (the covariance change between market share and productivity for surviving firms Δcov_S). The third and four terms account for the contribution of entry and exit, and are constructed as the difference in aggregate (average) productivity between entering and exiting firms with respect to the aggregate productivity of surviving firms, weighted by the market share associated to each group of firms.[45]

First, we apply the decomposition method of Melitz and Polanec (2015) and recover the contribution of the channels accounting for changes in industry TFP. Then, we regress industry TFP change and each decomposed mechanism in the change in CIP during the corresponding time period, instrumenting this variable with the change in average Chinese industry import share across high-income countries. To take into account that plants may not be able to adjust productivity immediately after the shock, we make the decomposition for 1-, 2-, and 3-year periods. We present these results in Table A5. The first column shows the coefficients on CIP for the total change in TFP, and columns (2) to (5) report the coefficients associated to each component of the decomposition (surviving within, surviving between, exit and entry, respectively). We find no effect of CIP on industry TFP. Consistent with the productivity regressions at the plant-level, we do not find effects of CIP on the productivity of surviving plants (column 2).

In line with our results of the heterogeneous impact of the shock on plant's revenue, we find a little effect of CIP on the between component, explained by reallocation of sales towards more productive plants, which is statistically significant only in the 1-year change analysis (column 3 of Panel A). Finally, and also in line with our heterogeneous results on plant's exit, we find that the exit of least productive plants slightly contributes to increase industry agreggate productivity in the 3-year analysis (column 3 of Panel C). The small magnitude of the exit component can be partially explained by the fact that exiting plants

[45]Note that the productivity difference for exiting/entering firms is done with respect to aggregate productivity of surviving firms in the first/second period.

are smaller than the average plant, and thus have a little weight when computing industry average TFP.

Table A5
TFP decomposition and CIP

	Change in TFP				
	Total	Within	Between	Exit	Entry
	(1)	(2)	(3)	(4)	(5)
Panel A. 1-year change					
Change in CIP	0.004	-0.010	0.014*	0.001	-0.001
	(0.005)	(0.008)	(0.008)	(0.001)	(0.003)
Weak IV F-stat	15.77	15.77	15.77	18.46	15.16
N	858	858	858	780	780
Panel B. 2-year change					
Change in CIP	0.004	-0.004	0.006	0.001	0.001
	(0.005)	(0.004)	(0.004)	(0.001)	(0.002)
Weak IV F-stat	26.72	26.72	26.72	26.96	26.61
N	780	780	780	767	766
Panel C. 3-year change					
Change in CIP	0.001	-0.003	0.002	0.002***	-0.001
	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)
Weak IV F-stat	41.18	41.18	41.18	41.54	41.83
N	702	702	702	693	694

Notes. Dependent variable in column (1) of Panel A, B, and C, is the 1-, 2-, and 3-year change in industry TFP, respectively, calculated by aggregating plant's TFP using plant's revenue as weights. Columns (2) to (5) decompose industry-level change in TFP in four channels: surviving plants (within and between), exiting, and entering plants, using the method proposed by Melitz and Polanec (2015). Independent variable is the corresponding 1/2/3-year change in China import penetration, which is is instrumented using the change in average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Industries defined at 4-digit ISIC Rev. 3. All regressions include year fixed effects and pre-trends in all outcome variables. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Other robustness

We perform additional robustness exercises in several dimensions to check the sensitivity of our results. Table A6 presents the estimates of the preferred specification of baseline regression when we drop extreme values of the distribution of CIP, employment, revenue, and physical capital, separately, and the intersection of all these outliers (columns (2) to (6), respectively). In all cases, estimated coefficients have the same sign and are statistically significant. The most important variation of the effects occur when we drop outliers only in terms of CIP (column (2)). In this case, the exit coefficient presents an increase of 58% (0.29 percentage points). It is important to note that, when we drop outliers of CIP but at the same time eliminate outliers in terms of dependent variables (column (6)), which is quite a demanding test, estimated coefficients are very similar to the baseline ones.

