Globalization, technological change and market power in Latin America: Evidence for Chile and Colombia[1]

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Abstract

This paper studies concentration and market power in Chile and Colombia and the role that globalization and automation have had on shaping these two phenomena. Using panels of firm surveys, we compute firm-level markups and industry-level concentration measures. Applying a difference in differences methodology that relies on variation across industries on exposure to robotization technology, import competition from China and tariff declines in US markets due to the signature of free trade agreements, we study the causal effects of these shocks on market power and concentration. We find that robotization technology has reduced markups on average, but has increased markups and total factor productivity of top industry firms; that the pro-competitive effect of Chinese imports has indeed led to a decrease in market power of domestic firms; and that increased export opportunities due to free trade agreements have led to an increase in market power with interesting heterogeneities across the two countries.

JEL Classification: L11, F14, F61, O33

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1 Introduction

There is substantial empirical evidence indicating a global rise in market concentration and firm market power. While much of the literature focuses on the U.S. economy (IMF, 2019; De Loecker and Eeckhout, 2018; De Loecker et al., 2020), the significant implications of market power for economic growth have led to increasing concern about the negative effects of reduced competition in Latin America and the Caribbean.[2] At the same time, recent decades have been marked by rapid global trade integration and technological advancement, phenomena that are deeply intertwined. These developments hold the potential to significantly benefit economies by advancing the technological frontier through enhanced access to new technologies, intermediate goods, larger markets, and heightened competition. However, they also bear implications for market concentration and market power, as they can influence firm dynamics and sectoral selection.

De Loecker et al. (2016) find that while India's trade liberalization reduced input costs, firm-level markups increased. Similarly, Autor et al. (2020) argue that globalization and technological progress have driven market shares toward the most productive firms, leading to the rise of "superstar" firms characterized by heightened product market concentration and elevated sales-weighted average markups. Related studies by Autor and Salomons (2018) and Autor et al. (2017) connect these trends to labor market outcomes, suggesting that the growth of capital-intensive superstar firms, particularly in digital and IT sectors, has contributed to a declining share of labor in income (Autor et al., 2020; Bauer and Lashkari, 2018). Although these superstar firms are more commonly observed in the digital and service sectors benefiting from platform economies, similar patterns, albeit less pronounced, have also emerged among leading manufacturing firms (Stiebale, 2016).

In this paper, we examine long-term trends in market concentration and firm market power within the manufacturing sector in Latin America, with a focus on Chile and Colombia—two countries for which rich, multi-year datasets are available. To compute markups, we employ production-side methods based on estimated output elasticities and cost minimization first-order conditions, following the framework of De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). Furthermore, we explore the influence of international trade and technological change on the evolution of market concentration and market power by analyzing three distinct episodes: (i) the availability of robotics at global

[2] Historical data from the U.S., as analyzed by De Loecker et al. (2020), reveals that while median markups have remained relatively stable, the upper percentiles of the markup distribution have risen sharply, contributing to a potential decline in labor's share of income (Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019). De Loecker and Eeckhout (2018) and Diez et al. (2021) document a global increase in markups, primarily driven by a redistribution of market shares from low to high-markup firms. Eslava et al. (2021) study the link between market power and inequality in Latin America.

and local levels, (ii) competitive pressures arising from Chinese import competition, and (iii) export opportunities created by free trade agreements (FTAs) with a high-income country as the United States.

Our analysis draws on a combination of different data sources, including comprehensive datasets on Colombian and Chilean manufacturing plants, trade flows and tariffs from COMTRADE and WITS, and robot adoption data from the International Federation of Robotics (IFR). We exploit industry-level variation in exposure to trade and automation shocks over recent decades in Chile and in Colombia. By conducting both firm- and industry-level analyses, we capture not only the reactions of individual firms but also broader industry-level dynamics that may reflect reallocation effects in response to these shocks.

Automation and robotization, though relatively recent phenomena in Latin America, have the potential to widen disparities among firms due to scale-biased technological advancements. Despite being behind developed economies in the adoption of robotics, Latin American countries have experienced a significant increase in automation over the past two decades. Using IFR data, we analyze the impact of global and local robot adoption on domestic firms, finding that industry-level exposure to robots generally leads to a reduction in firm-level markups. However, top firms in both Chile and Colombia have been largely unaffected by robot exposure, with some top firms even increasing their markups and total factor productivity (TFP) in response to robot exposure. We interpret these findings as evidence of top firms adopting global technologies more rapidly than their domestic competitors.

The period under study also includes China's accession to the World Trade Organization in December 2001, a pivotal event that had profound effects on global trade. This period provides a unique opportunity to measure the causal effects of trade on market power. For identification, we exploit the fact that during our studied period Chinese import penetration (measured as the total value of imports from China relative to domestic absorption) increased sharply in Colombia and Chile, but this expansion varied widely across manufacturing industries. To address potential endogeneity concerns, we implement an instrumental variable strategy, following methodologies employed by Autor et al. (2013, 2014) and Acemoglu et al. (2016). We find that the pro-competitive effect of Chinese imports has led to reduced firm-level markups in both Colombia and Chile.

Finally, we examine the impact of free trade agreements (FTAs) signed with the United States, on firm-level outcomes in Chile and Colombia. The U.S. has historically been the largest destination for Colombian manufacturing exports and the second largest for Chilean products. Using U.S. export tariffs as a proxy for market expansion opportunities in high-income countries, we show that reductions in U.S. export tariffs resulting from the signature of these FTAs have positively affected firm-level profitability, TFP, and markups. In Chile, results are quantitatively more among firms that were initially non-exporters, consistent with existing research emphasizing the importance of the extensive margin of exports in driving firm performance (Lileeva and Trefler, 2010; Bustos, 2011; Atkin, Khandelwal, and Osman, 2017; Garcia-Marin and Voigtländer, 2019).

The rest of the paper is organized as follows. In Section 2 we briefly discuss the data from the firm surveys for Chile and Colombia. In Section 3 we provide a description of the evolution of market concentration and markups, and their empirical association with other firm and industry level variables. In Section 4 we explore whether globalization and technological change have shaped the evolution of concentration and market power. In section 5 we conclude the paper with some final reflections.

2 Data

Our analysis is based on widely-used firm panel surveys that span several years of data. In the case of Chile, we use the Annual Industrial Survey (ENIA, *Encuesta Nacional Industrial Anual*). The ENIA collects information on all manufacturing plants that employ at least 10 workers and that have operated for at least one semester during the reference period. In the case of Colombia, we use the Colombian Annual Manufacturing Survey (EAM, *Encuesta Anual Manufacturera*). The EAM is a panel of all manufacturing plants with at least 10 employees or with revenue above a given threshold that is updated annually.

Both datasets include information on revenue, investment, capital, labor, wage bill, expenditures in materials and energy, other expenditures, industry affiliation, plant age, and in some cases plant import and export status. This information allows us to compute industry concentration measures, markups, and profit rates.

The datasets are available for the period 1979-2016 for Chile and 1995–2021 for Colombia. Table 1 summarizes the structure of the data periods. In the case of Chile, we discard years before 1985 as some variables are not available. There is a first group of surveys which is a panel spanning the period 1985–1994, and a second group of surveys which is a panel spanning the period 1995-2007. The industry classification changes from the first to the second panel, from ISIC Rev.2 to ISIC Rev.3, a finer level of disaggregation. The firm identification numbers also change between 1994 and 1995 and it is not possible to establish a concordance. Starting in 2008 the surveys are repeated cross sections and there are changes in the sample design, with some industries in the ISIC Rev.3 classification not being represented in the data. Our estimates of technology parameters and markups are based on surveys from the period 1985–2011, and the regression analysis on the second panel period 1995–2007. There are 67,780 firm-level observations and 1,412 industry level

Table 1: Summary of firm surveys

	Firm-year (1)	Industry-year Rev.2 (2)	Industry-year Rev.3 (3)
Chile (ENIA)			
Panel 1985-1994	45707	858	0
Panel 1995-2007	67780	927	1412
Cross section 2008-2016	27363	561	787
Colombia (EAM)			
Panel 1995-2000	38907	0	0
Panel 2001-2011	72932	645	992
Panel 2012-2021	70198	294	457

Notes: Number of observations at the firm level and at the 4-digit industry level. Industries are defined according to the ISIC Rev.2 and ISIC Rev.3 classifications. Source: Annual Industrial Survey (ENIA) for Chile and Colombian Annual Manufacturing Survey (EAM) for Colombia.

