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Heterogeneous Effects of Chinese Import Competition on Chilean Manufacturing Plants

ABSTRACT We study the effect of a trade-induced competitive shock, defined as rising import competition from China, on Chilean manufacturing plants. For identification, we exploit the fact that in 1995–2006, Chinese import penetration increased sharply in Chile, but this expansion varied widely across manufacturing industries. We use Chinese export growth in high-income industry-country pairs as an instrument for Chinese import penetration. 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 Codes: F14, D22

Keywords: Trade shock, Chinese import penetration, manufacturing plants, Chile, productivity

There is consensus in mainstream economics that globalization and trade liberalization tend to improve long-term welfare by allowing the economy to reallocate resources toward sectors with a comparative advantage and toward more productive firms within narrowly defined industries, to increase consumer surplus by means of pro-competitive gains and the availability of a greater number of products, and to ease access to foreign intermediate inputs, capital goods, and new technologies. Reallocation is also likely to create short- and medium-term losses that tend to be unevenly distributed across regions, industries, firms, and workers. Overcoming the adjustment costs and

ACKNOWLEDGMENTS Special thanks to the editor, Rafael Dix-Carneiro. We also thank Irene Brambilla, Leonardo Gasparini, Daniel Lederman, Guido Porto, Joana Silva, and Dario Tortarolo for helpful comments.

securing the 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.

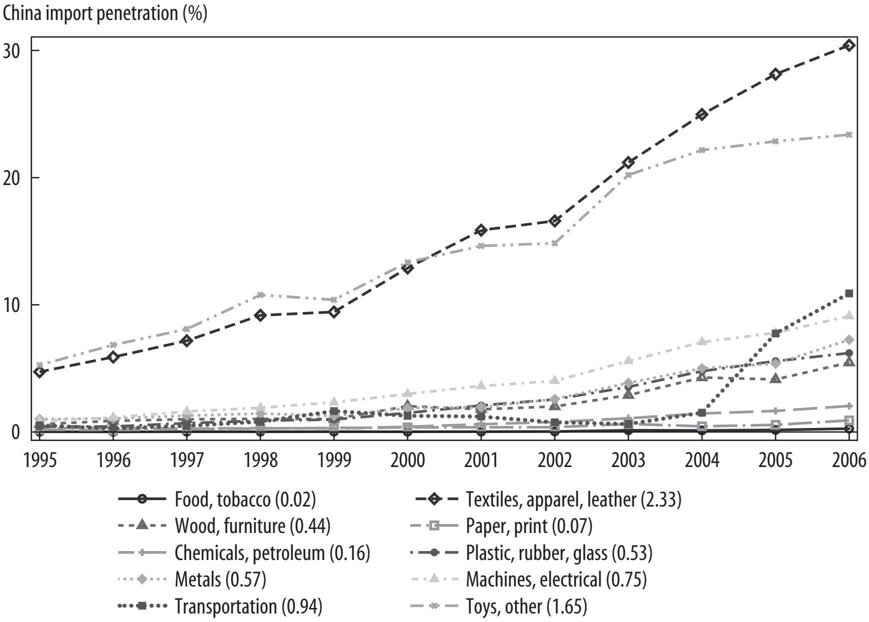
In this paper, we empirically characterize short-term plant- and industry-level responses to a trade-induced competitive shock defined as rising import competition from China. The remarkable growth of China in the last decades provides a unique opportunity to measure the causal effect of trade on relevant 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 positioned China as one of the world's leading producers of manufactures.[1] For identification, we exploit the fact that in 1995–2006, Chinese import penetration (measured as the total value of imports from China relative to domestic absorption) increased sharply in Chile, from 1.5 percent in 1995 to 9.9 percent in 2006, but this expansion varied widely across manufacturing industries. For instance, sectors such as textiles, toys, and machines and electrical equipment present the highest rates of exposure to Chinese import competition, while sectors such as food, paper, and chemicals remain barely exposed (see figure 1).

During the period under study, Chilean manufacturing employment decreased through 2001 and fully recovered by 2006 (see figure 2). Notably, growth patterns differed substantially across industries, with those that were more exposed to Chinese import competition contracting the most and recovering the least.[2] In 1995, industries with a low exposure to China were 18.2 percent larger in terms of employment than industries with a high exposure; this gap increased to 96 percent in 2006. While many potential factors may explain these divergent patterns, our estimates predict that the trade-induced competitive shock, defined as rising import competition from China, explains around one-third of the relative employment contraction in exposed industries. Importantly, exploiting Chinese import penetration variation across industries delivers only relative effects. Plants in unexposed industries may

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).

2. We find a similar pattern if, instead of manufacturing employment, we plot the evolution of revenue, physical capital, or the number of plants with ten or more employees. Thus, industries that are more exposed to growing Chinese import penetration end up smaller in terms of all these outcomes.

FIGURE 1. Evolution of Chinese Import Penetration by Sector



Source: INE and UN COMTRADE.

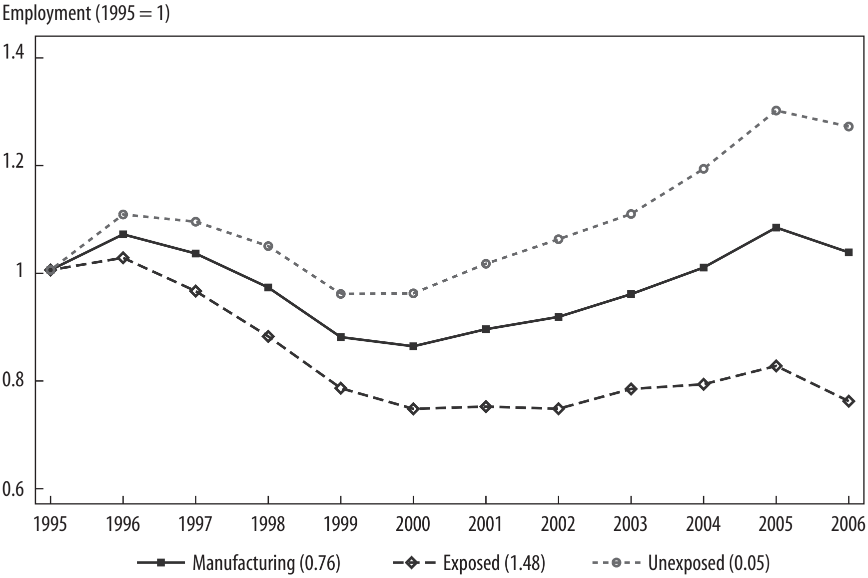
Notes: Chinese import penetration is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. Manufacturing industries are defined at the four-digit ISIC rev. 3 level and are grouped into ten broad sectors comprising similar industries. The sectoral average annual change (in percentage points) in Chinese import penetration is given in parentheses.

also be affected by the China shock if there are spillovers across plants or other general equilibrium effects (for example, reallocation of productive factors and aggregate demand multiplier effects).[3]

We use microdata on the universe of Chilean manufacturing plants in 1995–2006, obtained from the national industrial survey collected annually by the Chilean National Statistics Institute (INE). The main module of the survey includes information on plant characteristics that allows us to estimate total factor productivity (TFP) at the plant level, following the method proposed by Ackerberg, Caves, and Frazer (2015). We then evaluate the

3. In this line, we study indirect effects using industry input-output linkages, exploiting information from 1996 Chilean input-output tables (see Acemoglu, Autor, Dorn, and others [2016] and Pierce and Schott [2016], who use this approach for the United States).

FIGURE 2. Evolution of Manufacturing Employment



Source: INE and UN COMTRADE.

Notes: Exposed (unexposed) industries are those above (below) the fiftieth percentile of the average annual growth in Chinese import penetration (CIP) in 1995–2006, which equals 0.2 percent. CIP is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at the industry-year level. The average annual growth (in percentage points) in CIP across industries of each group is listed in parentheses. Manufacturing industries are defined at the four-digit ISIC rev. 3 level.

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 (IV) strategy that is also used in other papers in the literature (Autor, Dorn, and Hanson, 2013; Autor and others, 2014; Acemoglu and others, 2016).

We employ a secondary publicly available data set from the United Nations Commodity Trade Statistics Database (UN COMTRADE). It contains annual information on import and export values, quantities, partners, and product

4. Exiting plants leave the sample because of either plant closure or plant contraction below ten employees (given the survey design). The distribution of employment in the last year of the sample has a mean of 52.5, a median of 22.0, and a standard deviation of 97.4.

codes (at the six-digit level of the Harmonized System of tariff nomenclature) reported by statistical authorities of close to 200 countries and regions. By merging this data set with the Chilean plant-level data, we construct a measure of Chinese import penetration (CIP), which varies at the four-digit industry-year level.[5] CIP is measured as the total value of imports from China divided by domestic absorption (production minus net exports).

CIP is endogenous because industry shocks affecting the outcome variables could be correlated with demand for imports, so we instrument it with Chinese export growth in high-income industry-country pairs (as in Bernard, Jensen, and Schott, 2006; Autor, Dorn, and Hanson, 2013; and Autor and others, 2014). This identification strategy aims to capture supply-driven shocks that caused China to gain market share across these economies over time.[6] First-stage regressions show a strong predictive power of the instrument, with a coefficient of 1.95 (0.34) and an R^2 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 (for example, workers that exit declining plants and get jobs at other establishments in 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 and exit of plants from the panel (extensive margin).

Our main results suggest that plants in industries that are 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 one percentage point increase in CIP reduces plant revenue by 0.70 percent, employment by 0.68 percent, and physical capital by 1.24 percent, and it increases the plant's probability of leaving the panel by 0.50 percentage points, 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 tenth percentile of within-sector TFP distribution is 1.39 times larger than the marginal effect for a plant situated at the fiftieth percentile. This ratio is 1.60, 1.64, and 1.46 when the marginal effect

5. International Standard Industrial Classification (ISIC), revision 3.

6. The identifying assumptions are that Chinese export growth is exogenous (driven by TFP, infrastructure, migration, and so on) and that industry import demand shocks are uncorrelated between Chile and high-income countries.

of CIP on employment, capital, and exit, respectively, is compared across these plants. Moreover, these effects are not statistically significant for plants located in the highest quantiles of TFP distribution.

The literature shows the relevance of studying both the supply- and demand-side effects of the China shock (Artuc, Lederman, and Rojas, 2015; Costa, Garred, and Pessoa, 2016). Our findings suggest that the Chinese demand shock has not affected Chilean manufacturing plants either directly or indirectly through linkages between manufacturing and the primary sector. 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 experiencing 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, in which all our estimated coefficients remain virtually unchanged. Our results are also robust to accounting for preexisting trends, excluding outliers, using alternative instrumental variables, employing different measures of plant productivity, and expanding the period of study.[7]

This work is connected to the literature studying the effects of Chinese import competition on domestic firms, workers, and markets (Autor, Dorn, and Hanson, 2013; Autor and others, 2014; Bloom, Draca, and Van Reenen, 2015; Acemoglu and others, 2016; Pierce and Schott, 2018).[8] For instance, Autor, Dorn, and Hanson (2013) find that rising imports from China in the United States between 1990 and 2007 caused higher unemployment, lower labor force participation, and lower wages in more exposed local labor markets. Relatedly, Autor and others (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, Draca, and Van Reenen (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

7. We present these robustness exercises in appendix D.

8. 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, Jensen, and Schott, 2006; Khandelwal, 2010).

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 Álvarez and Claro (2009). Using Chilean plant-level data from 1990 to 2000, they show that imports from China have negatively affected employment growth in surviving plants and increased the probability of plant closure. Relative to that paper, our contribution is threefold. First, we extend the analysis to focus on a more dramatic period of Chinese productivity growth (the early 2000s). Second, we adopt the identification strategy originally proposed by Autor, Dorn, and Hanson (2013). Finally, we estimate plant-level TFP and document heterogeneous effects of Chinese competition on several outcomes. Álvarez and Opazo (2011) studied the impact of Chinese import penetration on relative wages in Chilean manufacturing plants in 1996–2005. They found a significant reduction in relative wages for the five sectors that experienced the largest increases in Chinese imports, and the effect was concentrated among small firms. Our approach differs from the latter paper in terms of identification strategy and outcome variables. Moreover, while those authors studied differential effects by plant size, we focus on plant productivity. In a related paper for Mexico, Iacovone, Rauch, and Winters (2013) studied the effect of increasing Chinese competition on selection and reallocation at both the firm and product levels, documenting negative effects for small plants and noncore products. 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. Similarly, Fernandes and Paunov (2013) find that increasing import competition led Chilean manufacturing plants to increase unit values, and they present complementary evidence suggesting that this price increase indeed captures 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; García-Marín 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. The next section presents a brief historical background on Chile and China and argues that Chinese imports represent a real competitive shock for Chilean manufacturing plants. We subsequently present the data and descriptive statistics and then discuss the estimation strategy. After analyzing the main empirical findings, we finish with some concluding remarks. Additional results are presented in the appendixes.