Throughout this paper, we have used high-income countries to construct the instrument for CIP. One concern about using these countries is that they are different from Chile in several dimensions. Related to this point, we believe that the more different countries used as instruments are from Chile the better, since common shocks affecting specific sectors or regions would be more unlikely. In order to confirm that our instrument is indeed capturing a supply-driven shock in China that made this country gained participation in the imports of many countries and regions worldwide, we instrument CIP with the China's average industry import share for different groups of countries: subset of high-income countries (Autor et al. (2013, 2014)), middle-income (World Bank), and all countries in the World. Table A7 presents the results. In the three cases, regressions pass the weak IV test, and estimated coefficients in the second stage have the same sign and are statistically significant (columns (2) to (4)). Additionally, Table A8 shows the results of the heterogeneous regressions using these three groups of alternative countries (and their interaction with plant's initial productivity level) as instruments for CIP and the interaction term. As before, both estimated coefficients remain robust to the use of alternative groups of countries included in the instrumental variable.

In Table A9, we control for pre-existing trends in a large set of variables, such as import penetretion from other countries, TFP, importing and exporting condition, share of imported inputs, share of exports in sales, wagebill, number of strikes, and a dummy indicating foreign ownership. In all cases, estimated coefficients remain virtually unchanged. Finally, for the set of regressions capturing heterogeneous effects, we test the robustness of our results to the use of the two alternative measures of TFP (explained in Section A.2) and labor productivity (see Table A10). Also in these cases, the sign, magnitude and statistical significance of estimated coefficients change very little compared to the baseline heterogeneous regressions.

As we explained before in Section III, after 2007 the INE interrupted the panel structure of the data alleging confidentiality issues regarding plant's identifiers, so we can not perform a plant-level analysis thereafter. Despite this issue, we can still perform industry-level regressions including more recent years in the sample period. Table A11 presents industry-level regressions for revenue, employment, physical capital, and the total number of active plants with 10 or more employees, separately for the original period 1995-2006 (columns 1 and 2) and for the extended period 1995-2012 (columns 3 and 4). The reported coefficient in all cases correspond to the effect of Chinese import penetration, which is instrumented with the average Chinese industry import share across high-income countries. The difference between uneven and even columns is that the latter include industry-level pre-existing trends in the corresponding outcome variable. Estimated coefficients are robust to extending the period of analysis, and magnitudes change very little.[46]

Table A12 presents a robustness exercise including sector-year fixed effects in both main and heterogeneous regressions. Uneven columns present our preferred specification and even columns add sector-year fixed effects. We construct 10 broad sectors, where each sector includes a set of similar manufacturing industries (number of industries 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). Although all results remain statistically significant, the inclusion of these fixed effects increases the magnitude of the standard errors considerably. This is mainly explained by the fact that most CIP occurs at the level of broad manufacturing sectors (a simple descriptive regression of CIP on sector-year dummies has an R-squared of 0.67). Nevertheless, the remaining within sector variation across industries over time is enough to capture a significant causal effect of the competitive shock on domestic plants' outcomes.

Finally, Table A13 presents our preferred specification of both main and heterogeneous regressions for log-revenue, log-employment and log-capital for two different subsamples of plants: (i) excluding entrant plants (columns 2 and 5), and (ii) excluding entrant and exiting plants (balanced sample, columns 3 and 6). It is important to note that these are very strong requirements, as we drop more than 36% or 60% of our original sample in cases (i) and (ii), respectively. Despite this, all estimated coefficients present the same sign and are statistically significant, with the only exception of the revenue coefficient in the balanced sample (column 3 of Panel A).

[46] The only exception is the estimated coefficient for number of plants which reduces around 50%.

Table A6
Robustness to outliers

		Dropping 10% extreme values of:				
	Baseline	China IP	Employment	Revenue	Capital	(2) to (5)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Revenue						
China import pen.	-0.0070**	-0.0084**	-0.0072**	-0.0071**	-0.0074**	-0.0082**
	(0.0031)	(0.0041)	(0.0031)	(0.0032)	(0.0031)	(0.0039)
Weak IV F-stat	32.23	21.65	32.58	32.02	31.87	21.29
Panel B. Employment						
China import pen.	-0.0068***	-0.0077***	-0.0076***	-0.0072***	-0.0074***	-0.0086***
	(0.0016)	(0.0021)	(0.0016)	(0.0015)	(0.0016)	(0.0018)
Weak IV F-stat	34.01	22.80	34.35	33.77	33.51	22.37
Panel C. Capital						
China import pen.	-0.0124***	-0.0161***	-0.0130***	-0.0130***	-0.0126***	-0.0146***
	(0.0035)	(0.0044)	(0.0033)	(0.0033)	(0.0033)	(0.0037)
Weak IV F-stat	32.57	21.43	32.89	32.29	32.02	21.09
N	44,340	40,319	39,980	39,979	39,979	32,949
Plants	6,680	5,824	5,949	5,938	5,938	4,586
Panel D. Plant's exit						
China import pen.	0.0050***	0.0079***	0.0050***	0.0047***	0.0050***	0.0078***
	(0.0007)	(0.0013)	(0.0007)	(0.0008)	(0.0007)	(0.0012)
Weak IV F-stat	35.96	22.97	36.83	35.91	35.65	22.56
N	36,761	33,603	33,230	33,218	33,212	27,549
Plants	6,012	5,299	5,397	5,399	5,380	4,233