Table 2: Manufacturing sectors. Share in revenue

	Chile			**Colombia**		
	1995 (1)	2000 (2)	2005 (3)	1995 (4)	2000 (5)	2005 (6)
Food, beverages	0.27	0.28	0.18	0.29	0.32	0.26
Textiles, apparel	0.07	0.04	0.02	0.12	0.13	0.12
Wood products	0.05	0.05	0.04	0.02	0.01	0.01
Paper, printing	0.09	0.07	0.05	0.07	0.07	0.07
Chemicals	0.19	0.21	0.26	0.20	0.21	0.19
Mineral products	0.04	0.03	0.02	0.05	0.03	0.04
Basic metals	0.18	0.25	0.38	0.02	0.02	0.03
Machinery, equipment	0.10	0.07	0.05	0.12	0.08	0.10
Other manufacturing	0.01	0.00	0.00	0.12	0.12	0.18

Notes: Participation of 2-digit sectors in total manufacturing revenue. Annual Industrial Survey (ENIA) for Chile and Colombian Annual Manufacturing Survey (EAM) for Colombia.

observations during 1995–2007.

In the case of Colombia the surveys are available from 1995 to 2021. They are a continuous panel that allows us to follow all active firms across all years. Between 2000 and 2001 there is a change in the industry classification from ISIC Rev.2 to ISIC Rev.3. We use all available years of data to estimate technology parameters and markups, and a reduced panel 2001-

2016 in the regression analysis, with 117,281 firm level observations and 1,713 industry level observations.

We complement the firm data with annual industry level information from two additional data sources. We use information on tariffs and trade flows from the World Integrated Trade Solution (WITS) compiled by the World Bank from COMTRADE and TRAINS. The information from WITS follows the 6-digit harmonized system and can be matched with the firm panels at the 4-digit level of disaggregation of the ISIC classification. We also use information on robot adoption from the International Federation of Robotics (IFR). IFR conducts annual surveys of the number of industrial robots shipped to firms worldwide by robot manufacturers. The data from IFR is constructed at a higher level of aggregation for a total of 13 manufacturing industries.

3 Some empirical facts about concentration and markups

This section is based exclusively on data from the firm surveys and the objective is to provide a description of the evolution of market concentration and markups, and their empirical association with other firm and industry level variables. Table 2 shows the relative importance of each 2-digit manufacturing sector in terms of share in total manufacturing revenue. Sectors with largest shares in revenue in both countries are Food and beverages, Chemicals, and Machinery and equipment. Basic metals is a relevant sector in Chile and Textiles and apparel is in Colombia. Chemicals and Basic metals are of increasing importance in Chile between 1995 and 2005, at the expense of Food and beverages, Textiles and apparel, Paper and printing, and Machinery and equipment. The sectoral structure is more stable in Colombia, with the exception of an increase in the share of Other manufacturing.

3.1 Market concentration

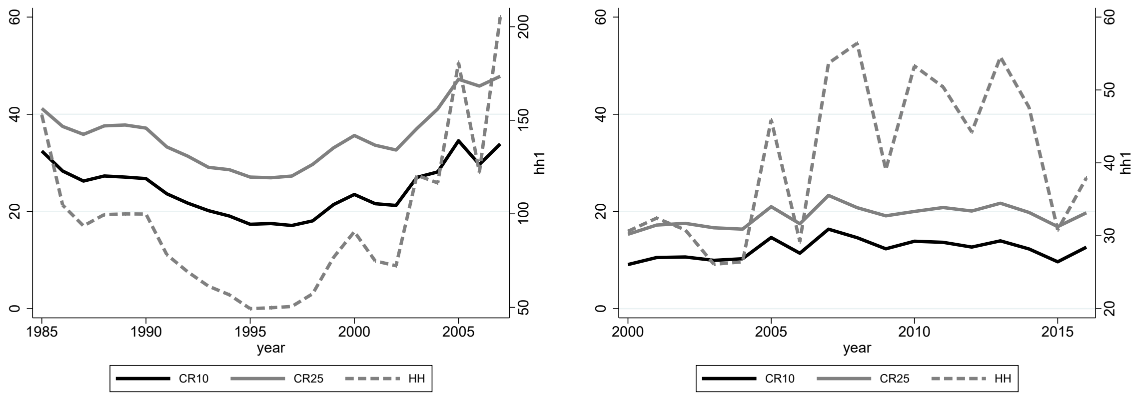
We compute three different measures of aggregate concentration: concentration ratios CR_{10} and CR_{25}, and the Herfindahl-Hirschman index (HHI). The concentration ratios are defined as the revenue market share accounted for by the 10, and 25 largest firms in the manufacturing sector. The HHI is the sum of squares of the revenue market shares of all firms in the manufacturing sector.[3]

Figure 1 shows the evolution of the aggregate concentration measures. In Chile there is a decrease in concentration between 1985 and 1995. After 1995 concentration sharply

[3]The n concentration ratio is defined as $CR_n = \sum_{i=1}^{n} Rev_i / \sum_{i=1}^{N} Rev_i$ where i indexes firms, Rev is revenue, N is the total number of firms, and, in summing from 1 to n, firms are sorted from largest to smallest revenue. The HHI is defined as $HHI = \sum_{i=1}^{N} (Rev_i / \sum_{i=1}^{N} Rev_i)^2$.

Figure 1: Concentration in manufacturing

(a) Chile (b) Colombia



Notes: Figure shows aggregate concentration measures for the manufacturing sector. CR10: solid black, CR25: solid gray, HHI: dashed gray.
Source: Annual Industrial Survey (ENIA) for Chile and Colombian Annual Manufacturing Survey (EAM) for Colombia.

increases. In 2007, the largest 25 firms account for almost 50 percent of all manufacturing revenue. In that same year, 19 out of the 25 largest firms are affiliated to the four digit industry "Manufacture of basic precious and non-ferrous metals," which includes extraction and refining of copper, 4 firms are in "Manufacture of basic chemicals," and one firm is in "Processing of meat and meat products."

In Colombia there is a sharp increasing trend in concentration between 2000 and 2007. Between 2008 and 2016 concentration fluctuates. Aggregate concentration is substantially lower in Colombia than in Chile, with the largest 25 firms accounting for less than 25 percent of all manufacturing revenue. The industry affiliation of the largest 25 firms is more dispersed than in Chile, with 9 firms in "Other manufacturing," 8 firms in food related industries (Dairy, Sugar, Cocoa, chocolate and sugar confectionery, Malt liquors, Soft drinks and mineral water), and the remaining 8 firms in different 4 digit industrial categories.

The increase in concentration in Chile and Colombia is in line with the findings of Autor et al (2020) for the U.S., which they attribute to the growth of "superstar firms".

3.2 Markups

To estimate markups at the firm level we apply the production method of De Loecker and Warzynski (2012) and De Loecker, Eeckhout and Unger (2020). The method relies on the first order conditions of the cost minimization problem in flexible inputs of a firm that faces exogenous and constant unit prices in input markets. The first order conditions establish an equation that relates markups, the share of flexible inputs in revenue, and the output elasticity of flexible inputs. The revenue share is obtained in a straightforward manner from the survey data. The output elasticity is calibrated or estimated econometrically.

In our context we define two flexible factors of production: intermediate inputs, which is the sum of materials and energy, and labor, which is the number of workers. We estimate markups using a minimum distance strategy so that the overidentified system of first order conditions of both flexible inputs is as close to zero as possible. Details are provided in Appendix B.

We explore robustness to different estimates of markups. Our baseline estimate is computed using output elasticities estimated econometrically in the context of a production function, following Olley and Pakes, 1996 (investment control). Our second estimate is based on output elasticities obtained using the approach of Ackerberg, Caves and Frazer, 2015 (intermediate input control). Our third estimate is based on output elasticities calibrated from cost shares. Details about the estimation of the output elasticities are discussed in Appendix B.

We estimate markups at the firm level. Descriptive statistics are shown in Table 3. During 2000-2007, the average markup is 83 percent in Chile and 63 percent in Colombia. The median markups are 73 and 52 percent. The weighted average markup, where firm shares in revenue are used as weights, is much higher, at 131 percent in Chile and 98 percent in Colombia, suggesting that markups are higher in larger firms. The variability of markups across firms is indeed very high, with the 10th and 90th percentiles ranging from 23 to 159 percent in Chile, and 7 to 143 percent in Colombia.