Background

After a period of state intervention and the implementation of an import-substitution policy regime in the 1960s and early 1970s, the Chilean military government carried out a large set of market-oriented reforms in 1974–79. As part of the trade liberalization program, Chile eliminated most nontariff barriers (NTBs) and reduced tariffs significantly.[9] All these reforms positioned Chile as one of the most trade-oriented economies in Latin America at the beginning of the 1990s. For instance, Chile's trade-to-GDP ratio was 61.8 percent in 1990, compared to an average ratio of 33 percent across Latin American countries.[10]

Another aspect of reforms focused on labor market regulations. The government banned unions and replaced collective bargaining with a wage-setting plan.[11] The new Labor Code approved in 1979 replaced national unions with firm-level ones, curtailed workers' rights to strike, and significantly reduced the costs of hiring and firing. A few modifications to the Labor Code were introduced in 1991. Perhaps the most relevant was the increase in the limit on the wage compensation of fired workers, from five to eleven months of wages. Chile experienced a macroeconomic turndown between 1998 and 2001, which triggered an intense debate on labor regulations and ultimately led to the implementation of new changes in the labor laws in December 2001. The reform increased collective bargaining rights and extended some margins of flexibility related to hiring practices, apprenticeships, part-time jobs, and

9. While some tariffs exceeded 100 percent in 1974, five years later they were reduced to a uniform ad valorem tariff of 10 percent. The uniform tariff was raised to 35 percent during the recession of 1982–84, but then reduced to 20 percent in 1985. NTBs were not applied during this transitory period. See Levinsohn (1999) and Pavcnik (2002).

10. The World Bank, World Development Indicators database.

11. Although labor laws did not change, there was considerable de facto deregulation, with courts favoring firms in employee dismissals. After June 1978, firms were legally allowed to dismiss workers at will for economic reasons, without any requirement of just cause.

short-term contracts. Together with changes in the compensation scheme, these reforms remain in practice.

Overall, Chile is a small open economy with a relatively flexible labor market. The Chilean case provides a nice scenario in which 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.

China, in turn, conducted a broad set of structural reforms beginning in the 1980s, which 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 promoting growth and trade, the country's accession to the World Trade Organization (WTO) in December 2001 gave China the permanent status of most-favored nation among the WTO members. According to the World Bank's World Development Indicators, China's exports-to-GDP ratio increased from 5.9 percent in 1980 to a peak of 36 percent in 2006.

Much of China's growth was driven by massive migration from rural to urban regions, strong investment 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 (TFP). According to Brandt, Van Biesebroeck, and Zhang (2012), China had an average annual growth in manufacturing TFP of 8 percent 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 all over the world. Insofar as China exports labor-intensive low-price consumer products, rising imports from China represent increasing competitive pressure for domestic manufacturing plants. 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 toward final goods relative to imports from the rest of the world, which have a larger share of intermediate and capital goods.

We focus on China instead of all low-wage countries for two main reasons. First, China is by far the main country of origin in the list of low-wage

TABLE 1. Average Composition of Chilean Imports by Origin, 1995–2006

	Type of good			
Country of origin	*Capital*	*Intermediate*	*Consumer*	*Other*
United States	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 countries	5.3	41.0	46.9	7.4
Other	26.5	44.6	19.1	9.8
Weighted average	27.2	45.5	22.1	5.2

Source: UN COMTRADE.
Notes: Product classification is by Broad Economic Categories (BEC). Low-wage countries had a GDP per capita less than 5 percent that of the United States in 1972–2001 (Bernard, Jensen, and Schott, 2006).

countries, representing on average more than 90 percent of total imports from these countries during the sample period. In dynamic terms, China became the second source of Chilean manufacturing imports in 2006 (reaching 14 percent), after the United States (18.8 percent). In the first year of our sample, China was in seventh position (3 percent of total imports). It gained participation mainly at the expense of United States, which went from 27 percent in 1995 to 18.8 percent in 2006 (see table 2). Second, China exports manufacturing products at significantly lower prices than other low-wage countries.

Data

The plant-level panel data set is obtained from the national industrial survey (*Encuesta Nacional Industrial Anual,* ENIA) collected annually by the Chilean National Statistics Institute (INE).[12] The ENIA covers the universe of manufacturing plants with ten 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, citing confidentiality issues regarding plants' unique identifiers, so we cannot perform a plant-level

12. This data set is also used by Levinsohn (1999), Pavcnik (2002), Levinsohn and Petrin (2003), Álvarez and Claro (2009), Brambilla, Lederman, and Porto (2017), and García-Marín and Voigtländer (2019).

TABLE 2. Evolution of Chilean Import Composition by Origin

Percent share

Country of origin	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*
United States	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 countries	0.3	0.4	0.5	0.5	0.9	1.0	1.0	1.0	0.9	0.8	0.7	0.8
Other	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	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: UN COMTRADE.

Note: Low-wage countries have a GDP per capita less than 5 percent that of the United States in 1972–2001 (Bernard, Jensen, and Schott, 2006).

analysis thereafter. However, we can still perform industry-level regressions to include more recent years in the sample period.[13]

The main module of the survey includes information on plant characteristics such as revenue, employment, spending on intermediate inputs and raw materials, wage bill, value of the physical capital stock, import/export status, industry affiliation, and region of activity. The main outcomes of interest for our analysis are the value of products sold (revenue), number of employees, the value of the physical capital stock, and the plant's probability of exiting the panel.[14] Exiting plants include both true plant closures and plant contractions below ten employees (given the ENIA design). Nevertheless, the distribution of employment in the last year for plants exiting the panel has a mean of 52.5, a median of 22, and a standard deviation of 97.4. Importantly, these data allow us to estimate TFP at the plant level, following the method proposed by Ackerberg, Caves, and Frazer (2015). We present the production function estimates in appendix B. 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 data set is the United Nations Commodity Trade Statistics Database (UN COMTRADE).[15] It contains information on import and export dollar values, quantities, partners, and product codes (at the six-digit level of the Harmonized System of tariff nomenclature) reported by the 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 Chinese import penetration (CIP), which varies at the industry-year level (at the four-digit level of the International Standard Industrial Classification [ISIC], revision 3). CIP is measured as the total value of imports from China divided by domestic absorption:

13. Results at the industry level are robust to extending the sample period to 1995–2012 (see appendix D). Although we could extend the analysis back to 1992 (which is the first year for which we have UN COMTRADE data), we decided to exclude these years for three reasons. First, there were some methodological changes in the survey in 1995, such as the change in plants' unique identifiers and in the industrial classification (from ISIC revision 2 to ISIC revision 3). Consequently, the INE data are available only starting in 1995. Second, the 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.

14. Capital is the value of the physical capital stock (less accumulated depreciation) and includes land, buildings, machinery, equipment, tools, and vehicles.

15. The data are publicly available at https://comtrade.un.org/ and are also used by many other papers, including Autor, Dorn, and Hanson (2013), Autor and others (2014), Amiti and Khandelwal (2013), and Acemoglu and others (2016).

$$\text{CIP}_{jt} = \frac{M_{jt}^{China}}{\left(Q_{jt} + M_{jt} - X_{jt}\right)}, \tag{1}$$

where Q_{jt}, M_{jt}, and X_{jt} are the value of production, imports, and exports for industry j in year t, respectively.[16]

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

$$\text{SHARE}_{jt}^{China} = \frac{1}{c}\sum_{C}\frac{M_{jct}^{China}}{M_{jct}^{World}}, \tag{2}$$

where M_{jct}^{China} is the total industry-year value of 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 as defined by the World Bank.[17] Intuitively, this variable serves as an instrument for Chilean CIP if it is capable of capturing Chinese supply-driven shocks that caused China to gain market share across high-income countries.

To increase the quality of the data and avoid inconsistencies, we trim the sample on some dimensions. First, we eliminate plants that do not report information on some input (labor, physical capital, intermediate goods) or the value of production. Second, we drop plants that are present just in a single year or that have gaps in reporting.[18] 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.[19]

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

16. 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 the INE ENIA survey.

17. We also test the robustness of our results to alternative groups of countries (namely, a subset of eight high-income countries, middle-income countries, and all countries in the world); see appendix D.

18. 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, Caves, and Frazer (2015).

19. These industries represent 1 percent of total employment and 0.25 percent of total value of production. Our results remain virtually unchanged if we include them in the analysis.

TABLE 3. Summary Statistics of Chilean Manufacturing Plants by Quintile of TFP

Statistic	*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 exit (percent)	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 (percent)	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 (percent)	8.95	11.88	19.03	26.71	48.35	22.98
	(28.55)	(32.36)	(39.25)	(44.25)	(49.98)	(42.07)
No. observations	8,859	8,873	8,871	8,873	8,864	44,340

Source: INE ENIA survey and UN COMTRADE.

Notes: TFP is calculated by the method proposed by Ackerberg, Caves, and Frazer (2015) and normalized by average sector-year TFP. Quintiles are constructed for two-digit ISIC rev. 3 industries. Plant exit is a dummy variable equal to zero in active years and equal to one the year before a given plant leaves the panel. Revenue, capital, and wage are measured in millions of 1995 Chilean pesos. Importing (exporting) is a dummy variable equal to one if the plant exports (imports) in the corresponding year and zero otherwise. Average 1995 exchange rate: 396.8 pesos to the U.S. dollar. Standard deviations are given in parentheses.

between a plant's productivity and number of workers, physical capital, and trade participation, in line with previous findings in the literature (for example, Bernard and others, 2007).[20] 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, 7.5 percent of plants fall below the threshold of ten employees every year and thus exit our panel, given the ENIA design. As we would expect, exit rates decrease with plant-level productivity. While 10.49 percent of plants in the first quintile exit the sample every year, the share is only 5.48 percent for plants in the fifth quintile. The average number of workers per plant is seventy-six. On average, plants in the fifth quintile are almost ten times larger than plants in the first quintile in terms of employment and fifty times larger in terms of physical capital stock (215 versus 22 employees and

20. 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 the variables these plants are relatively similar.

TABLE 4. Summary Statistics of Chinese Imports

Statistic	*Chinese import penetration*	*China's import share in high-income countries*
Mean	4.89	6.43
	(11.76)	(6.77)
25th percentile	0.02	2.17
50th percentile	0.42	3.65
75th percentile	3.19	7.34
Minimum	0.00	0.09
Maximum	91.86	40.99

Source: INE ENIA survey and UN COMTRADE.

Notes: The table presents descriptive statistics for a sample of seventy-eight industries across twelve years ($N = 936$). Industries are defined at the four-digit level of the ISIC rev. 3. Chinese import penetration (CIP) is measured as the total value of imports from China divided by domestic absorption (production minus net exports). China's import share is the average Chinese share in total imports across high-income countries (defined using the World Bank's classification). Standard deviations are given in parentheses.