Notes. Column (1) presents the baseline estimates (column 4 of Table 6). Columns (2) to (5) exclude the 5% tails of the corresponding variable's distribution, and column (6) excludes the conjunction of all these variables. All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A7
Robustness to instrumental variables in main regressions

	Baseline	High-income*	Middle-income	World
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0070**	-0.0092**	-0.0050	-0.0054*
	(0.0031)	(0.0037)	(0.0030)	(0.0030)
Weak IV F-stat	32.23	11.57	46.78	46.74
Panel B. Employment				
China import pen.	-0.0068***	-0.0083***	-0.0066***	-0.0065***
	(0.0016)	(0.0021)	(0.0016)	(0.0016)
Weak IV F-stat	34.01	12.01	49.10	48.78
Panel C. Capital				
China import pen.	-0.0124***	-0.0179***	-0.0103***	-0.0106***
	(0.0035)	(0.0054)	(0.0031)	(0.0030)
Weak IV F-stat	32.57	10.96	45.93	46.31
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0050***	0.0055***	0.0050***	0.0048***
	(0.0007)	(0.0009)	(0.0007)	(0.0007)
Weak IV F-stat	35.96	13.32	55.82	56.51
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012

Notes. Column (1) presents the baseline estimates when China import penetration (CIP) is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). *In column (2) the IV is constructed with the subset of high-income countries used by Autor et al. (2013) (i.e. Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). In column (3) the IV is constructed using middle-income countries using the World Bank classification. In column (4) the IV is constructed using all countries around the world (with information available in UN-COMTRADE data). All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A8

Robustness to instrumental variables in heterogeneous regressions

	Baseline	High-income*	Middle-income	World
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0072**	-0.0094**	-0.0053*	-0.0056*
	(0.0031)	(0.0037)	(0.0030)	(0.0029)
China IP x TFP_0	0.0054*	0.0064*	0.0068**	0.0061**
	(0.0028)	(0.0036)	(0.0029)	(0.0027)
Weak IV F-stat	16.01	5.758	23.49	23.76
Panel B. Employment				
China import pen.	-0.0072***	-0.0084***	-0.0070***	-0.0069***
	(0.0016)	(0.0021)	(0.0016)	(0.0016)
China IP x TFP_0	0.0085***	0.0102***	0.0087***	0.0084***
	(0.0027)	(0.0035)	(0.0026)	(0.0026)
Weak IV F-stat	16.85	6.081	24.58	24.78
Panel C. Capital				
China import pen.	-0.0131***	-0.0181***	-0.0111***	-0.0114***
	(0.0035)	(0.0054)	(0.0030)	(0.0030)
China IP x TFP_0	0.0167**	0.0242**	0.0180**	0.0168**
	(0.0081)	(0.0122)	(0.0080)	(0.0074)
Weak IV F-stat	16.13	5.562	22.90	23.38
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0052***	0.0055***	0.0052***	0.0050***
	(0.0008)	(0.0010)	(0.0008)	(0.0008)
China IP x TFP_0	-0.0046***	-0.0060***	-0.0053***	-0.0051***
	(0.0013)	(0.0015)	(0.0014)	(0.0013)
Weak IV F-stat	18.65	6.782	28.43	29.60
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012

Notes. Column (1) presents the baseline estimates when China import penetration (CIP) and its interaction with initial TFP are instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank) and its interaction. *In column (2) the IV is constructed using the subset of high-income countries used by Autor et al. (2013) (i.e. Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland). In column (3) the IV is constructed using middle-income countries using the World Bank classification. In column (4) the IV is constructed using all countries around the world (with information available in UN-COMTRADE data). All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9