Price above marginal cost need not imply positive profits in the presence of fixed costs. Table 3 shows estimates of the profit rate defined as accounting profits over revenue.[4] Simple average profits are lower than weighted average profits (24 percent vs. 32 percent in Chile and 6 percent vs. 9 percent in Colombia). The estimated profit rates are negative for firms in the lower tail of the size distribution.

Figure 2 shows the evolution of weighted average and simple average markups. In both countries there is an increasing trend in weighted average markups, while the simple average markup is more stable. This result is consistent with the increase in concentration: as manufacturing revenue becomes more concentrated, the weighted average markup increases even if the simple average markup does not, provided that larger firms charge higher markups.

[4] We define profits as the difference between revenue, the cost of production (materials, energy, labor, and the user cost of capital), and other expenditures. Other expenditures include freights, insurance premia, leases, communications, licenses, legal and technical advice, publicity and promotion, representation expenses, storage and refrigeration services, commissions to distributors, maintenance and repairs, leasing, commissions paid to sellers and other services. The profit rate is defined as profits over revenue.

Table 3: Estimates of markups and profits

	Chile				Colombia			
	Markup		Profit rate		Markup		Profit rate	
	1995-1999	2000-2007	1995-1999	2000-2007	2000-2007	2008-2016	2000-2007	2008-2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Weighted average	2.24	2.31	1.26	1.32	1.98	2.06	1.09	1.11
Mean	1.85	1.83	1.21	1.24	1.63	1.66	1.06	1.06
Median	1.76	1.73	1.17	1.20	1.52	1.56	1.06	1.06
p10	1.26	1.23	0.90	0.94	1.07	1.07	0.77	0.74
p90	2.58	2.59	1.59	1.61	2.39	2.43	1.34	1.38
Food, beverages	2.25	2.27	1.26	1.29	2.07	2.12	1.08	1.11
Textiles, apparel	1.97	1.93	1.29	1.28	1.77	1.87	1.09	1.10
Wood products	2.12	2.26	1.16	1.29	1.63	1.65	1.11	1.11
Paper, printing	2.40	2.36	1.20	1.32	2.15	2.07	1.07	1.07
Chemicals	2.29	2.29	1.36	1.39	1.89	2.08	1.08	1.10
Mineral products	2.34	2.36	1.26	1.34	2.05	2.11	1.13	1.14
Basic metals	2.26	2.42	1.15	1.30	2.07	2.04	1.02	1.03
Machinery, equipment	2.12	2.08	1.25	1.28	1.91	1.93	1.10	1.11
Other manufacturing	2.33	2.32	1.18	1.26	2.17	2.20	1.15	1.20

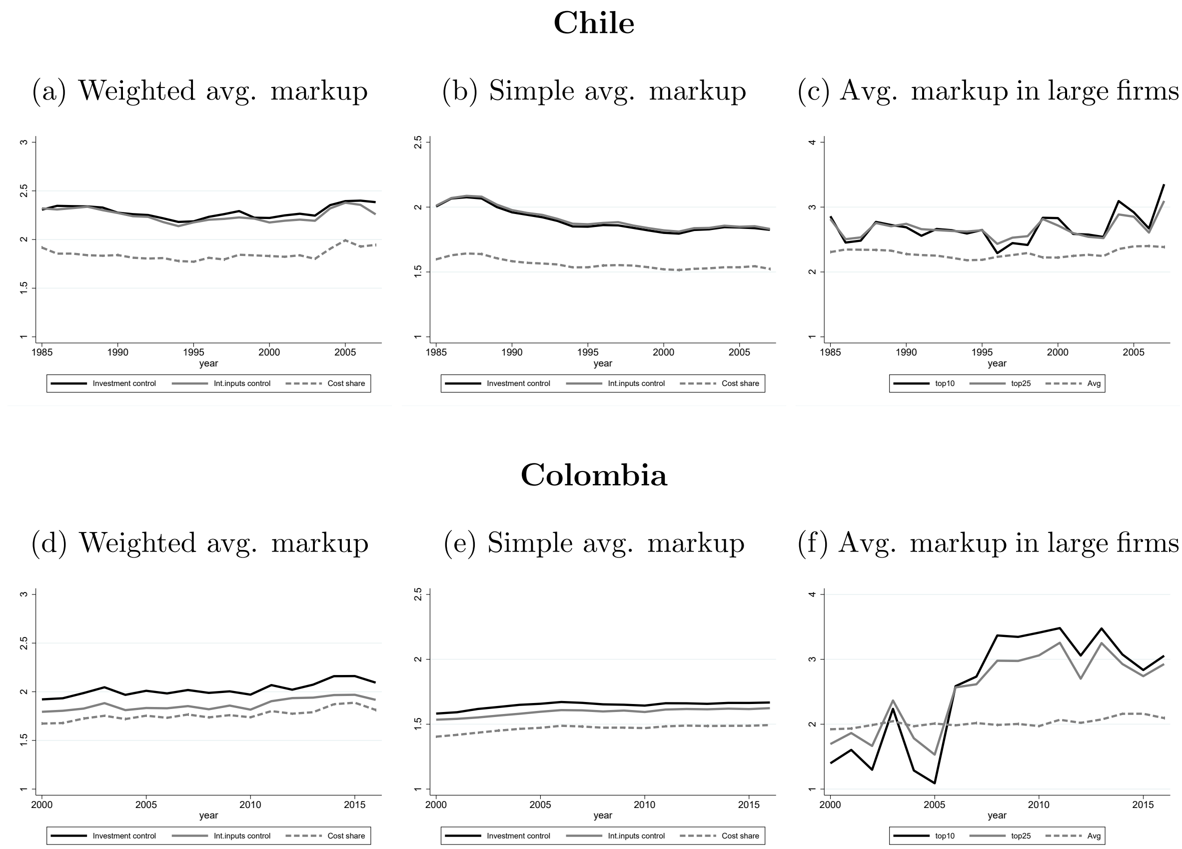
Notes: Table shows estimates of markups and profit rates at the aggregate level (top panel) and by two-digit sector of the ISIC Rev.2 classification (bottom panel). The bottom panel shows averages weighted using firm sales.

Panels (c) and (f) show the weighted average markup of the top 10 (solid black) and top 25 (solid gray) firms relative to the weighted average markup across all firms (dashed gray). Markups are indeed higher in the largest firms, moreover, in the case of Chile, they are increasing in the later years of the sample.

3.3 Industries

We are interested in exploring differences across broadly defined manufacturing sectors and also across more narrowly defined 4-digit industries. Table 3 shows weighted average markups for firms grouped into nine manufacturing sectors. There are important differences across sectors, with largest average markups in Paper and printing, Chemicals, Mineral products, Basic metals, and Other manufacturing. Figures A1 to A4 in Appendix A plot concentration ratios and average markups for the nine sectors. In both Chile and Colombia, the least concentrated sectors are Food and beverages, and Textiles and apparel, which are comparatively