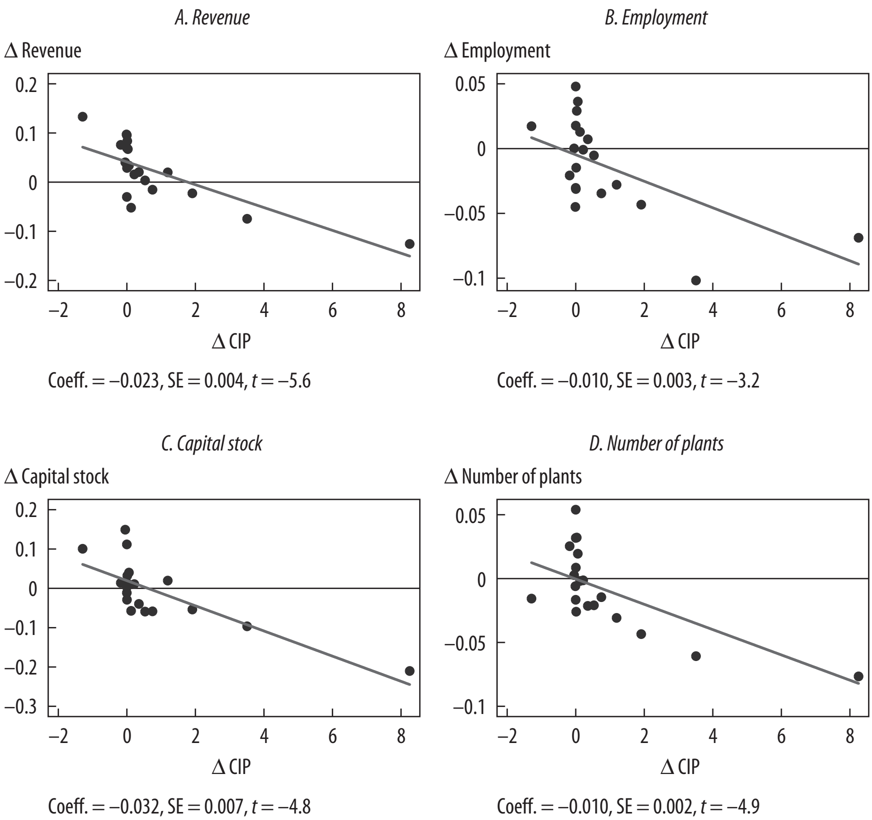
9,152 versus 195 constant 1995 U.S. dollars, respectively). Only 5.76 percent (8.95 percent) of plants in the least productive quintile export (import), versus 50.52 percent (48.35 percent) for plants in the most productive quintile.

Table 4 presents some descriptive statistics for the distribution of the independent variable (Chinese import penetration) and the instrumental variable (China's import share across high-income countries). CIP has a mean of 4.89 and a standard deviation of 11.76, and it takes a value close to zero for about a quarter of industries. A zero means that an industry is not exposed to Chinese imports in that year, and this happens mainly in the food and tobacco sectors. China's import share has a mean of 6.43 and a standard deviation of 6.77. Both variables grew significantly over the period. For instance, average CIP increased by a factor of 6.6, from 1.5 in 1995 to 9.9 in 2006.

Figure 3 presents a nonparametric visualization of the relationship between increasing CIP and the main outcome variables, providing a preview of 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 ten or more employees at the four-digit industry level. In line with figure 2, this graph shows that increasing Chinese competition is negatively correlated with industry revenue, employment, physical capital, and number of active plants.[21] While

21. This exercise is robust to excluding the 10 percent upper tail of the CIP annual change distribution, which are the two outliers on the right side of each plot. Each point represents forty-three industry-year combinations. After these observations are excluded, all coefficients remain statistically significant, and the magnitude increases compared to figure 3.

FIGURE 3. Chinese Import Penetration and Industry Outcomes



Source: INE and UN COMTRADE.

Notes: Industry-year observations are grouped into twenty segments of the same size according to the variable on the horizontal axis, which is the average annual change in Chinese import penetration ($N = 858$). Each point represents the conditional expectation of each outcome variable for each segment. Outcome variables on the vertical axis are the average log annual change in industry revenue, employment, capital, and number of active plants, respectively. The line represents the linear prediction.

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.

Empirical Strategy

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

$$Y_{ijt} = \beta_0 + \beta_1 \mathrm{CIP}_{jt} + \alpha_i + \delta_t + \varepsilon_{ijt}, \quad (3)$$

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 a plant's probability of exiting the panel. In the latter case, an observation takes a value of one in the year t if the plant leaves the sample in the following year ($t + 1$) and zero otherwise. The main variable of interest is Chinese import penetration (CIP_{jt}), which varies at the four-digit industry-year level. We also include region-year fixed effects to control for time-varying shocks that have different impacts on geographically distant regions.[22] Additionally, the preferred specification controls for preexisting trends in industry-outcomes.[23]

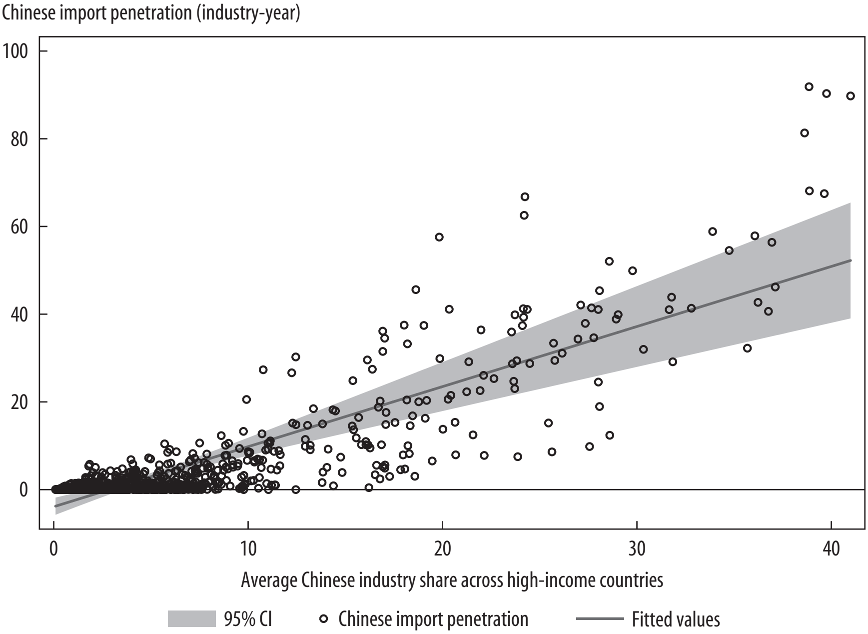
CIP_{jt} is potentially endogenous because industry demand shocks affecting plant-level outcomes could be correlated with demand for imports. To account for this endogeneity concern, we apply an instrumental variable (IV) strategy that is also used in other papers in the literature (for example, Autor, Dorn, and Hanson, 2013; Autor and others, 2014; Acemoglu and others, 2016). We instrument CIP_{jt} with the simple average of China's industry import share across high-income countries (as defined by the World Bank).[24] Again, this variable aims to capture supply-driven shocks inherent to the Chinese

22. Additionally, we present a robustness exercise including sector-year fixed effects to control for time-varying shocks affecting differently broad manufacturing sectors (see the discussion in appendix D).

23. Industry outcome preexisting trend corresponds to the five-year change (1989–94) in each industry's dependent variable interacted with year fixed effects.

24. We also test the robustness of our results to alternative groups of countries (namely, a subset of eight high-income countries, middle-income countries, and all countries in the world); see appendix D.

FIGURE 4. First-Stage Correlation



Source: INE and UN COMTRADE.

Notes: Each point represents an industry-year combination. High-income countries are defined using the World Bank's classification. The 95 percent confidence interval is based on standard errors clustered by two-digit industries (ISIC rev. 3). The slope coefficient is 1.37, the standard error is 0.17, and the regression has an R^2 of 0.75.

economy, which allowed the country to gain market share across some of the most competitive industrial economies in the world, within specific industries over time. We then use this variable to predict CIP 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 an R^2 of 0.75 (see figure 4).

Next, we estimate equation 3 by two-stage least squares (2SLS) regression analysis. The first stage for the main specification includes plant and region-year fixed effects and controls for preexisting trends in industry-level oucomes. Table 5 presents the first stage of the baseline case without interaction (column 1) and the first stage of the specification with heterogeneous effects (columns 2 and 3), which we explain below. In the former

TABLE 5. First-Stage Regressions

	Main	Heterogeneous	
Explanatory variable	*(1)*	*(2)*	*(3)*
China's import share in high-income countries	1.9518***	1.9568***	–0.0317
	(0.3410)	(0.3444)	(0.0341)
China's import share in high-income countries × TFP_0		–0.0830	1.7244***
		(0.0997)	(0.2966)
Summary statistic			
R^2	0.6754	0.6757	0.6308
No. observations	44,340	44,340	44,340
No. plants	6,680	6,680	6,680
Weak IV *F* statistic	32.23		16.01

***$p < 0.01$.

Notes: The dependent variable in columns 1 and 2 is Chinese import penetration (CIP); in column 3, CIP*TFP_0. CIP is measured as the total value of imports from China divided by domestic absorption. China's import share is the average Chinese share in total imports across high-income countries (as defined by the World Bank). Both vary at the industry-year level. Industries are defined at the four-digit ISIC rev. 3 level. Regressions include plant and region-year fixed effects and control for industry-level preexisting trends. These trends are constructed using the change in in industry revenue in the five-year period before the start of the sample (1989–94) interacted with year fixed effects. TFP is measured following Ackerberg, Caves, and Frazer (2015). The weak instrumental variable (IV) *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

case, the estimated coefficient for the IV (1.95) is precisely estimated (with a standard error of 0.34), and the R^2 of this regression is 0.68. In the latter case, the relevant coefficients are also statistically significant.

In all cases, first-stage regressions amply satisfy the *F* test of excluded instruments. The identifying assumptions are that China's export growth is exogenous (driven by TFP, infrastructure, migration, and so forth) and that 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 shocks in high-income countries. The specifications including sector-year fixed effects, presented as a robustness check in appendix D, will account for any contemporaneous shock affecting specific sectors in both Chile and this group of countries (for example, automation, changes in preferences, and so forth). 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 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 plants' initial level of TFP. To estimate TFP, we follow the method proposed by Ackerberg, Caves, and Frazer (2015).[25] We present different estimates of the production function in appendix B.[26] We run the following regression, including initial plant-level TFP interacted with CIP:

$$Y_{ijt} = \beta_0 + \beta_1 \mathrm{CIP}_{jt} + \beta_2 \mathrm{CIP}_{jt} \times \mathrm{TFP}_{i0} + \alpha_i + \delta_t + \varepsilon_{ijt}, \tag{4}$$

where TFP_{i0} is the initial level of a plant's TFP, and the remaining terms are the same as in equation 3. Estimated TFP is normalized by two-digit industry-year averages.[27]

The inclusion of initial plant-level TFP interacted with CIP is key for capturing 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.

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 (for example, 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 and exit of plants from the panel (extensive margin). We estimate the following regression equation:

$$Y_{jt} = \beta_0 + \beta_1 \mathrm{CIP}_{jt} + \alpha_j + \delta_t + \varepsilon_{jt}, \tag{5}$$

25. 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) under the classic OLS estimator. Second, firm-level data sets 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 Ackerberg, Benkard, Berry, and Pakes (2007), Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015).

26. 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).

27. 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.

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 the number of active plants, but they are aggregated at the four-digit industry-year level. Regressions also control for preexisting trends in the corresponding industry outcome.

Results

Table 6 presents the baseline plant-level estimates of equation 3 for the log of total revenue, log of total employment, log of the physical capital stock, and a plant's exit probability. 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 the 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, which biases the OLS estimates toward zero. Column 3 incorporates region-year fixed effects. Column 4 incorporates the corresponding industry outcome preexisting trend, which is constructed as the interaction between the industry-level change in the five-year period before the start of the sample (that is, 1989–94) of each dependent variable and year fixed effects.[28]

The results in table 6 suggest that plants in industries that are 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 one percentage point increase in CIP reduces plant revenue by 0.70 percent, employment by 0.68 percent, and physical capital by 1.24 percent, and it increases a plant's probability of exiting the panel by 0.50 percentage points, ceteris paribus, relative to comparable plants in

28. In appendix D, we present a robustness exercise including sector-year fixed effects (see table D7). 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^2 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.