Robustness to pre-existing trends in control variables

	Revenue	Employment	Capital	Plant's exit
	(1)	(2)	(3)	(4)
China import pen.	-0.0072**	-0.0068***	-0.0113***	0.0049***
	(0.0030)	(0.0015)	(0.0026)	(0.0006)
Weak IV F-stat	32.90	34.43	33.24	35.90
N	44,340	44,340	44,340	36,761
Plants	6,680	6,680	6,680	6,012

Notes. This table presents estimated coefficients from the preferred specification of baseline regressions (in column 4 of Table 6) including a large set of pre-existing trends in control variables (import penetration from other countries, TFP, importing and exporting condition, share of imported inputs, share of exports in sales, log wagebill, number of strikes, and a dummy indicating foreign ownership). These trends are constructed interacting each variable in the initial year with year fixed effects. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A10
Robustness to productivity measures

	Baseline	TFP2	TFP3	LP
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0072**	-0.0072**	-0.0071**	-0.0116***
	(0.0031)	(0.0031)	(0.0031)	(0.0035)
China IP x TFP_0	0.0054*	0.0047	0.0039	0.0044**
	(0.0028)	(0.0032)	(0.0036)	(0.0020)
Weak IV F-stat	16.01	15.93	15.87	16.39
Panel B. Employment				
China import pen.	-0.0072***	-0.0072***	-0.0072***	-0.0176***
	(0.0016)	(0.0016)	(0.0016)	(0.0035)
China IP x TFP_0	0.0085***	0.0095***	0.0107***	0.0104***
	(0.0027)	(0.0029)	(0.0032)	(0.0027)
Weak IV F-stat	16.85	16.76	16.71	17.38
Panel C. Capital				
China import pen.	-0.0131***	-0.0131***	-0.0131***	-0.0160***
	(0.0035)	(0.0035)	(0.0035)	(0.0046)
China IP x TFP_0	0.0167**	0.0184**	0.0201**	0.0035
	(0.0081)	(0.0092)	(0.0102)	(0.0024)
Weak IV F-stat	16.13	16.03	15.96	16.51
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0052***	0.0051***	0.0051***	0.0066***
	(0.0008)	(0.0008)	(0.0008)	(0.0010)
China IP x TFP_0	-0.0046***	-0.0046***	-0.0046***	-0.0015***
	(0.0013)	(0.0016)	(0.0017)	(0.0005)
Weak IV F-stat	18.65	18.71	18.76	9.972
N	36,757	36,757	36,744	36,757
Plants	6,011	6,011	6,008	6,011

Notes. In columns (1), (2) and (3) TFP is estimated following the method proposed by Ackerberg, Caves and Frazer (2015). The second-stage of the ACF method is estimated by GMM instrumenting labor with its lag. In TFP1 we invert the demand of intermediate inputs to control for unobserved productivity shocks, while in TFP2 we invert the demand of raw materials. In TFP3 the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers applying the formula: L=(wageratio*white + blue). The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average. Labor productivity is measured as sales per worker. CIP and its interaction with initial TFP/LP are instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank) and its interaction with initial TFP/LP. All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A11

Robustness to sample period extension. Industry-level effects

	1995-2006		1995-2012	
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.016**	-0.016**	-0.017**	-0.018**
	(0.007)	(0.007)	(0.008)	(0.008)
Weak IV F-stat	53.68	48.46	56.18	60.70
Panel B. Employment				
China import pen.	-0.017***	-0.016***	-0.015***	-0.014***
	(0.005)	(0.005)	(0.005)	(0.005)
Weak IV F-stat	53.68	49.51	56.18	71.55
Panel C. Capital				
China import pen.	-0.027***	-0.027***	-0.022***	-0.020***
	(0.006)	(0.006)	(0.006)	(0.006)
Weak IV F-stat	53.68	53.61	56.18	51.39
Panel D. Number of plants				
China import pen.	-0.016***	-0.015***	-0.010***	-0.010***
	(0.004)	(0.005)	(0.003)	(0.003)
Weak IV F-stat	53.68	53.00	56.18	60.46
N	936	936	1,380	1,380
Industries	78	78	78	78
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry outcome pre-trend	-	Yes	-	Yes

Notes. Revenue and capital are deflated using specific 4-digit industry deflators obtained from Chilean Institute of Statistics- INE. China import penetration measured as total value of imports from China divided by domestic absorption (production minus net exports). This variable is instrumented with the average Chinese industry import share across high-income countries (using the classification conducted by The World Bank). Industries defined at 4-digit ISIC Rev. 3. Industry outcome pre-existing trend corresponds to 5-year change (1989-1994) in dependent variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A12
Robustness to including sector-year fixed effects