Figure 2: Markups in manufacturing



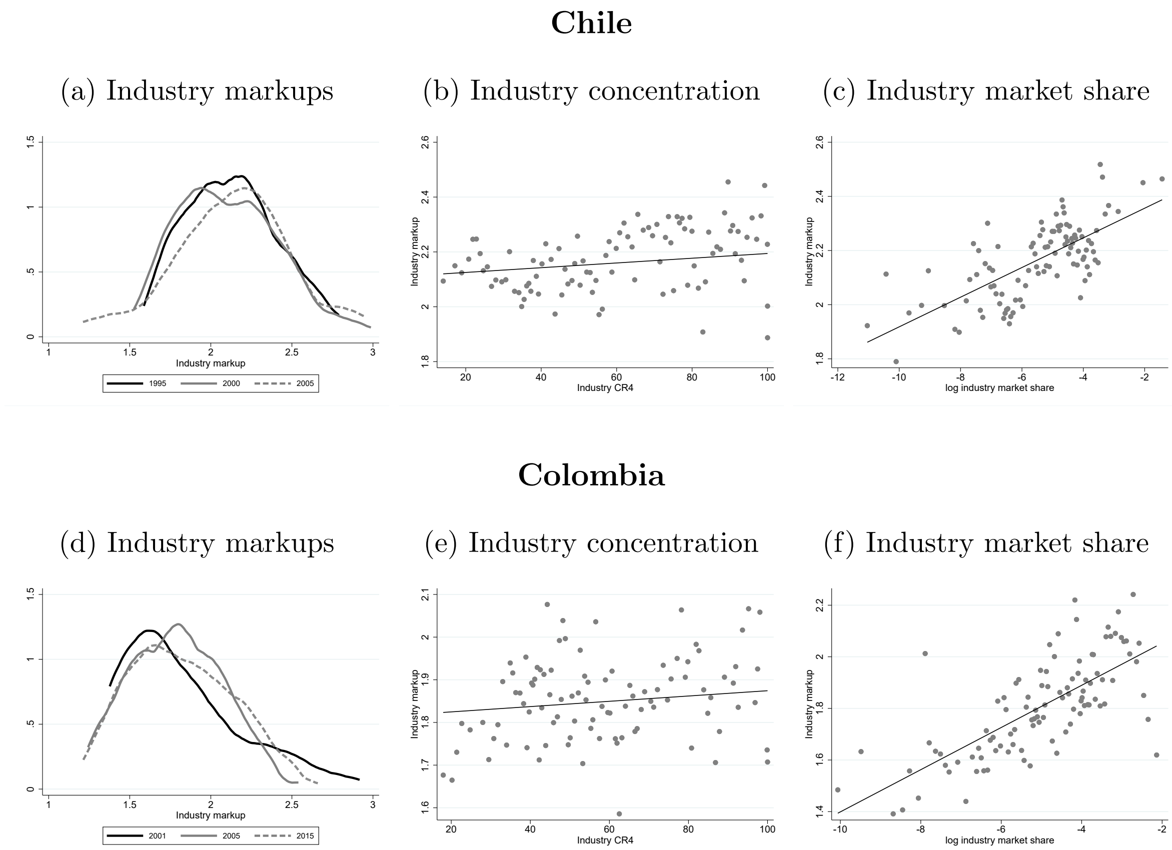
Notes: Figure shows sales weighted average markup by minimum distance approach (estimation based on investment control function: solid black, estimation based on intermediate inputs control function: solid gray, estimation based on cost shares: dashed gray); simple average markup; sales weighted average markup for top 10 firms (solid black), for top 25 firms (solid gray), and all firms (dashed gray).

low markup sectors.

The evolution of concentration and markups is not homogeneous across sectors or countries. Some sectors show markedly decreasing trends in concentration, other sectors show an opposite pattern, and in the remaining sectors concentration fluctuates. Notable cases are Textiles and apparel and Chemicals, with increasing concentration ratios in both countries. Concentration is markedly decreasing in Basic Metals and Mineral products in Chile, but not in Colombia. Regarding markups, in the case of Chile, they are increasing in Chemicals, a sector in which concentration is increasing, as well as in Mineral products and Basic metals, sectors in which concentration has decreased. A similar pattern is observed in Colombia, with the addition of increasing markups in Textiles and apparel.

In our regression analysis of Section 4, we define industries at the 4-digit level of aggregation of the ISIC Rev.3 classification. We define concentration ratios and weighted average

Figure 3: Industries



Notes: Figure shows the distribution of sales weighted average markups by minimum distance approach at the 4 digit level of aggregation (1985: solid black, 1995: solid gray, 2005: dashed gray); mean industry-level weighted markup conditional on industry level CR4; mean industry-level weighted markup conditional on log industry market share.

markups at the industry level. Figure 3, panels (a) and (d), shows that there is large dispersion in the distribution of 4-digit markups, and that the distribution tends to shift to the right in the later years of the sample (dashed gray). Panels (b)–(e) and (c)–(f) plot the average industry markup conditional on industry concentration and industry market share in manufacturing. Markups are increasing in concentration and industry size.

3.4 Firm and industry characteristics

Table 4 displays results of an OLS regression of firm-level markups on firm characteristics, and of 4-digit industry average markups on industry characteristics. Markups are higher in larger and more capital intensive firms and industries. Capital intensity is defined as the ratio of the capital stock to the number of workers. The association between markups and the average wage is negative at the firm level, in line with findings that increases in markups

Table 4: Markups and characteristics of firms and industries

	Chile		Colombia	
	Firms	Industries	Firms	Industries
	(1)	(2)	(3)	(4)
Log sales	0.11***	0.08***	0.09***	0.07***
	(0.00)	(0.02)	(0.00)	(0.01)
Obs.	61898	1408	108629	1438
Log sales	0.16***	0.06***	0.13***	0.07***
	(0.00)	(0.03)	(0.00)	(0.01)
K intensity	0.07	1.16**	0.12***	0.22*
	(0.06)	(0.68)	(0.04)	(0.16)
Log wage	-0.27***	0.07	-0.24***	-0.03
	(0.01)	(0.06)	(0.01)	(0.07)
Obs.	58835	1408	107507	1438

Notes: Table shows OLS regressions of markups on firms (columns 2 and 4) and 4-digit industry (columns 1 and 3) characteristics. Capital intensity is defined as the ratio of capital stock to number of workers (weighted average for columns 2 and 4). Log wage is the log average wage at the industry or firm level. Time periods: 1995-2007 (Chile) and 2000-2016 (Colombia). Standard errors are clustered at the firm (columns 1 and 3) or industry level (columns 2 and 4).

and concentration are associated with a decrease in the labor share.

Figure A5 in on-line Appendix A shows a non-parametric positive association between firm size and markups and it confirms that there is indeed a positive association between markups and the profit rate at the firm-level.

4 The role of globalization and automation technology

In this section we explore whether globalization and technological change have shaped the evolution of concentration and market power. We define several scenarios (case studies for each country during specific relevant time periods within our sample) in which we establish a causal relationship between shocks and markups. Each scenario has unique features, but as a general rule we work with difference-in-difference regression specifications at the firm level given by

$$y_{ijt} = \gamma R_{jt} + x'_{ijt}\beta + \psi_j + D_t + \epsilon_{jt}. \tag{1}$$

In the regression above j are industries, i are firms and t is year. The variable y is the firm-level markup, profit rate and total factor productivity, in separate regressions. The variable R is a treatment variable at the industry level and takes three different forms (described below). The regressions also include other control variables, firm fixed effects, time effects, and random error terms. In what follows we describe the different empirical scenarios that we study, and their results.

4.1 Robots

The recent phenomena of automation and robotization is a factor that may affect markups and profitability through decreases in variable costs, adjustment costs of the labor force and of course the cost of innovation itself, it may also exacerbate differences across firms through scale-biased technological change, as larger more productive firms are able to invest in robots and sophisticated ICT further increasing their productivity and size advantage (Autor et al, 2020; Unger, 2019). To study these effects we use robotization data from the International Federation of Robotics (IFR) as a proxy for automation technology and define a treatment variable that is robot exposure across industries.

IFR conducts annual surveys of the number of industrial robots shipped to firms worldwide by robot manufacturers.[5] The IFR uses its own industry classification, which closely follows the ISIC revision 4 classification, with fifteen manufacturing sectors.[6] Figure 4 displays the evolution of the stock of robots for Chile and Colombia from 1994 to 2016. The stock of robots grew significantly between 2004 and 2016, from values close to zero to 124 in Colombia and 151 in Chile. Panel (c) shows that the increase has been heterogeneous across industries (year 2016). We define industry-level robot exposure as the number of robots ($Robots$) relative to the number of workers ($Workers$) in a given industry, given by

$$RobotExp_{jt} = \frac{Robots_{jt}}{Workers_{jt}}. \tag{2}$$

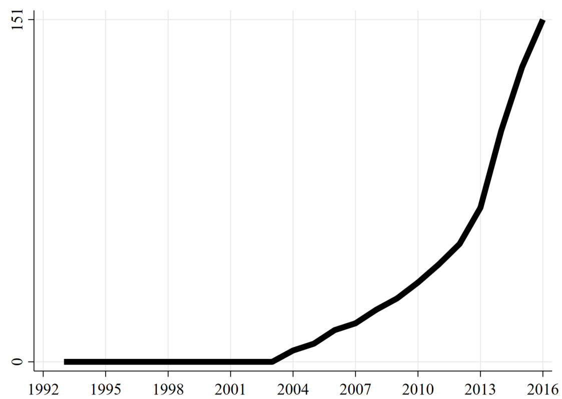
The number of robots is computed from the IFR data and the number of workers (in thousands) from the firm surveys.