TABLE 6. Plant-Level Effects of Chinese Import Penetration

	OLS	2SLS		
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*	*(4)*
A. Revenue				
Chinese import penetration	–0.0073***	–0.0084**	–0.0076**	–0.0070**
	(0.0021)	(0.0035)	(0.0032)	(0.0031)
Weak IV *F* statistic	—	34.50	32.50	32.23
B. Employment				
Chinese import penetration	–0.0070***	–0.0078***	–0.0068***	–0.0068***
	(0.0011)	(0.0019)	(0.0017)	(0.0016)
Weak IV *F* statistic	—	34.50	32.50	34.01
C. Capital				
Chinese import penetration	–0.0136***	–0.0208***	–0.0126***	–0.0124***
	(0.0026)	(0.0048)	(0.0034)	(0.0035)
Weak IV *F* statistic	—	34.50	32.50	32.57
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0029***	0.0040***	0.0052***	0.0050***
	(0.0006)	(0.0007)	(0.0008)	(0.0007)
Weak IV *F* statistic	—	30.35	28.60	35.96
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012
Year fixed effects	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
Region-year fixed effects	—	—	Yes	Yes
Industry PT–year fixed effects	—	—	—	Yes

**$p < 0.05$; ***$p < 0.01$.

Notes: Revenue is the log of plants' total sales of manufactured products. Employment is the log of plants' total number of workers. Capital is the log of plants' physical capital stock (less depreciation) and includes land, buildings, machinery, equipment, tools, and vehicles. Revenue and capital are deflated using specific four-digit industry deflators obtained from the INE. Plant exit is a dummy variable equal to zero in active years and equal to one the year before a given plant leaves the panel. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at the four-digit industry-year level. This variable is instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank). Industries are defined at the four-digit ISIC rev. 3 level. Regions correspond to the country's first-level administrative division. Industry preexisting trend (PT) is defined as the change in the corresponding dependent variable in the five-year period before the start of the sample (1989–94) interacted with year fixed effects. In the case of plant exit, the preexisting trend (PT) variable is the change in the number of plants in the 1989–94 period. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

less exposed industries.[29] 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 only in a single year, making the exit rate artificially zero in 1995. Second, because exit takes the value of one if a plant leaves the sample in the following year, we cannot construct this variable for 2006.[30]

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 preexisting trends in the dependent variable at the industry level, which are constructed analogously to those included in column 4 of table 6. In line with the plant-level results, table 7 suggests that industries that are more exposed to growing Chinese import competition present relative declines in revenue, employment, physical capital, and number of plants with ten or more employees, with respect to less exposed industries.

Compared with the plant-level regressions, the 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 a plant's probability of surviving, plant-level estimates might also be attenuated in this context. These results are also in line with previous findings by Autor and others (2014) and also with the heterogeneous effects we find in this paper. For further discussion, see appendix A.

29. To increase the confidence in our estimates, we carried out 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 regressed the (log) change in each dependent variable in 1984–94 (or 1989–94) on the change in industry CIP in 1995–2005 (or 1995–2000). In the second test, we conducted similar regressions but separated plants according to their size, to verify that future Chinese competition is not related to past changes in industry outcomes for different type of plants. In both cases, we found no correlation, supporting the idea that our identification strategy isolates industry-level shocks caused by rising CIP instead of other confounders. The results are available in an online appendix (www.dropbox.com/s/m4sx8ejdb084tb1/2019%20-%20Cesar%20%26%20Falcone%20%28Online%20Appendix%29.pdf?dl=0).

30. As a robustness exercise, table D8 in appendix D presents our preferred specifications for log-revenue, log-employment, and log-capital for two different subsamples: one excluding entrant plants and one excluding entering and exiting plants (balanced sample). All estimated coefficients present the same sign and are statistically significant, with the sole exception of the revenue coefficient in the balanced sample.

TABLE 7. Industry-Level Effects of Chinese Import Penetration

	OLS	2SLS	
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*
A. Revenue			
Chinese import penetration	−0.028***	−0.016**	−0.016**
	(0.006)	(0.007)	(0.007)
Weak IV *F* statistic	—	53.68	48.46
B. Employment			
Chinese import penetration	−0.021***	−0.017***	−0.016***
	(0.005)	(0.005)	(0.005)
Weak IV *F* statistic	—	53.68	49.51
C. Capital			
Chinese import penetration	−0.034***	−0.027***	−0.027***
	(0.007)	(0.006)	(0.006)
Weak IV *F* statistic	—	53.68	53.61
D. Number of plants			
Chinese import penetration	−0.017***	−0.016***	−0.015***
	(0.003)	(0.004)	(0.005)
Weak IV *F* statistic	—	53.68	53.00
Summary statistic			
No. observations	936	936	936
Industries	78	78	78
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Industry outcome PT	—	—	Yes

**$p < 0.05$; ***$p < 0.01$.

Notes: Revenue and capital are deflated using specific four-digit industry deflators obtained from the INE. Chinese import penetration is measured as the 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 (as defined by the World Bank). Industries are defined at the four-digit ISIC rev. 3 level. Industry outcome preexisting trend (PT) corresponds to the change in the dependent variable in the five-year period before the start of the sample (1989–94). Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

Heterogeneous Effects

Table 8 presents the results for the estimates of equation 4, which includes an interaction term between CIP and a plant's initial level of TFP. Dependent variables are, again, the log of total revenue, log of total employment, log of physical capital, and a plant's probability of leaving the panel. The 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 is shown by the estimated coefficient of the

TABLE 8. Heterogeneous Effects of Chinese import Penetration

Dependent and explanatory variables	*OLS* (1)	*2SLS* (2)	(3)	(4)
A. Revenue				
Chinese import penetration	−0.0074***	−0.0086**	−0.0078**	−0.0072**
	(0.0021)	(0.0035)	(0.0032)	(0.0031)
CIP × TFP_0	0.0041*	0.0046*	0.0047	0.0054*
	(0.0023)	(0.0027)	(0.0028)	(0.0028)
Weak IV *F* statistic	—	16.34	15.97	16.01
B. Employment				
Chinese import penetration	−0.0072***	−0.0081***	−0.0072***	−0.0072***
	(0.0011)	(0.0018)	(0.0017)	(0.0016)
CIP × TFP_0	0.0042	0.0082***	0.0084***	0.0085***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Weak IV *F* statistic	—	16.34	15.97	16.85
C. Capital				
Chinese import penetration	−0.0138***	−0.0214***	−0.0132***	−0.0131***
	(0.0026)	(0.0048)	(0.0035)	(0.0035)
CIP × TFP_0	0.0067*	0.0133	0.0166**	0.0167**
	(0.0036)	(0.0081)	(0.0080)	(0.0081)
Weak IV *F* statistic	—	16.34	15.97	16.13
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0030***	0.0042***	0.0053***	0.0052***
	(0.0007)	(0.0008)	(0.0009)	(0.0008)
CIP × TFP_0	−0.0044***	−0.0051***	−0.0047***	−0.0046***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Weak IV *F* statistic	—	15.12	14.54	18.65
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012
Year fixed effects	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
Region-year fixed effects	—	—	Yes	Yes
Industry PT–year fixed effects	—	—	—	Yes

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: Revenue is the log of plants' total sales of manufactured products. Employment is the log of plants' total number of workers. Capital is the log of plants' stock value of physical capital (discounted depreciation) and includes land, buildings, machinery, equipment, tools, and vehicles. Revenue and capital are deflated using specific four-digit industry deflators obtained from the INE. Plant exit is a dummy variable equal to zero in active years and equal to one the year before a given plant leaves the panel. Chinese import penetration (CIP) is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at the four-digit industry-year level. TFP is measured following Ackerberg, Caves, and Frazer (2015). CIP and its interaction with initial TFP are instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank) and its interaction with initial TFP. Regions correspond to a country's first-level administrative division. Industry preexisting trend (PT) is defined as the change in the corresponding dependent variable in the five-year period before the start of the sample (1989–94) interacted with year fixed effects. In the case of Plant exit, the PT variable is the past change in the number of plants. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

interaction term, which has the opposite sign of 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 tenth 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 fiftieth percentile.[31] For example, a one percentage point increase in CIP reduces plant revenue, employment, and capital by 1.01 percent, 1.18 percent, and 2.21 percent, respectively, for a plant located at the tenth percentile, while this effect is 0.73 percent, 0.73 percent, and 1.34 percent, respectively, for a plant situated at the fiftieth 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, together with the 95 percent confidence intervals, for plants located at different percentiles of the initial within-sector TFP distribution.[32] These figures show that the marginal effect of CIP on the outcome variables is statistically indistinguishable from zero for 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, Draca, and Van Reenen, 2015), boosting investment in new technologies (Bustos, 2011), switching their product mix (Bernard, Redding, and Schott, 2010), or modifying their hierarchical structure (Caliendo and others, 2017). However, looking for evidence on the different mechanisms behind these heterogeneous responses is beyond the scope of this paper.

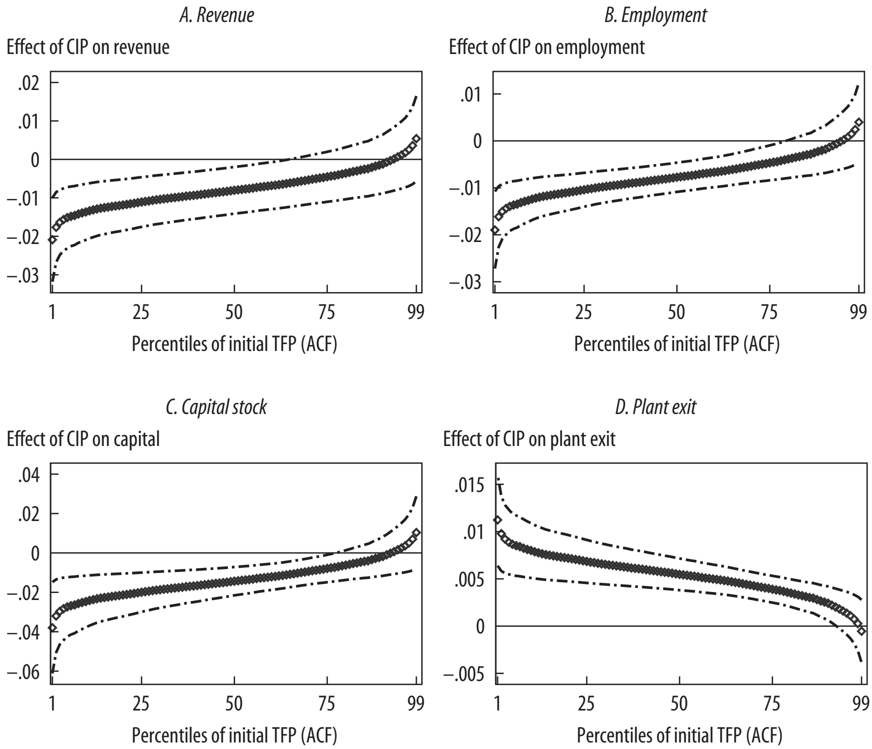
Chinese Demand Shock

Thus far, we have focused only on the supply side of the China shock. However, recent papers show the relevance of studying the economic effects of the growing Chinese demand for commodities. For instance, Costa, Garred,

31. The marginal effect for a plant located at the twenty-fifth percentile is 1.60, 2.13, 2.27, and 2.80 times larger, respectively, than the marginal effect for a plant situated at the seventy-fifth 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 seventy-fifth percentile.

32. The standard error for each TFP percentile p is constructed as $\sqrt{\mathrm{var}\left(\hat{\beta}_1 + \hat{\beta}_2 \cdot \overline{\mathrm{TFP}}_p\right)}$.

FIGURE 5. Predicted Effect of CIP across the TFP Distribution



Notes: Linear predictions and 95 percent confidence intervals of the effect of Chinese import penetration (CIP) 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). ACF denotes method of Ackerberg, Caves, and Frazer (2015).

and Pessoa (2016) study the heterogeneous effects of both the supply and demand sides 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 toward formal jobs. Relatedly, Artuc, Lederman, and Rojas (2015) calibrate a model of labor mobility using surveys for Argentina, Brazil, and Mexico. They find that rising trade with China has had negative effects on manufacturing employment and wages, which were offset by positive effects on agriculture and mining in the cases of Argentina and Brazil but not Mexico, where total employment decreased in the long run.