	Main		Heterogeneous	
	(1)	(2)	(3)	(4)
Panel A. Revenue				
China import pen.	-0.0070**	-0.0143*	-0.0072**	-0.0145*
	(0.0031)	(0.0079)	(0.0031)	(0.0079)
China IP x TFP0			0.0054*	0.0043
			(0.0028)	(0.0029)
Weak IV F-stat	32.23	31.20	16.01	15.50
Panel B. Employment				
China import pen.	-0.0068***	-0.0058*	-0.0072***	-0.0063*
	(0.0016)	(0.0033)	(0.0016)	(0.0033)
China IP x TFP0			0.0085***	0.0084***
			(0.0027)	(0.0027)
Weak IV F-stat	34.01	32.52	16.85	16.16
Panel C. Capital				
China import pen.	-0.0124***	-0.0197***	-0.0131***	-0.0205***
	(0.0035)	(0.0070)	(0.0035)	(0.0069)
China IP x TFP0			0.0167**	0.0162**
			(0.0081)	(0.0078)
Weak IV F-stat	32.57	31.66	16.13	15.72
N	44,340	44,340	44,340	44,340
Plants	6,680	6,680	6,680	6,680
Panel D. Plant's exit				
China import pen.	0.0050***	0.0065***	0.0052***	0.0067***
	(0.0007)	(0.0012)	(0.0008)	(0.0013)
China IP x TFP0			-0.0046***	-0.0046***
			(0.0013)	(0.0014)
Weak IV F-stat	35.96	31.69	18.65	15.77
N	36,761	36,761	36,761	36,761
Plants	6,012	6,012	6,012	6,012
Year FE	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Industry PT x Year FE	Yes	Yes	Yes	Yes
Sector x Year FE	-	Yes	-	Yes

Notes. Columns (1) and (3) present the baseline estimates for main and heterogeneous regressions (columns 4 of Tables 6 and 7), respectively. These regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Columns (2) and (4) include additional controls for sector-year fixed effects. We construct 10 broad sectors that include a subset of similar 4-digit manufacturing industries (see Figure 1). Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.

Table A13
Robustness to balanced-sample estimation

	Main			Heterogeneous		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Revenue						
China import pen.	-0.0070**	-0.0066**	-0.0025	-0.0072**	-0.0076***	-0.0037
	(0.0031)	(0.0028)	(0.0030)	(0.0031)	(0.0027)	(0.0030)
China IP x TFP_0				0.0054*	0.0110***	0.0101**
				(0.0028)	(0.0039)	(0.0043)
Weak IV F-stat	32.23	40.78	31.24	16.01	19.91	14.39
Panel B. Employment						
China import pen.	-0.0068***	-0.0074***	-0.0047***	-0.0072***	-0.0083***	-0.0060***
	(0.0016)	(0.0019)	(0.0018)	(0.0016)	(0.0018)	(0.0016)
China IP x TFP_0				0.0085***	0.0100***	0.0105***
				(0.0027)	(0.0033)	(0.0036)
Weak IV F-stat	34.01	42.59	32.85	16.85	20.71	15.03
Panel C. Capital						
China import pen.	-0.0124***	-0.0132***	-0.0122***	-0.0131***	-0.0152***	-0.0145***
	(0.0035)	(0.0036)	(0.0035)	(0.0035)	(0.0037)	(0.0041)
China IP x TFP_0				0.0167**	0.0219***	0.0188**
				(0.0081)	(0.0082)	(0.0077)
Weak IV F-stat	32.57	42.00	31.94	16.13	20.42	14.65
N	44,340	29,248	17,508	44,340	29,248	17,508
Plants	6,680	3,555	1,459	6,680	3,555	1,459

Notes. Columns (1) and (3) present the baseline estimates for main and heterogeneous regressions (columns 4 of Tables 6 and 7), respectively. Columns (2) and (4) exclude entrant plants from the sample. Columns (3) and (6) include only those plants that are present in all years of the studied period 1995-2006 (balanced sample). All regressions include plant- and region-year fixed effects, plus industry-level pre-trends in the corresponding outcome variable. Weak IV F-Stat is the Kleibergen-Paap weak instrument F statistic. Robust standard errors clustered by industries. *** p<0.01, ** p<0.05, * p<0.1.