[5] An industrial robot is defined by IFR according to the International Standard Organization (ISO 8373:2012) as an *automatically controlled, multipurpose manipulator, (re)programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.* These devices are able to perform a wide range of tasks, such as welding, painting, packaging and transporting, with very little human involvement.

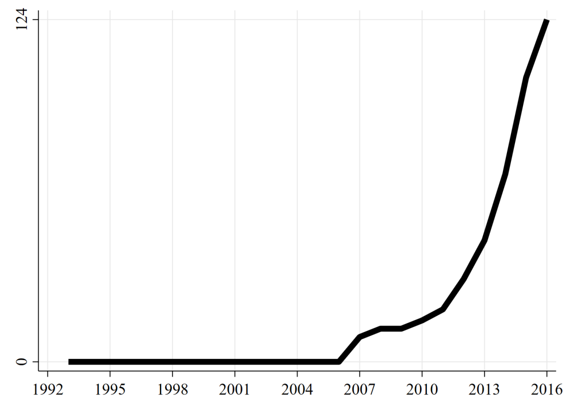
[6] Food and beverages; Textiles and apparel; Wood and furniture; Paper and printing; Pharmaceutical and cosmetics; Chemical products; Rubber and plastics; Glass, stone, and minerals; Basic metals; Metal products; Electronics; Industrial machinery; Automotive; Shipbuilding and aerospace industries; and Other manufacturing.

Figure 4: Manufacturing robots

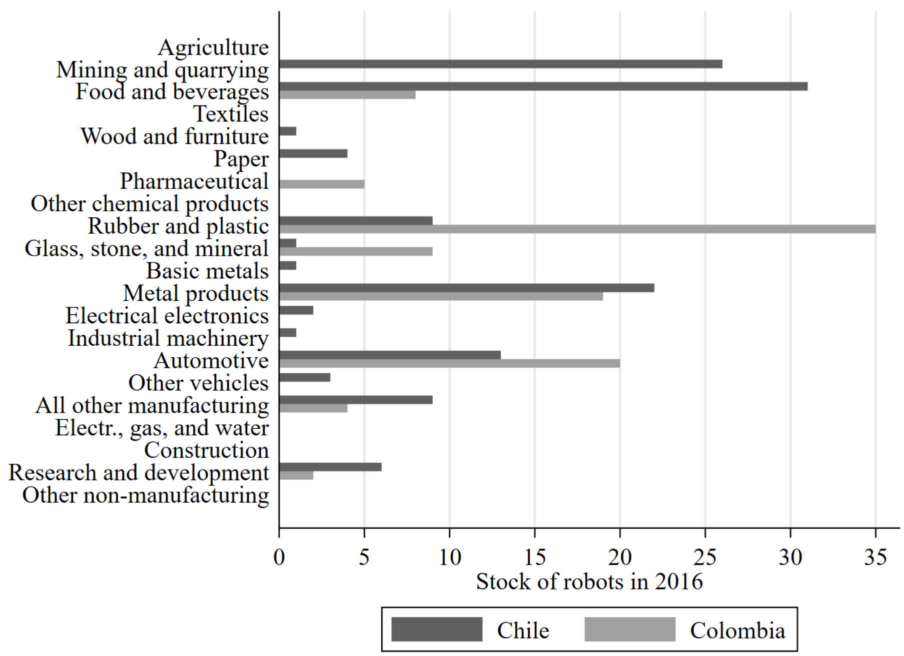
(a) Chile



(b) Colombia



(c) Robots by sector. 2016



Notes: Number of manufacturing robots.
Source: International Federation of Robotics (IFR).

There are two empirical challenges in this exercise. The first one is the panel availability for Chile, that spans the period 1995-2007. While the panel is relatively long, the last year of data corresponds to a very early stage of robot adoption, which implies that Chilean robot adoption from IFR data is not a precise proxy for automation technology adopted by firms. The second concern is that industry exposure to robots, both in Chile and in Colombia, is potentially endogenous, as industry level shocks may affect the outcome variables and the decision to invest in robotics.

We deal with both issues using global industry exposure to robotics as in Acemoglu and Restrepo (2020). Industry-level robot adoption in developed countries, which are technologically ahead of Latin America, as well as in other Latin American or developing countries, capture industry supply shifters such as advances in technology, availability, and prices, and is therefore an exogenous source of variation in robot exposure in Chile and Colombia. We define global industry exposure as the simple average of robot exposure across 54 countries with complete and comparable information of robot adoption and number of workers.[7]

$$RobotExp^{*}_{jt} = \frac{1}{n} \sum_{c} \frac{Robots^{c}_{jt}}{Workers^{c}_{jt}}. \tag{3}$$

In the expression above, data on number of robots by industry and country are from IFR and data on number of workers (in thousands) are from OECD, the variable n is the number of countries, and countries are indexed by c.

In the case of Chile, we estimate a reduced form OLS version of regression equation (1), in which we use global robot adoption $RobotExp^{*}$ as the treatment variable. In the case of Colombia, in which the panel spans a longer period post rise in robot adoption, we estimate a reduced form OLS version of equation (1), same as for Chile, and also a 2SLS version in which we instrument domestic $RobotExp$ with global $RobotExp^{*}$, as in Acemoglu and Restrepo (2020). All specifications include firm and year fixed effects and control for industry preexisting trends and firm initial characteristics interacted with year dummies.[8] Standard errors are clustered at the IFR sector level.

Tables 5 and 6 display results for the reduced form version based on global robot exposure for Chile and Colombia, respectively. The tables have five columns, with five different dependent variables. The first three variables are three different measures of firm-level markups which in turn differ in how the elasticities of output are estimated: in column (1) the output elasticities are computed using a control function based on investment as in Olley and Pakes (1996); in column (2) they are computed using a control function based on intermediate inputs as in Ackerberg et al (2015); in column (3) they are computed from cost shares.[9] In

[7]Those economies include OECD members (with exception of Iceland and Luxembourg), Argentina, Brazil, Bulgaria, China, Colombia, Croatia, Hong Kong, India, Indonesia, Latvia, Lithuania, Malaysia, Malta, Peru, Philippines, rest of South America, Romania, Singapore, South Africa, Taiwan, Thailand and Vietnam.

[8]Industry preexisting trends include log revenue, log employment and the corresponding dependent variable in the five-year period before the start of the sample. Firm initial characteristics consist of log revenue, log employment, log wage and log capital. All of these controls are fixed at the initial year of the panel and interacted with year effects.

[9]Details about estimation of markups and output elasticities are discussed in Appendix B. The markups shown in the tables in the main text are computed using a minimum distance strategy between labor and

Table 5: Global automation and markups. Chile

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	−0.015**	−0.013**	−0.013*	−0.009*	−0.006
	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)
Observations	65627	65649	65591	62216	63619
Panel B: Top firms					
RobotExp*	−0.016***	−0.014***	−0.013**	−0.010*	−0.007
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
RobotExp* × Top 1	0.012***	0.007	0.030***	0.026***	0.023***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.004)
Observations	43340	43356	43324	41481	42330
Panel C: Imports of robots					
RobotExp* × Imports	−0.003*	−0.002	−0.003**	−0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	65627	65649	65591	62216	63619
Panel D: Imports of robots and top firms					
RobotExp* × Imports	−0.003**	−0.002	−0.002**	−0.003**	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RobotExp* × Imports × Top 1	0.000***	0.000***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43340	43356	43324	41481	42330

Notes: FE regressions at the firm level. Dependent variables sorted by columns: (1) markup based on investment control estimates of output elasticities; (2) markup based on intermediate input control estimates of output elasticities; (3) markup based on cost share estimates of output elasticities; (4) profit rate; (5) total factor productivity based on investment control estimates of output elasticities. The main regressor is global robot exposure at the industry level. Interactions include: Panels B and D, indicator variable for largest firm in the 4 digit industry in the first year of data (Top 1); Panels C and D, country imports of automation technology and robots (Imports). All regressions include firm fixed effects, year effects, and industry and firm preexisting trends (initial characteristics interacted with year effects). Standard errors are clustered at the same sector level as the shock variable. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *. Time period: 1995-2007.

column 4 the dependent variable is the profit rate. In column 5 the dependent variable is total factor productivity, computed from the same output elasticities as the markups in column (1).