In this section, we investigate whether the increasing Chinese demand for commodities affected Chilean manufacturing plants either directly or indirectly through linkages between the manufacturing and primary sectors. 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 experiencing 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 the industry value of production. This variable, like CIP, varies at the four-digit industry-year level (ISIC revision 3). Figure 6 presents the evolution of CIP and CEP for the Chilean manufacturing sector in 1995–2006, distinguishing between weighted and unweighted measures of CIP and CEP.[33] As the figure shows, the variable capturing the 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 (namely, fish products; pulp, paper, and paperboard; and basic precious and nonferrous metals).[34]

To incorporate the indirect effect of CEP through linkages between the manufacturing and primary sectors, that is, the Chinese demand for primary products that propagates upstream to manufacturing suppliers, we calculate the following measure:

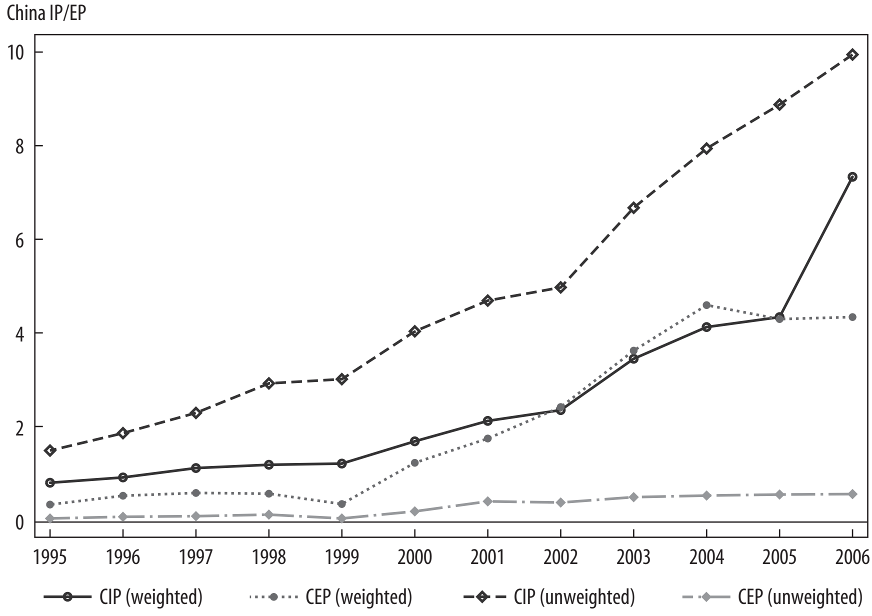
$$\text{CEP}^U_{jt} = \textstyle\sum_b \theta^U_{bj} \text{CEP}_{bj}, \tag{6}$$

which is a weighted average of the CEP of all primary industries b that purchase from industry j. The weights θ^U_{bj} 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 increasing Chinese demand for commodities, the shock 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 period, from 0.08 in 1995 to 0.59 in 2006, the level is still very low compared to CIP.

33. Weights are defined as the share of each industry in total manufacturing value of production. The weighted CEP is equal to total manufacturing exports to China divided by total manufacturing value of production.

34. Below we present a robustness exercise excluding these industries.

FIGURE 6. Evolution of Chinese Import and Export Penetration



Source: INE and UN COMTRADE.

Notes: Chinese import penetration is measured as the total value of imports from China divided by domestic absorption (production minus net exports). China export penetration is measured as the total value of exports to China divided by domestic production. Both vary at the four-digit industry-year level (ISIC rev. 3). Weights are given by the share of each industry in total manufacturing value of production.

We now estimate equation 3 incorporating CEP and CEP^U. Both variables are subject to similar endogeneity concerns as 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 UN 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 using CEP instead of CIP as the main regressor. Unlike the instrument for CIP, which works quite well for explaining CIP in Chile with the share of China in the imports of high-income countries, the instrument for CEP presents a weak first stage (the weak IV F statistic in column 2 is very small).[35] The inclusion of CEP^U in column 3 does not improve

35. We also constructed similar IVs using exports to China from high-income, middle-income, or Latin American countries, all of which resulted in weak first stages.

TABLE 9. Robustness to Chinese Demand Shock

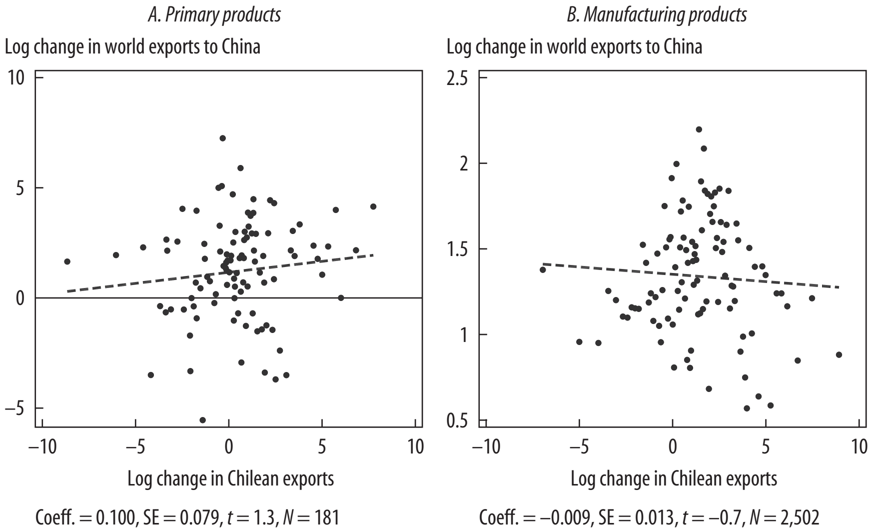
	Baseline	IV (Export share)			IV (China dummy variable)		
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
A. Revenue							
Chinese import penetration	−0.0070**			−0.0068*			−0.0067*
	(0.0031)			(0.0037)			(0.0038)
China export pen.		−0.0479	−0.0484	0.0161	−0.0575	−0.0598	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* statistic	32.230	3.504	1.439	1.158	3.270	1.205	1.037
B. Employment							
Chinese import penetration	−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* statistic	34.010	3.680	1.328	1.092	3.464	1.049	0.932

C. Capital							
Chinese import penetration	−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* statistic	32.570	3.515	1.555	1.267	3.272	1.332	1.164
No. observations	44,340	44,340	44,340	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680	6,680	6,680	6,680
D. Plant exit							
Chinese import penetration	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* statistic	35.960	3.186	0.540	0.462	2.951	0.373	0.359
No. observations	36,761	36,761	36,761	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012	6,012	6,012	6,012

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: China export penetration (CEP) is defined as the ratio of exports to China over sales and varies at the four-digit industry-year level. China export penetration (PL) includes indirect exports to China given by manufacturing sales to primary activities exporting to China (calculated as the interaction of China's share in Chilean exports of primary sectors and the share of manufacturing sales to each primary sector using Leontieff coefficients from the 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 5 to 7, CEP is instrumented with China-specific dummy variables (from an auxiliary regression), representing the deviation in Chinese industry export share relative to the cross-country average (following Costa, Garred, and Pessoa, 2016). All regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

FIGURE 7. Chilean Exports versus Chinese Imports from the World



Source: UN COMTRADE.

Notes: Products are grouped into 100 segments of the same size according to the variable on 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. The outcome variable on the vertical axis is the log change of Chinese imports from the world in the same period. The line represents the linear prediction. The slope coefficient, standard error, and *t* statistic are presented below each graph.

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 the baseline estimates including CIP as the sole explanatory variable.

To address potential concerns about the IV, we follow the identification strategy proposed by Costa, Garred, and Pessoa (2016). The idea is to clean out potentially correlated world-level shocks by running an auxiliary regression to obtain China-specific dummy variables that measure the deviation in Chinese industry export share relative to the cross-country average. As in the case of the raw IV measure, the first stage is weak, and the 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 of 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 six-digit product level relating the log change in Chinese imports from the world and the log change in Chilean exports during the period. We present separate plots for primary and manufacturing products. 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 when we include the indirect effects of CEP.

Given that this identification strategy does not perform as expected, we present two additional exercises to test the robustness of the estimated coefficients for CIP when industries or plants that benefit directly from increasing demand from China are excluded from the analysis. We start by excluding the three industries that experienced a disproportionately large increase in CEP. As shown in table 10, all coefficients remain virtually unchanged. Next, we implement a second robustness check based on the exclusion of manufacturing plants that exported to China during the sample period. We identify these plants using administrative customs records on the plant of origin and product destination of Chilean exports, which are available only for 2001–05.[36] To provide a basis for comparison, we first run the analysis using the full sample and limiting the time frame to this five-year period. All our results are robust to using the shorter period (see table 10).[37] The estimated coefficients for plant exit are larger than in the baseline by an order of magnitude, which could reflect the fact that this period captures a more dramatic increase in Chinese import competition after China joined the WTO in 2001.[38] Finally, we further restrict the sample by excluding plants that exported to China in at least one year in 2001–05. Our results remain robust.

Input-Output Linkages

As we previously acknowledged, exploiting CIP variation across industries delivers relative and not aggregate effects. Plants in unexposed industries could also be affected by the China shock if there are spillovers across plants or other general equilibrium effects (for example, reallocation of production factors or aggregate demand multiplier effects). In this section, we bring into the analysis one source of indirect propagation of the shock, namely, industry input-output

36. The share of plant-years featuring exports to China is 5.1 percent, and among these plants, the average share of China in the plant's total exports is 2.1 percent.

37. The only exception is revenue, which has a p value of 1.19.

38. While the estimated coefficients for capital and revenue change very little compared with our baseline estimates, the coefficient for employment declines around 30 percent.

TABLE 10. Robustness to Excluding Industries or Plants Exporting to China

Sample and explanatory variable	*Revenue* (1)	*Employment* (2)	*Capital* (3)	*Plant exit* (4)
A. Excluding industries that export to China (1995–2006)				
Chinese import penetration	–0.0072**	–0.0070***	–0.0123***	0.0050***
	(0.0033)	(0.0017)	(0.0035)	(0.0007)
Weak IV *F* statistic	32.26	34.34	32.58	36.69
No. observations	42,241	42,241	42,241	35,066
No. plants	6,332	6,332	6,332	5,714
B. All plants (2001–2005)				
Chinese import penetration	–0.0074	–0.0046*	–0.0145***	0.0101***
	(0.0062)	(0.0025)	(0.0047)	(0.0020)
Weak IV *F* statistic	10.91	11.83	10.75	14.12
No. observations	18,081	18,081	18,081	18,081
No. plants	4,451	4,451	4,451	4,451
C. Excluding plants that export to China (2001–2005)				
Chinese import penetration	–0.0071	–0.0046*	–0.0136***	0.0099***
	(0.0063)	(0.0025)	(0.0047)	(0.0020)
Weak IV *F* statistic	10.75	11.64	10.54	13.89
No. observations	17,153	17,153	17,153	17,153
No. plants	4,224	4,224	4,224	4,224

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: Panel A presents estimated coefficients from the baseline regressions excluding the three industries that experienced a disproportionately large growth in China export penetration. Panel B shows estimated coefficients from the baseline regressions run for the period 2001–2005, using the full sample. Panel C excludes plants that exported to China in at least one year in 2001–2005. All regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

linkages.[39] These links may have both positive and negative effects on plants' outcomes, thus generating an ambiguous net effect. The upstream propagation of CIP from customers to suppliers should be unambiguously negative, because customers exposed to Chinese import competition may reduce their demand for intermediate inputs. In contrast, the downstream propagation of CIP from suppliers to customers is theoretically ambiguous: while some

39. This channel is also studied by Acemoglu and others (2016) and Pierce and Schott (2016) for the United States. For instance, Acemoglu and others (2016), who study the effects of rising Chinese competition in U.S. manufacturing in 1999–2011, including input-output linkages and other general equilibrium channels, find estimated job losses in the range of 2.0 million to 2.4 million. Caliendo, Dvorkin, and Parro (2019) develop a dynamic trade model incorporating many of these channels and find that the China shock resulted in a loss of 0.8 million jobs (25 percent of the observed decline in manufacturing employment between 2000 and 2007) but increased aggregate U.S. welfare by 0.35 percent, with significant heterogeneous effects across local labor markets due to trade and migration frictions.

buyers clearly benefit from cheaper inputs imported from China, others might be hurt if they use highly customized inputs that are no longer provided by (directly exposed) domestic suppliers.

The framework for studying these indirect effects is based on Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). The idea is that each industry uses the output of other industries as inputs, to varying degrees. To quantify these links, we employ data from the Chilean input-output table for 1996.[40] We cannot account for the indirect effects of propagation to nonmanufacturing activities because we are working with manufacturing data.

The upstream effect, that is, an industry's exposure to CIP through its buyers, is calculated as follows:

$$\text{CIP}_{jt}^{U} = \sum\nolimits_{b} \theta_{bj}^{U} \text{CIP}_{bj}, \tag{7}$$

which is a weighted average of the Chinese 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, this exposure 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, an industry's exposure to CIP through its suppliers, is calculated as

$$\text{CIP}_{jt}^{D} = \sum\nolimits_{s} \theta_{sj}^{D} \text{CIP}_{sj}, \tag{8}$$

which is a weighted average of the Chinese 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 be hurt because they use highly customized inputs

40. 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 in the period. The information can be found at https://si3.bcentral.cl/estadisticas/Principal1/Excel/CCNN/cdr/excel.html.

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

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 and others, 2016).[41] 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 and others, 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. Specifically, we estimate the following regressions:

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

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 $\mathrm{SHARE}^{China}_{bt}$ and $\mathrm{SHARE}^{China}_{st}$ 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).[42] Columns 2 and 3 present the results when we include downstream and upstream effects, separately. In column 4 we include both variables simultaneously.[43] In all cases, the estimated coefficients associated with indirect effects of CIP are statistically indistinguishable from zero. Importantly, the estimated coefficients for direct CIP effects change very little and remain statistically significant.

41. 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*.

42. Remember that this specification includes plant-level and region-year fixed effects and controls for preexisting trends in the corresponding industry-level outcome variable.

43. CIP^U and CIP^D are highly correlated with each other (the Pearson correlation coefficient is 0.94), but not so much with CIP (0.32 and 0.44, respectively). Because of this multicollinearity concern, estimates in column 4 should be interpreted with caution.

TABLE 11. Direct and Indirect Effects of CIP

Dependent and explanatory variables	*Baseline* *(1)*	*Baseline plus indirect effects* *(2)*	*(3)*	*(4)*
A. Revenue				
CIP (Direct)	–0.0070**	–0.0077**	–0.0083*	–0.0081*
	(0.0031)	(0.0033)	(0.0047)	(0.0046)
CIP (Upstream)		0.0050		0.0049
		(0.0091)		(0.0086)
CIP (Downstream)			0.0044	0.0013
			(0.0168)	(0.0142)
Weak IV *F* statistic	32.23	13.63	7.595	5.341
B. Employment				
CIP (Direct)	–0.0068***	–0.0069***	–0.0081***	–0.0081***
	(0.0016)	(0.0018)	(0.0028)	(0.0028)
CIP (Upstream)		0.0007		0.0003
		(0.0032)		(0.0032)
CIP (Downstream)			0.0046	0.0044
			(0.0075)	(0.0074)
Weak IV *F* statistic	34.01	14.20	7.667	5.373
C. Capital				
CIP (Direct)	–0.0124***	–0.0122***	–0.0147***	–0.0144***
	(0.0035)	(0.0025)	(0.0049)	(0.0048)
CIP (Upstream)		0.0076		0.0071
		(0.0060)		(0.0064)
CIP (Downstream)			0.0123	0.0081
			(0.0121)	(0.0108)
Weak IV *F* statistic	32.57	13.36	7.643	5.324
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
CIP (Direct)	0.0050***	0.0046***	0.0044***	0.0044***
	(0.0007)	(0.0006)	(0.0011)	(0.0011)
CIP (Upstream)		–0.0010		–0.0011
		(0.0017)		(0.0016)
CIP (Downstream)			0.0002	0.0009
			(0.0040)	(0.0039)
Weak IV *F* statistic	35.96	15.09	6.504	4.417
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: The first column presents the baseline estimates (the preferred specification in column 4 of table 6). The second (third) column includes the upstream (downstream) effect of CIP. The fourth column includes both indirect effects. In all cases, CIP is instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank). Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. All regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Robust standard errors (in parentheses) are clustered by industry.

Conclusion

In this paper, we have 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, with the least productive plants suffering the most.

Using a panel of Chilean manufacturing plants for the period 1995–2006, we found that plants belonging to industries that were more exposed to growing Chinese 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 the Chinese demand shock has not affected Chilean manufacturing plants either directly or indirectly through linkages between manufacturing and the primary sector.

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 are able to respond to growing CIP by increasing innovation, 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 uncompetitive sectors or low-productivity firms.

Appendix A: 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^{sim} as the difference between the actual level of each variable and the predicted effect of CIP:

$$Y_{ijt}^{sim} = Y_{ijt} - Y_{ijt}e^{\left(\hat{\beta}_1 \cdot \Delta \mathrm{CIP}_{jt} - 1\right)}, \tag{A1}$$

where $\hat{\beta}_1$ is the 2SLS estimated coefficient for CIP from equation 3 and $\Delta\mathrm{CIP}_{jt}$ 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 preexisting trends in outcome variables). Additionally, following Autor, Dorn, and Hanson (2013) and Acemoglu and others (2016), we present a more conservative estimation by multiplying the observed CIP with the partial R^2 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 partial R^2 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 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, respectively, that would have occurred if CIP had not grown over this period (calculated using equation A1). Columns 4, 7, and 10 report the corresponding counterfactual changes using a more conservative approach (adjusting the estimated coefficient with the partial R^2 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 percentage points more than the observed growth in 1995–2006 (6.2 percent or 7.6 percent versus 3.2 percent, 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 textiles sector, employment contracted by 43.7 percent during the period, and Chinese competition explains 23.5 percent or 34.3 percent of this variation. Relatedly, going back to figure 2, which defines exposed (unexposed) industries as the ones above (below) the fiftieth percentile of 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 percent or 40.0 percent lower than the observed contraction.

TABLE A1. Simulated Changes Using Plant-Level Estimates

		Total change in 1995–2006 (%)								
		Revenue			Employment			Capital		
Sector	*Average annual change in CIP (%)* (1)	*Observed* (2)	*Raw counterfactual* (3)	*Adjusted counterfactual* (4)	*Observed* (5)	*Raw counterfactual* (6)	*Adjusted counterfactual* (7)	*Observed* (8)	*Raw counterfactual* (9)	*Adjusted counterfactual* (10)
Food and tobacco	0.01	65.6	65.7	65.7	18.5	18.7	18.6	12.1	12.3	12.3
Textiles, apparel, and leather	3.10	−26.5	−9.2	−14.7	−43.7	−28.7	−33.5	−45.4	−19.9	−27.9
Wood and furniture	0.34	204.6	206.7	206.1	29.8	31.8	31.1	33.7	36.3	35.5
Paper and print	0.08	100.6	100.9	100.8	−5.3	−5.0	−5.1	10.6	10.9	10.8
Chemicals and petroleum	0.16	181.3	182.8	182.3	10.9	12.3	11.8	116.6	119.0	118.2
Plastic, rubber, and glass	0.50	84.1	90.5	88.5	4.9	8.6	7.4	36.1	46.8	43.3
Metals	0.47	430.9	434.5	433.4	47.9	51.0	50.1	290.4	294.4	293.2
Machines and 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 and 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 Chinese import penetration across plants in each sector. 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 corresponding counterfactual changes that would have occurred if we assume that Chinese import penetration remained constant at the 1995 level. Columns 4, 7, and 10 adjust the counterfactuals with the partial R^2 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 preexisting trends in the corresponding outcome variable. The last row reports these numbers for all manufacturing industries (full sample).

Table A2 presents analogous simulations using the estimated coefficients for CIP from the industry-level regressions. This table incorporates a simulation for the number of active plants with ten 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 percent or 6 percent instead of contracting by 5.6 percent, 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. If CIP had remained constant over 1995–2006, manufacturing employment would have grown by 6.6 or 10.2 percentage points more than the observed growth in 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 and others (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 and exit of plants from the panel (extensive margin). Given the negative effect of CIP on a plant's probability of exiting the sample, plant-level estimates might also be attenuated in this context.

Appendix B: Production Function Estimation

A production function is a relation that specifies how firms transform inputs (for example, labor and capital) into output. The main econometric challenge in estimating production functions is that firms make decisions about inputs based on determinants of production that are not observed by the econometrician. This generates an endogeneity problem (simultaneity bias) with the classic OLS estimator.[44] To estimate TFP, we follow the method proposed by Ackerberg, Caves, and Frazer (2015), who propose an alternative estimation procedure that uses moment conditions very similar to Olley and Pakes (1996) and Levinsohn and Petrin (2003), but that avoids what they call a

44. For an excellent exposition of these topics, we recommend Ackerberg and others (2007), Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015).

TABLE A2. Simulated Changes Using Industry-Level Estimates

		Total change in 1995–2006 (%)					
		Revenue			*Employment*		
Sector	*Average annual change in CIP (%) (1)*	*Observed (2)*	*Raw counterfactual (3)*	*Adjusted counterfactual (4)*	*Observed (5)*	*Raw counterfactual (6)*	*Adjusted counterfactual (7)*
Food and tobacco	0.02	65.6	65.9	65.8	18.5	18.9	18.8
Textiles, apparel, and leather	2.33	–26.5	12.0	–1.4	–43.7	–9.3	–21.4
Wood and furniture	0.43	204.6	209.2	207.7	29.8	34.3	32.7
Paper and print	0.07	100.6	101.2	101.0	–5.3	–4.7	–4.9
Chemicals and petroleum	0.16	181.3	184.7	183.5	10.9	14.2	13.0
Plastic, rubber, and glass	0.53	84.1	98.6	93.4	4.9	13.7	10.5
Metals	0.57	430.9	438.9	436.1	47.9	55.1	52.6
Machines and electrical	0.75	21.4	41.1	34.1	–18.7	–5.0	–9.9
Transportation	0.94	–39.2	–37.4	–38.0	–30.7	–25.6	–27.3
Toys and other	1.65	106.9	116.2	113.0	–27.0	–11.6	–16.9
Total manufacturing	0.76	135.5	142.4	140.0	3.2	13.4	9.8

Notes: First data column reports the average annual change in Chinese import penetration across industries in each sector. Columns 2, 5, 8, and 11 present the observed change in sector revenue, employment, capital, and number of plants, respectively, between 1995 and 2006. Columns 3, 6, 9, and 12 report the corresponding counterfactual changes that would have occurred if we assume that Chinese import penetration remained constant at the 1995 level. Columns 4, 7, 10, and 13 adjust the counterfactuals with the partial R^2 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 preexisting trends). The last row reports these numbers for all manufacturing sectors (full sample).

functional dependence problem. Particularly, while Olley and Pakes (1996) and Levinsohn and Petrin (2003) invert either an investment demand function or an intermediate input demand function that is unconditional on the labor input, Ackerberg, Caves, and Frazer (2015) suggest inverting investment or intermediate input 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), and physical capital stock (less accumulated depreciation) including land, buildings, machinery, equipment, tools, and vehicles. The measures of revenue, capital, materials, electricity, and fuels are deflated using specific four-digit industry deflators obtained from the Chilean National Statistics Institute (INE).

Table B1 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 Ackerberg,

TABLE A2. (*Continued*)

Capital			No. plants		
Observed (8)	*Raw counterfactual (9)*	*Adjusted counterfactual (10)*	*Observed (11)*	*Raw counterfactual (12)*	*Adjusted counterfactual (13)*
12.1	12.7	12.5	8.4	8.6	8.6
–45.4	8.0	–10.3	–41.6	–1.0	–15.2
33.7	38.9	37.3	–14.4	–9.2	–11.1
10.6	11.3	11.0	14.0	15.4	14.9
116.6	121.7	119.9	1.0	3.9	2.8
36.1	59.2	50.9	0.0	8.7	5.6
290.4	298.9	295.9	8.0	16.5	13.5
–19.9	14.6	2.5	–2.0	11.6	6.8
–25.1	–15.6	–18.9	–25.0	–16.2	–19.2
–7.2	3.5	–0.1	0.0	16.4	10.7
76.7	86.1	82.9	–5.6	6.0	1.9

Caves, and Frazer (2015).[45] Columns 2 and 3 both use as labor input the total number of employees, but in column 2 we invert the intermediate input demand function to control for unobserved productivity shocks, while in column 3 we invert the raw material demand function. In column 4, we make an additional adjustment to improve the measure of employment, taking into account the fact that workers are heterogeneous in their productivity. Using information about the type of workers employed by each plant and their average compensation, we disaggregate blue- and white-collar workers to construct a new measure of labor that takes into account that white-collar workers should be, on average, more productive than blue-collar workers.[46]

45. The larger OLS bias on the labor coefficient vis-à-vis the capital coefficient is consistent with most empirical results and models of input choice, where labor is easier to adjust than capital and thus is highly correlated with productivity shocks (Ackerberg and others, 2007).

46. In particular, $L = (\text{wage ratio} * \text{white} + \text{blue})$. The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average.

TABLE B1. Production Function Estimates

		Ackerberg, Caves, and Frazer (2015)		
Explanatory variable	*OLS (1)*	*Proxy: Intermediate inputs (2)*	*Proxy: Raw materials (3)*	*Adjusted labor (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)
Intermediate 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)
Summary statistic				
R^2	0.928			
No. observations	44,340	37,657	37,657	37,643
No. plants	6,680			

***$p < 0.01$.

Notes: Revenue is the log of plants' total sales of manufactured products. Employment is the log of plants' total number of employees. Capital is the log of plants' physical capital stock (less 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 four-digit industry deflators obtained from the 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 the generalized method of moments (GMM), instrumenting labor with its lag. In column 2, we invert the intermediate input demand function to control for unobserved productivity shocks, while in column 3, we invert the raw material demand function. In column 4, the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers, applying the formula $L = (\text{wageratio*white} + \text{blue})$. The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average. Robust standard errors (in parentheses) are calculated by bootstrap ($n = 100$).