Panel A of Tables 5 and 6 show that on average, the increase in global industry-level automation has reduced firm-level markups. Coefficients are negative and statistically significant for Chile and Colombia and for most measures of markups (Columns 1 to 3). These

intermediate input first order conditions. Robustness to the use of markups computed solely from labor and solely from intermediate inputs is explored in Appendix A.

Table 6: Global automation and markups. Colombia

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	-0.006^{***}	-0.001	-0.006^{***}	-0.002^{***}	-0.004^{***}
	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)
Observations	111005	111005	111003	109508	112044
Panel B: Top firms					
RobotExp*	-0.005^{***}	-0.002	-0.006^{***}	-0.002^{***}	-0.004^{**}
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
RobotExp* × Top 1	0.005^{*}	0.009^{**}	0.005^{*}	0.010	0.017^{***}
	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)
Observations	58647	58612	58683	57849	58977
Panel C: Imports of robots					
RobotExp* × Imports	-0.000	-0.002^{*}	-0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	111005	111005	111003	109508	112044
Panel D: Imports of robots and top firms					
RobotExp* × Imports	-0.003^{***}	-0.001	-0.003^{***}	-0.002^{***}	-0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
RobotExp* × Imports × Top 1	0.002^{*}	0.003^{***}	0.002	0.005^{**}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	58647	58612	58683	57849	58977

Notes: FE regressions at the firm level. Analogous to Table 5. Time period: 2001–2016.

results are in line with previous findings by Kugler et al. (2020) and by Haarburger and Stemmler (2023), which show that a larger stock of robots reduces industry markups. Results also show a reduction in firm profitability (column 4), while results on firm-level TFP are not so clear, with negative findings for Colombia but not significant estimations for the case of Chile.

Because large firms may be more inclined to invest in automation (scale biased technological change), it is worth studying whether the effects of automation are heterogeneous. In Panel B, we include an interaction term between industry level automation and a dummy variable that takes the value of one for the largest firm in the 4-digit industry, in the initial year of the sample.[10] Results show that markups, profitability and TFP of top firms *in-*

[10]Notice that the number of observations is smaller in Panel B than in Panel A. This is because in Panel

Table 7: Domestic automation and markups. Colombia

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp	-0.139^{***}	-0.034	-0.146^{***}	-0.060^{***}	-0.093^{**}
	(0.041)	(0.049)	(0.037)	(0.019)	(0.036)
KP F-stat	34.3	34.4	34.1	34.8	31.6
Observations	111005	111005	111003	109508	112044
Panel B: Top firms					
RobotExp	-0.149^{***}	-0.050	-0.161^{***}	-0.068^{***}	-0.106^{**}
	(0.042)	(0.054)	(0.038)	(0.025)	(0.042)
RobotExp × Top 1	0.156	0.244	0.136	0.257	0.462^{**}
	(0.218)	(0.234)	(0.211)	(0.185)	(0.225)
KP F-stat	10.0	10.1	9.9	9.9	9.7
Observations	58647	58612	58683	57849	58977

Notes: 2SLS regressions at the firm level. Dependent variables and controls are analogous to Table 5 and 6. The main regressor is domestic robot exposure at the industry level. Table reports Kleibergen-Paap weak instrument F statistics. Time period: 2001–2016.

crease with automation technology, as in De Loecker, Eeckhout, and Mongey (2021). These results suggest that top firms invest in robots at a faster rate than their smaller competitors and that they see their performance and market power increase as a result. The increase in profitability and TFP suggest a resulting more efficient technology, while the increase in markups could be due to an increase in concentration or quality upgrading. Interestingly, heterogeneous effects of automation on markups are restricted to top 1 firms. We have experimented with interaction terms for top 2 and top 3 firms in each industry and we find that positive effects of automation on firm performance is either drastically reduced or non-existent (results not shown in the tables). This is in line with the rise of superstar firms described in Autor et al (2020).

It is important to consider that given the delay in the incorporation of cutting-edge technology, the adoption of robotics in developed countries could represent a competitive shock for Chilean and Colombian firms but may not be indicative of the adoption of such technologies in these economies. To address this concern, in Panels C and D we perform similar regressions as in Panels A and B, with the addition of an interaction term between global industry-level adoption of robots and country-level imports of robots in Chile and Colombia,

B we restrict the sample to firms that are on the survey in the initial year of data.

Table 8: Automation and industry concentration

	CR1	CR2	CR3
Chile			
RobotExp*	0.574	0.047	−0.030
	(0.354)	(0.251)	(0.194)
Observations	1358	1358	1358
RobotExp* × Imports	0.121	−0.060	−0.087*
	(0.091)	(0.063)	(0.051)
Observations	1358	1358	1358
Colombia			
RobotExp*	0.038	−0.037	0.026
	(0.319)	(0.326)	(0.309)
Observations	1713	1713	1713
RobotExp* × Imports	−0.025	−0.037	−0.002
	(0.144)	(0.156)	(0.152)
Observations	1713	1713	1713
RobotExp	0.875	−0.842	0.592
	(7.253)	(7.557)	(6.838)
KP F-stat	20.7	21.0	21.3
Observations	1713	1713	1713

Notes: FE and 2SLS (last panel) regressions at the 4-digit industry level. Dependent variables are concentration ratios CR_1, CR_2 and CR_3. In the first four panels the main regressor is global robot exposure. In the last panel, the main regressor is domestic robot exposure instrumented with global robot exposure. In some panels the main regressor is interacted with country imports of automation technology and robots (Imports). Regressions include industry and year effects and industry preexisting trends (initial industry characteristics interacted with year effects). Table reports Kleibergen-Paap weak instrument F statistics. Standard errors are clustered at the same sector level as the shock variable. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

as in Acemoglu and Restrepo (2022). Country level imports of robots are from COMTRADE and include, alongside the import of robots, the imports of additional automation technologies.[11] The variable captures availability of automation technology by industry at the world level and country-level actual purchases of robots in Chile and Colombia. Results confirm that on average there are negative impacts of robotization on markups, profitability, and TFP, and either positive or zero net effects for the top 1 firm in each industry.

In the case of Colombia, we have a longer panel sample that allows us to use domestic robot adoption at the industry level (equation 2). Because robot adoption might be endogenous, we instrument domestic robot adoption with global robot adoption (equation 3) as in Acemoglu and Restrepo (2020). The instrument isolates the growth in robot use that is due

[11] We identify imports of robots and additional automation technologies with the following HS codes: 8428, 8444, 8445, 8446, 8447, 8448, 8456, 8457, 8468, 8470, 8471, 847321, 847330, 847780, 847989, 8515, and 9032.

to exogenous technological change. Table 7 shows 2SLS estimation results. The first stage is not very strong and, as a result, confidence intervals for the top 1 interaction of the second stage are large. The table shows that average effects are negative, while effects for top 1 firm are positive but imprecisely estimated.

In Table 8 we study industry concentration in both countries. We run regressions at the 4-digit industry level in which the dependent variables are concentration ratios CR_1, CR_2, CR_3. These ratios represent the market share of the top firm, and the cumulative market shares of the top 2 and top 3 firms. The regressors are the same shock variables as in the firm-level regressions. Controls are industry preexisting trends computed as changes in log revenue, log employment, log capital and the corresponding dependent variable, all in the five year period prior to the initial year of the sample and interacted with year effects. Results are inconclusive as confidence intervals are very large. When looking at point estimates two patterns emerge. The first one is that there seems to be an increase in the industry market share of the top 1 firm (given by CR_1). The second one is that there are no evident increases of the joint market share of the top 2 or top 3 firms, suggesting that increases in the market share of the top 1 firm might actually occur at the expense of their next competitors.

4.2 China Shock

China's accession to the WTO in December 2001 was a huge shock to world trade. Since then Chile and Colombia have been exposed to the increase of low-price Chinese imports, which represents a competitive pressure for local producers and may affect firm differently according to their productivity and size, reshaping market concentration, markups and profitability. Imports from China increased sharply in Chile and Colombia. In Chile, Chinese imports increased from 230 million dollars in 1995 to 6,40 billion dollars in 2016, an increase of about 2700 percent. In the case of Colombia, imports from China increased from 93 million dollars in 1995 to 5,400 million dollars in 2016, an increase of about 5700 percent.