Appendix C: Productivity Changes

Other papers in the literature find that Chinese import competition triggered productivity improvements in firms (Bloom, Draca, and Van Reenen, 2015). To test this hypothesis, we run the baseline regression using the three different estimates of TFP described in appendix B as dependent variables. Table C1 presents the results. Although positive in columns 4 to 6, the 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, such as firm reorganization through changes in the number of layers, investment in new technologies, or product quality upgrading (for example, Caliendo and others, 2017; Bustos, 2011; Fernandes and Paunov, 2013; Medina, 2018).

TABLE C1. Plant-Level TFP and Chinese Import Penetration

Dependent and explanatory variables	OLS (1)	2SLS (2)	2SLS (3)	2SLS (4)
A. TFP 1				
Chinese import penetration	−0.0017	−0.0011	−0.0016	−0.0015
	(0.0012)	(0.0019)	(0.0018)	(0.0018)
Weak IV *F* statistic	—	34.50	32.50	34.82
B. TFP 2				
Chinese import penetration	−0.0014	−0.0007	−0.0011	−0.0010
	(0.0012)	(0.0019)	(0.0018)	(0.0018)
Weak IV *F* statistic	—	34.50	32.50	34.82
C. TFP 3				
Chinese import penetration	−0.0013	−0.0008	−0.0011	−0.0010
	(0.0012)	(0.0018)	(0.0018)	(0.0018)
Weak IV *F* statistic	—	34.48	32.49	34.83
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
Year fixed effects	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
Region-year fixed effects	—	—	Yes	Yes
Industry PT–year fixed effects	—	—	—	Yes

Notes: TFP is 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 intermediate input demand function to control for unobserved productivity shocks, while in panel B, we invert the raw material demand function. In panel C, the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers, applying the formula $L = (\text{wageratio}*\text{white} + \text{blue})$. The wage ratio is constructed as the industry average compensation of white-collar employees over the blue-collar average. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at four-digit industry-year level. This variable is instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank). Industries are defined at the four-digit ISIC rev. 3 level. Regions correspond to a country's first-level administrative division. Industry preexisting trend (PT) is defined as the change in the corresponding dependent variable in the five-year period before the start of the sample (1989–94). interacted with year fixed effects. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

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 reflect not only shifts in the distribution of plant productivity but also compositional changes across plants (including changes in market shares among surviving plants due to the entry and exit of new and old establishments, respectively). Our results on the heterogeneous effects of CIP, presented in the main text, show that the negative effects of the competitive shock were unevenly distributed among plants, with the least productive suffering the most.

To investigate the effects of CIP on aggregate productivity, we follow Melitz and Polanec (2015), who propose an extension of Olley and Pakes's (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

$$\text{(C1)} \qquad \Phi_t = \bar{\phi}_t + \sum_i \left(s_{it} - \bar{s}_t\right)\left(\phi_{it} - \bar{\phi}_t\right)$$

$$\text{(C2)} \qquad \Phi_t = \bar{\phi}_t + \operatorname{cov}\left(s_{it}, \phi_{it}\right),$$

where $\bar{\phi}_t = \frac{1}{n}\Sigma_1^n \phi_{it}$ is the unweighted plant-level productivity mean, s_{it} is the market share of plant i at time t, and $\bar{s}_t = 1/n$ 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 that measures shifts in the productivity distribution (due to the change in the first moment, $\Delta\bar{\phi}_t$) and another component that captures 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 $s_{Gt} = \Sigma_{i\in G} s_{it}$ represent the aggregate market share of a group G of firms and define $\Phi_{Gt} = \Sigma_{i\in G}\left(\frac{s_{it}}{s_{Gt}}\right)\phi_{it}$ as the 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):

$$\text{(C3)} \qquad \Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}\left(\Phi_{X1} - \Phi_{S1}\right)$$

and

$$\text{(C4)} \qquad \Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}\left(\Phi_{E2} - \Phi_{S2}\right),$$

where S corresponds 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:

$$\text{(C5)} \qquad \Delta\Phi = \left(\Phi_{S2} - \Phi_{S1}\right) + s_{E2}\left(\Phi_{E2} - \Phi_{S2}\right) + s_{X1}\left(\Phi_{X1} - \Phi_{S1}\right).$$

We then apply the Olley and Pakes (1996) decomposition to the survivors component:

$$\text{(C6)} \qquad \Delta\Phi = \Delta\overline{\phi}_S + \Delta\,\text{cov}_s + s_{E2}\left(\Phi_{E2} - \Phi_{S2}\right) + s_{X1}\left(\Delta\Phi_{X1} - \Delta\Phi_{S1}\right).$$

The first two terms measure the aggregate productivity change due to the contribution of surviving firms, disaggregated into a shift in the distribution of firm productivity (the unweighted mean change in the productivity of surviving firms, $\Delta\overline{\phi}_S$), and market share reallocations (the covariance change between market share and productivity of surviving firms, Δcov_S). The third and fourth terms account for the contribution of entry and exit and are constructed as the difference in aggregate (average) productivity between entering and exiting firms relative to the aggregate productivity of surviving firms, weighted by the market share associated with each group of firms.[47]

First, we apply the decomposition method of Melitz and Polanc (2015) and recover the contribution of the channels accounting for changes in industry TFP. Second, we regress the industry TFP change and each decomposed mechanism on the change in CIP during the corresponding time period, instrumenting this variable with the change in the average Chinese industry import share across high-income countries. Given that plants may not be able to adjust productivity immediately after the shock, we make the decomposition for one-, two-, and three-year periods. We present these results in table C2. The first column shows the coefficients on CIP for the total change in TFP, and columns 2 to 5 report the coefficients associated with 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).

47. The productivity difference for exiting and entering firms is calculated with respect to the aggregate productivity of surviving firms in the first and second periods.

TABLE C2. TFP Decomposition and CIP

	Change in TFP				
Dependent and explanatory variables	*Total* (1)	*Within* (2)	*Between* (3)	*Exit* (4)	*Entry* (5)
A. One-year change in TFP					
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* statistic	15.77	15.77	15.77	18.46	15.16
No. observations	858	858	858	780	780
B. Two-year change in TFP					
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* statistic	26.72	26.72	26.72	26.96	26.61
No. observations	780	780	780	767	766
C. Three-year change in TFP					
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* statistic	41.18	41.18	41.18	41.54	41.83
No. observations	702	702	702	693	694

*$p < 0.1$; ***$p < 0.01$.

Notes: The dependent variable in column 1 of panels A, B, and C is the one-, two-, and three-year change in industry TFP, respectively, calculated by aggregating plants' TFP using plants' revenue as weights. Columns 2 to 5 decompose the industry-level change in TFP into four channels: within surviving plants, between surviving plants, exiting plants, and entering plants, using the method proposed by Melitz and Polanec (2015). The independent variable is the corresponding one-, two-, or three-year change in Chinese import penetration, which is instrumented using the change in average Chinese industry import share across high-income countries (as defined by the World Bank). Industries are defined at the four-digit ISIC rev. 3 level. All regressions include year fixed effects and preexisting trends in all outcome variables. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

In line with our results on the heterogeneous impact of the shock on plant revenue, we find little effect of CIP on the between component, explained by the reallocation of sales toward more productive plants, which is statistically significant only in the one-year period. Finally, and also in line with our heterogeneous results on plant exit, we find that the exit of the least productive plants contributes to slightly increasing industry aggregate productivity in the three-year period. The small magnitude of the exit component can be partially explained by the fact that exiting plants are smaller than the average plant and thus have little weight in industry average TFP.

Appendix D: Other Robustness Exercises

We perform additional robustness exercises on several dimensions to check the sensitivity of our results. Table D1 presents the estimates of the preferred specification of the baseline regression when we drop extreme values of the

TABLE D1. Robustness to Outliers

Dependent and explanatory variables	Baseline (1)	*Dropping extreme values of* CIP (2)	Employment (3)	Revenue (4)	Capital (5)	(2) to (5) (6)
A. Revenue						
Chinese import penetration	−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* statistic	32.23	21.65	32.58	32.02	31.87	21.29
B. Employment						
Chinese import penetration	−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* statistic	34.01	22.80	34.35	33.77	33.51	22.37
C. Capital						
Chinese import penetration	−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* statistic	32.57	21.43	32.89	32.29	32.02	21.09
No. observations	44,340	40,319	39,980	39,979	39,979	32,949
No. plants	6,680	5,824	5,949	5,938	5,938	4,586
D. Plant exit						
Chinese import penetration	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* statistic	35.96	22.97	36.83	35.91	35.65	22.56
No. observations	36,761	33,603	33,230	33,218	33,212	27,549
No. plants	6,012	5,299	5,397	5,399	5,380	4,233

**$p < 0.05$; *** $p < 0.01$.

Notes: Column 1 presents the baseline estimates (column 4 of table 6). Columns 2 to 5 exclude the 5 percent 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 preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

distribution of CIP, employment, revenue, and physical capital, separately, as well as the intersection of all these outliers. In all cases, the estimated coefficients have the same sign and are statistically significant. The most important variation of the effects occurs when we drop outliers only in terms of CIP (column 2). In this case, the exit coefficient increases by 58 percent (0.29 percentage points). When we drop outliers of CIP but at the same time eliminate outliers in terms of the dependent variables (column 6), which is quite a demanding test, the 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 along several dimensions. We believe that the countries used as instruments should be significantly different from Chile, since common

TABLE D2. Robustness to Instrumental Variables in Main Regressions

Dependent and explanatory variables	Baseline (1)	High-income countries (2)	Middle-income countries (3)	World (4)
A. Revenue				
Chinese import penetration	−0.0070**	−0.0092**	−0.0050	−0.0054*
	(0.0031)	(0.0037)	(0.0030)	(0.0030)
Weak IV *F* statistic	32.23	11.57	46.78	46.74
B. Employment				
Chinese import penetration	−0.0068***	−0.0083***	−0.0066***	−0.0065***
	(0.0016)	(0.0021)	(0.0016)	(0.0016)
Weak IV *F* statistic	34.01	12.01	49.10	48.78
C. Capital				
Chinese import penetration	−0.0124***	−0.0179***	−0.0103***	−0.0106***
	(0.0035)	(0.0054)	(0.0031)	(0.0030)
Weak IV *F* statistic	32.57	10.96	45.93	46.31
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0050***	0.0055***	0.0050***	0.0048***
	(0.0007)	(0.0009)	(0.0007)	(0.0007)
Weak IV *F* statistic	35.96	13.32	55.82	56.51
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012

*$p < 0.1$; *$p < 0.05$; ***$p < 0.01$.

Notes: Column 1 presents the baseline estimates when Chinese import penetration (CIP) is instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank). In column 2, the IV is constructed with the subset of high-income countries used by Autor, Dorn, and Hanson (2013) (namely, Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). In column 3, the IV is constructed using middle-income countries (as defined by the World Bank). 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 preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

shocks affecting specific sectors or regions would be more unlikely. To confirm that our instrument is indeed capturing a supply-driven shock in China that caused this country to increase its share in the imports of many countries and regions worldwide, we instrument CIP with China's average industry import share for different groups of countries: a subset of eight high-income countries; middle-income countries (as defined by the World Bank); and all countries in the world. Table D2 presents the results. In the three cases, regressions pass the weak IV test, and the estimated coefficients in the second stage have the same sign and are statistically significant (columns 2 to 4). Additionally, table D3 shows the results of the heterogeneous regressions using these three groups of alternative countries (and their interaction with plants' initial

TABLE D3. Robustness to Instrumental Variables in Heterogeneous Regressions

Dependent and explanatory variables	*Baseline* (1)	*High-income countries* (2)	*Middle-income countries* (3)	*World* (4)
A. Revenue				
Chinese import penetration	−0.0072**	−0.0094**	−0.0053*	−0.0056*
	(0.0031)	(0.0037)	(0.0030)	(0.0029)
CIP × TFP_0	0.0054*	0.0064*	0.0068**	0.0061**
	(0.0028)	(0.0036)	(0.0029)	(0.0027)
Weak IV *F* statistic	16.01	5.758	23.49	23.76
B. Employment				
Chinese import penetration	−0.0072***	−0.0084***	−0.0070***	−0.0069***
	(0.0016)	(0.0021)	(0.0016)	(0.0016)
CIP × TFP_0	0.0085***	0.0102***	0.0087***	0.0084***
	(0.0027)	(0.0035)	(0.0026)	(0.0026)
Weak IV *F* statistic	16.85	6.081	24.58	24.78
C. Capital				
Chinese import penetration	−0.0131***	−0.0181***	−0.0111***	−0.0114***
	(0.0035)	(0.0054)	(0.0030)	(0.0030)
CIP × TFP_0	0.0167**	0.0242**	0.0180**	0.0168**
	(0.0081)	(0.0122)	(0.0080)	(0.0074)
Weak IV *F* statistic	16.13	5.562	22.90	23.38
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0052***	0.0055***	0.0052***	0.0050***
	(0.0008)	(0.0010)	(0.0008)	(0.0008)
CIP × TFP_0	−0.0046***	−0.0060***	−0.0053***	−0.0051***
	(0.0013)	(0.0015)	(0.0014)	(0.0013)
Weak IV *F* statistic	18.65	6.782	28.43	29.60
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes: Column 1 presents the baseline estimates when Chinese import penetration (CIP) and its interaction with initial TFP are instrumented with the average Chinese industry import share across high-income countries (as defined by the World Bank) and its interaction. In column 2, the IV is constructed with the subset of high-income countries used by Autor, Dorn, and Hanson (2013) (namely, Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). In column 3, the IV is constructed using middle-income countries (as defined by the World Bank). 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 preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

TABLE D4. Robustness to Preexisting Trends in Control Variables

Explanatory variable	*Revenue* (1)	*Employment* (2)	*Capital* (3)	*Plant exit* (4)
Chinese import penetration	−0.0072**	−0.0068***	−0.0113***	0.0049***
	(0.0030)	(0.0015)	(0.0026)	(0.0006)
Weak IV *F* statistic	32.90	34.43	33.24	35.90
No. observations	44,340	44,340	44,340	36,761
No. plants	6,680	6,680	6,680	6,012

**$p < 0.05$; ***$p < 0.01$.

Notes: This table presents estimated coefficients from the preferred specification of the baseline regressions (in column 4 of table 6), including a large set of preexisting trends in control variables (import penetration from other countries, TFP, importing and exporting conditions, share of imported inputs, share of exports in sales, log wage bill, number of strikes, and a dummy variable indicating foreign ownership). These trends are constructed interacting each variable in the initial year with year fixed effects. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

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 D4, we control for preexisting trends in a large set of variables, such as import penetration from other countries, TFP, importing and exporting conditions, share of imported inputs, share of exports in sales, wage bill, number of strikes, and a dummy variable indicating foreign ownership. In all cases, the 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 appendix B) and labor productivity (see table D5). Also in these cases, the sign, magnitude, and statistical significance of the estimated coefficients change very little compared to the baseline heterogeneous regressions.

As we explained in the text, the INE interrupted the panel structure of the data in 2007, alleging confidentiality issues regarding plants' unique identifiers, so we cannot perform a plant-level analysis thereafter. Nevertheless, we can still perform industry-level regressions including more recent years in the sample period. Table D6 presents industry-level regressions for revenue, employment, physical capital, and the total number of active plants with ten 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 corresponds 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 preexisting trends in

TABLE D5. Robustness to Productivity Measures

Dependent and explanatory variables	*Baseline* *(1)*	*TFP2* *(2)*	*TFP3* *(3)*	*LP* *(4)*
A. Revenue				
Chinese import penetration	–0.0072**	–0.0072**	–0.0071**	–0.0116***
	(0.0031)	(0.0031)	(0.0031)	(0.0035)
CIP × TFP_0	0.0054*	0.0047	0.0039	0.0044**
	(0.0028)	(0.0032)	(0.0036)	(0.0020)
Weak IV *F* statistic	16.01	15.93	15.87	16.39
B. Employment				
Chinese import penetration	–0.0072***	–0.0072***	–0.0072***	–0.0176***
	(0.0016)	(0.0016)	(0.0016)	(0.0035)
CIP × TFP_0	0.0085***	0.0095***	0.0107***	0.0104***
	(0.0027)	(0.0029)	(0.0032)	(0.0027)
Weak IV *F* statistic	16.85	16.76	16.71	17.38
C. Capital				
Chinese import penetration	–0.0131***	–0.0131***	–0.0131***	–0.0160***
	(0.0035)	(0.0035)	(0.0035)	(0.0046)
CIP × TFP_0	0.0167**	0.0184**	0.0201**	0.0035
	(0.0081)	(0.0092)	(0.0102)	(0.0024)
Weak IV *F* statistic	16.13	16.03	15.96	16.51
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0052***	0.0051***	0.0051***	0.0066***
	(0.0008)	(0.0008)	(0.0008)	(0.0010)
CIP × TFP_0	–0.0046***	–0.0046***	–0.0046***	–0.0015***
	(0.0013)	(0.0016)	(0.0017)	(0.0005)
Weak IV *F* statistic	18.65	18.71	18.76	9.972
No. observations	36,757	36,757	36,744	36,757
No. plants	6,011	6,011	6,008	6,011

*$p < 0.1$; $p < 0.05$; *** $p < 0.01$.

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 intermediate input demand function to control for unobserved productivity shocks, while in TFP2, we invert the raw material demand function. In TFP3, the number of employees is adjusted to consider potential productivity differences across white- and blue-collar workers by 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 (as defined by the World Bank) and its interaction with initial TFP/LP. All regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

TABLE D6. Robustness to Sample Period Extension: Industry-Level Effects

	1995–2006		*1995–2012*	
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*	*(4)*
A. Revenue				
Chinese import penetration	–0.016**	–0.016**	–0.017**	–0.018**
	(0.007)	(0.007)	(0.008)	(0.008)
Weak IV *F* statistic	53.68	48.46	56.18	60.70
B. Employment				
Chinese import penetration	–0.017***	–0.016***	–0.015***	–0.014***
	(0.005)	(0.005)	(0.005)	(0.005)
Weak IV *F* statistic	53.68	49.51	56.18	71.55
C. Capital				
Chinese import penetration	–0.027***	–0.027***	–0.022***	–0.020***
	(0.006)	(0.006)	(0.006)	(0.006)
Weak IV *F* statistic	53.68	53.61	56.18	51.39
D. Number of plants				
Chinese import penetration	–0.016***	–0.015***	–0.010***	–0.010***
	(0.004)	(0.005)	(0.003)	(0.003)
Weak IV *F* statistic	53.68	53.00	56.18	60.46
No. observations	936	936	1,380	1,380
Industries	78	78	78	78
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Industry outcome preexisting trend	—	Yes	—	Yes

**$p < 0.05$; ***$p < 0.01$.

Notes: Revenue and capital are deflated using specific four-digit industry deflators obtained from Chilean Institute of Statistics- INE. Chinese 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 four-digit ISIC Rev. 3. Industry outcome preexisting trend corresponds to the change in the dependent variable in the five-year period before the start of the sample (1989–94). Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

the corresponding outcome variable. The estimated coefficients are robust to extending the period of analysis, and magnitudes change very little.[48]

Table D7 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 ten broad sectors, where each sector includes a set of similar manufacturing industries (the number of industries is indicated in parentheses):

48. The only exception is the estimated coefficient for the number of plants, which decreases around 50 percent.

TABLE D7. Robustness to Including Sector-Year Fixed Effects

	Main		*Heterogeneous*	
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*	*(4)*
A. Revenue				
Chinese import penetration	–0.0070**	–0.0143*	–0.0072**	–0.0145*
	(0.0031)	(0.0079)	(0.0031)	(0.0079)
CIP × TFP_0			0.0054*	0.0043
			(0.0028)	(0.0029)
Weak IV *F* statistic	32.23	31.20	16.01	15.50
B. Employment				
Chinese import penetration	–0.0068***	–0.0058*	–0.0072***	–0.0063*
	(0.0016)	(0.0033)	(0.0016)	(0.0033)
CIP × TFP_0			0.0085***	0.0084***
			(0.0027)	(0.0027)
Weak IV *F* statistic	34.01	32.52	16.85	16.16
C. Capital				
Chinese import penetration	–0.0124***	–0.0197***	–0.0131***	–0.0205***
	(0.0035)	(0.0070)	(0.0035)	(0.0069)
CIP × TFP_0			0.0167**	0.0162**
			(0.0081)	(0.0078)
Weak IV *F* statistic	32.57	31.66	16.13	15.72
No. observations	44,340	44,340	44,340	44,340
No. plants	6,680	6,680	6,680	6,680
D. Plant exit				
Chinese import penetration	0.0050***	0.0065***	0.0052***	0.0067***
	(0.0007)	(0.0012)	(0.0008)	(0.0013)
CIP × TFP_0			–0.0046***	–0.0046***
			(0.0013)	(0.0014)
Weak IV *F* statistic	35.96	31.69	18.65	15.77
No. observations	36,761	36,761	36,761	36,761
No. plants	6,012	6,012	6,012	6,012
Year fixed effects	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes
Region-year fixed effects	Yes	Yes	Yes	Yes
Industry PT–year fixed effects	Yes	Yes	Yes	Yes
Sector-year fixed effects	—	Yes	—	Yes

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notes: Columns 1 and 3 present the baseline estimates for the main and heterogeneous regressions (columns 4 of tables 6 and 7), respectively. These regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Columns 2 and 4 include additional controls for sector-year fixed effects. We construct ten broad sectors that include a subset of similar four-digit manufacturing industries (see figure 1). Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

Food and tobacco (14), Textile, apparel, and leather (10), Wood and furniture (6), Paper and print (7), Chemical and petroleum (6), Plastic, rubber, and glass (4), Metal (7), Machines and electrical (13), Transportation (3), Toys and 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 dummy variables has an R^2 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 D8 presents our preferred specification of both the main and heterogeneous regressions for log-revenue, log-employment, and log-capital for two different subsamples of plants: (1) excluding entering plants (columns 2 and 5); and (2) entering entrant and exiting plants (balanced sample, columns 3 and 6). These are very strong requirements, as we drop more than 36 percent of our original sample in the first case and 60 percent in the second. Nonetheless, 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).

TABLE D8. Robustness to Balanced-Sample Estimation

	Main			*Heterogeneous*		
Dependent and explanatory variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
A. Revenue						
Chinese import penetration	−0.0070**	−0.0066**	−0.0025	−0.0072**	−0.0076***	−0.0037
	(0.0031)	(0.0028)	(0.0030)	(0.0031)	(0.0027)	(0.0030)
CIP × TFP_0				0.0054*	(0.0028)	0.0101**
				0.0110***	(0.0039)	(0.0043)
Weak IV *F* statistic	32.23	40.78	31.24	16.01	19.91	14.39
B. Employment						
Chinese import penetration	−0.0068***	−0.0074***	−0.0047***	−0.0072***	−0.0083***	−0.0060***
	(0.0016)	(0.0019)	(0.0018)	(0.0016)	(0.0018)	(0.0016)
CIP × TFP_0				0.0085***	0.0100***	0.0105***
				(0.0027)	(0.0033)	(0.0036)
Weak IV *F* statistic	34.01	42.59	32.85	16.85	20.71	15.03
C. Capital						
Chinese import penetration	−0.0124***	−0.0132***	−0.0122***	−0.0131***	−0.0152***	−0.0145***
	(0.0035)	(0.0036)	(0.0035)	(0.0035)	(0.0037)	(0.0041)
CIP × TFP_0				0.0167**	0.0219***	0.0188**
				(0.0081)	(0.0082)	(0.0077)
Weak IV *F* statistic	32.57	42.00	31.94	16.13	20.42	14.65
No. observations	44,340	29,248	17,508	44,340	29,248	17,508
No. plants	6,680	3,555	1,459	6,680	3,555	1,459

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Notes. Columns 1 and 3 present the baseline estimates for the main and heterogeneous regressions (column 4 of tables 6 and 7), respectively. Column 2 and 4 exclude entering plants from the sample. Columns 3 and 6 include only plants that are present in all years of the 1995–2006 period (balanced sample). All regressions include plant and region-year fixed effects, plus industry-level preexisting trends in the corresponding outcome variable. Weak IV *F* statistic is the Kleibergen-Paap weak instrument *F* statistic. Robust standard errors (in parentheses) are clustered by industry.

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