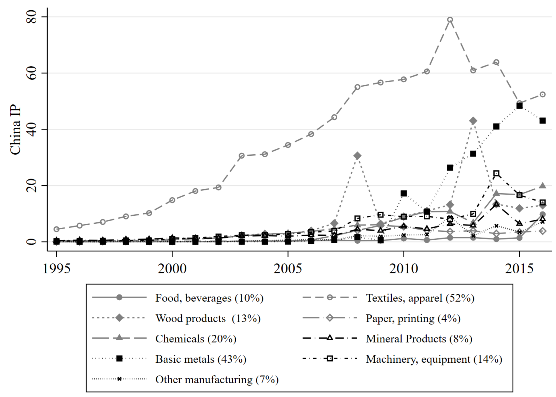
To estimate the causal impact of the China shock, we exploit the variability in industry exposure to imports of Chinese origin. We define the China import penetration ratio (CIP) as the total value of imports from China relative to domestic absorption, given by

$$CIP_{jt} = \frac{M_{jt}^{China}}{[Q_{jt} + M_{jt} - X_{jt}]} \tag{4}$$

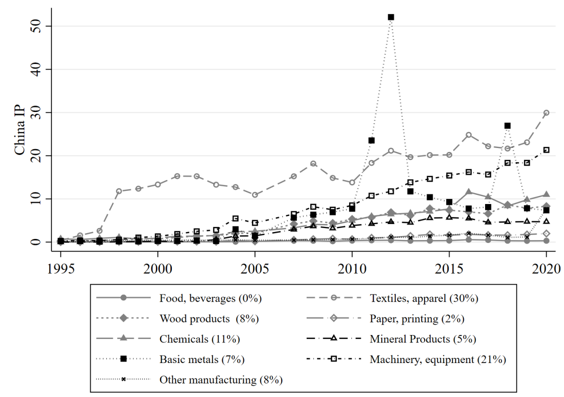
where Q_{jt}, M_{jt} and X_{jt} are the value of production, imports, and exports of 4-digit industry j, in year t, and where M_{jt}^{China} are industry imports from China. Imports and exports, M_{jt} and X_{jt}, are from COMTRADE, while we construct an approximate measure of domestic

Figure 5: Evolution of Chinese Import Penetration

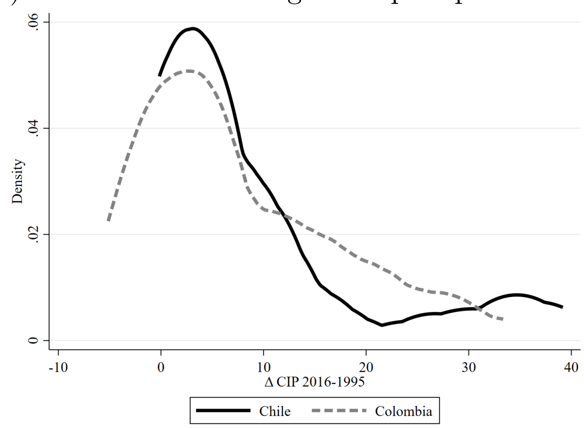
(a) Chile



(b) Colombia



(c) Distribution of change in import penetration



Notes: Panels (a) and (b) show the evolution of Chinese Import Penetration by 2-digit sectors of the ISIC3 classification. Panel (c) shows the distribution of the change in import penetration across industries in Chile (1995 to 2016) and Colombia (1995 to 2020).
Source: COMTRADE and firm surveys (ENIA and EAM).

production Q_{jt} by aggregating over plant level information from the firm surveys (ENIA and EAM).

Figure 5, Panels A and B, plots changes in exposure to China in Chile (1995 to 2016) and in Colombia (1995 to 2020) by 2 digit sectors. Sectors such as Textiles and Apparel and Basic Metals show the highest rates of exposure to Chinese import competition, while sectors such as Food and Beverages, and Paper and Publishing remain barely exposed. On average Chinese import penetration increased from 0.56 percent to 30.87 percent in Chile, and from 0.23 percent to 9.53 percent in Colombia. Panel C shows the distribution of the changes in exposure across 4-digit industries.

Unobserved industry shocks such as changes in productivity, input prices, or demand, may simultaneously affect the outcome variables as well as import demand of Chinese products.

To deal with this endogeneity concern, we instrument Chinese import penetration with the share of Chinese imports in total imports in world markets, as in Autor et al. 2013, 2014. This identification strategy is similar in spirit to the instrument for robot exposure in the previous subsection, and aims to capture industry-level supply-driven shocks that provide exogeneous variation to Chinese imports across industries and time. The instrument is defined as a simple average computed across 223 countries included in the BACI dataset, given by

$$CIP_{jt}^{Z} = \frac{1}{n}\sum_{c}\frac{M_{cjt}^{China}}{M_{cjt}} \tag{5}$$

where M_{cjt} are total imports of country c, industry j, in year t, M_{cjt}^{China} are imports of Chinese origin of country c, industry j, in year t, and n is the number of countries.[12]

The regression specification is analogous to the previous section, with a different shock variable and instrument. We estimate regression equation (1) by 2SLS. The main regressor is Chinese import penetration defined in (4) and the instrument is the average global share of Chinese imports defined in (5). The regression controls for industry and firm preexisting trends, as in the previous subsection. Standard errors are clustered at the 4-digit industry level.

Table 9 reports results of the firm-level regressions. On average, the pro-competitive effect of Chinese imports has driven markups down both in Chile and in Colombia (Panels A and C). Our results are in line with previous findings that discuss the idea that the China Shock has created competitive pressure on firms, leading them to reduce markups (Caselli and Schiavo, 2020), and that the increase in imports leads markups to decline (Feenstra and Weinstein, 2017). In Colombia, competition from Chinese imports has further lead to declines in profitability and total factor productivity. In Panels B and D we explore heterogeneous effects for the largest firm in each industry (Top 1). Result are not statistically significant, implying that, in a manner similar to the rest of the firms in the industry, large firms have seen their market power reduced by the competition of Chinese imports.

The impacts of industry concentration are reported in Table 10. These are industry-level regressions and the dependent variables are concentration ratios CR_1, CR_2 and CR_3. Results are fairly different across the two countries. We find that as a result of Chinese competitive pressure, concentration of domestic firms has increased in Chile and has experienced a reduction in Colombia. The increase in industry concentration rates in Chile can be attributed to the observation that 4-digit industries with higher concentration ratios at the initial year of the panel, such as Toys (with CR1 of 57 percent) and industries within Manufacturing of electrical and electronic devices (with CR1 of 44 percent), experienced relatively modest

[12]The BACI dataset is the *Base de Données sur le Commerce International.*

Table 9: Imports from China and markups. Chile and Colombia

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Chile					
Panel A: Average effect					
Import penetration	-0.002^{**}	-0.003^{***}	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
KP F-stat	58.2	58.3	59.0	60.6	63.8
Observations	65563	65585	65527	62152	63555
Panel B: Top firms					
Import penetration	-0.002^{**}	-0.003^{***}	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Import penetration x Top 1	-0.009	-0.011	-0.007	-0.002	0.001
	(0.008)	(0.008)	(0.007)	(0.004)	(0.004)
KP F-stat	19.2	19.4	19.1	23.7	26.6
Observations	43310	43326	43294	41451	42300
Colombia					
Panel C: Average effect					
Import penetration	-0.013^{***}	-0.014^{***}	-0.011^{***}	-0.006^{***}	-0.007^{*}
	(0.005)	(0.005)	(0.004)	(0.002)	(0.004)
KP F-stat	21.7	21.5	21.6	21.2	21.1
Observations	109365	109358	109356	107872	110385
Panel D: Top firms					
Import penetration	-0.013^{***}	-0.014^{***}	-0.011^{***}	-0.004^{***}	-0.004
	(0.005)	(0.005)	(0.004)	(0.002)	(0.003)
Import penetration x Top 1	0.005	0.007	0.005	0.003	0.006^{*}
	(0.005)	(0.006)	(0.005)	(0.003)	(0.003)
KP F-stat	9.3	9.2	9.3	9.4	9.3
Observations	57905	57871	57941	57111	58232

Notes: 2SLS regressions at the firm level. Dependent variables and controls are analogous to Table 5 and 6. The main regressor is Chinese import penetration at the industry level. In Panels B and D the shock variable is interacted with a dummy variable for the largest (top 1) firm in each 4 digit industry. Time periods: 1995–2007 (Chile) and 2001–2016 (Colombia).

increases in import penetration from China, at 312 and 899 percent, respectively. These percentages are significantly lower than the average import penetration across all industries, which stands at 3000 percent. On the other hand, sectors with lower concentration rates

Table 10: Imports from China and industry concentration

	CR1	CR2	CR3
Chile			
Import penetration	0.369**	0.357***	0.254**
	(0.151)	(0.136)	(0.118)
KP F-stat	91.1	89.1	89.6
Observations	1345	1345	1345
Colombia			
Import penetration	−0.376*	−0.355**	−0.238
	(0.199)	(0.181)	(0.163)
KP F-stat	90.4	83.3	80.5
Observations	1660	1660	1660

Notes: 2SLS regressions at the industry level. Industry-level dependent variables and controls are analogous to Table 8. The main regressor is Chinese import penetration at the industry level.

at the beginning of the sample, such as Food, beverages and tobacco (with CR1 of 24 percent), have experienced relatively higher increases in Chinese import penetration, at 1470 percent. In Chile, the China shock has had a larger impact on the market share of non-top firms. Conversely, in Colombia, sectors characterized by lower concentration ratios at the initial year of the sample, such as Textiles, apparel, and leather (with CR1 of 27 percent) as well as Wood and furniture (with CR1 of 28 percent), suffered relatively higher increases in Chinese import penetration. This negative competitive shock may have adversely affected the profitability of firms within these sectors, which have a diminished presence of important market players. It is also important to consider that the sample years differ for Chile and Colombia. In the case of Colombia we study a more prolonged exposure to Chinese import competition, with a sample period ending in 2016. In the case of Chile exposure to Chinese competition is more limited, with a sample that spans until 2007.

4.3 US Free trade agreements

Both Chile and Colombia have signed numerous free trade agreements (FTAs) during the last two decades. One of the most relevant FTAs is the one signed separately by each of the two countries with the US, in 2003 by Chile and in 2006 by Colombia. Even prior to the signature of the agreements, the US was a relevant trade partner for both countries, accounting for 16 percent of Chilean manufacturing exports in 2001 (the second most important export market) and for 32 percent of Colombian manufacturing exports in 2003 (the most important export market). The agreements went into effect in 2004 in Chile and in 2012 in Colombia, with the immediate elimination of tariffs for large groups of products and a subsequent phase-out period of several years.

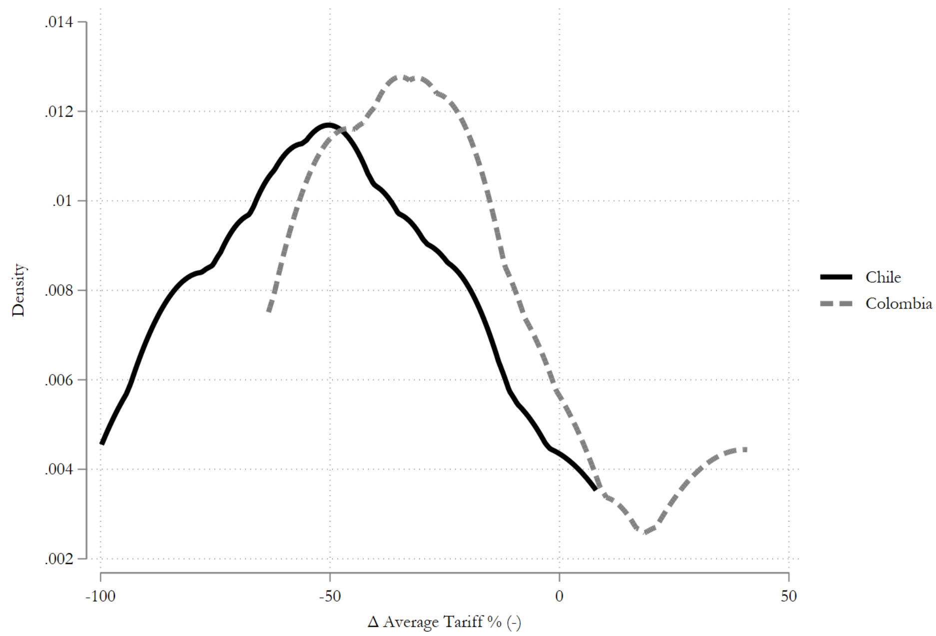
In this subsection we explore the effect on market power and concentration of the export opportunities generated by the FTAs with the US. The deepening of international trade relationship with high-income partners allows firms to access high quality intermediate inputs and to increase their market size by selling their products abroad. A large body of literature has shown that exporting to high-income countries generates important changes in firm outcomes, which may work through quality upgrading, changes in organizational structure, and changes in the labor force and intermediate input composition (Verhoogen, 2008; Bastos and Silva, 2010; Görg, Halpern, and Muraközy, 2017; Manova and Zhang, 2012; Brambilla, Lederman, and Porto, 2012 ; Brambilla and Porto, 2016; Brambilla, César, Falcone, and Porto, 2024). Moreover, expansion opportunities may favor larger and more productive firms (Melitz 2003, Autor et al 2020) and generate concentration.

We use tariff data from WITS that we match with the 4 digit ISIC Revision 3 classification from the manufacturing surveys. The signature of the FTAs implied sizeable reductions in tariffs. Figure 6 plots the percentage reduction in US tariffs across 4-digit industries due to the signature of the agreements. The differences are computed between 2006 and 2001 for Chile and between 2015 and 2006 in Colombia. The tariff reductions were quite heterogeneous across the different 4-digit industries. This is because of different initial tariff levels and due to the phase out period. We exploit this variability to study the differential impact of tariff cuts on firms according to their initial industry affiliation.

We run regression equation (1), with firm-level outcome variables on the left-hand side and the average 4-digit industry US import tariff as the shock variable. As in the previous subsections, regressions control for firm fixed effects, year fixed effects and firm and industry preexisting trends, interacted with year effects. In our strategy, we exploit these breaks in tariff trends across time and across industries. Exogeneity is given by the combination of tariff cuts due to the signature of FTAs and the initial industry affiliation of firms as in Lileeva and Trefler (2010), Bustos (2011), and Garcia-Marin and Voigtländer (2019). We assume that fixed effects control for time-invariant industry unobserved heterogeneity such as lobby capacity. The phase out period provides an additional source of variability, as changes in tariffs were not simultaneous across industries.

Tables 11 and 12 display results from the firm-level regressions. Coefficients in Panel A are negative and statistically significant. Since the shock is a *reduction* in tariffs, the average effect is an *increase* in markups, profitability and TFP. These results are in line with Garcia-Marin and Voigtländer (2019), who find that tariff-induced export expansions or the entrance of new exporters generated important efficiency gains on Chilean, Colombian,

Figure 6: Tariffs US



Notes: Change in ad-valorem US tariffs (percentage points) faced by Chilean (2001–2006) and Colombian (2006–2015) firms, across industries.
Source: World Integrated Trade Solution (WITS).

and Mexican plants, with partial increases in markups.

In panels B to D we explore whether the effects are heterogeneous according to initial industry or firm characteristics. We interact the shock variable with initial industry concentration CR_1 (Panel B), with initial industry share in domestic manufacturing (Panel C), with initial industry value of exports (Panel D), and in the case of Chile with initial firm exporting status (Panel E). For Chile, we find that the increase in markups, profitability and TFP was smaller in industries with a comparatively high level of exports prior to the signature of the FTA (Panel D), and for firms that were already exporters (Panel E), both of which points to a lower scope for expansion in export opportunities and the latter highlighting that the extensive margin of exports has important implications for firms outcomes (as also documented by Lileeva and Trefler, 2010; Bustos, 2011; Atkin, Khandelwal, and Osman, 2017; Garcia-Marin and Voigtländer (2019); Brambilla, César, Falcone, and Porto, 2024)). In the case of Colombia, effects are smaller in highly concentrated industries (Panel B), suggesting a reduced scope for increasing markup power, and higher in industries with larger share in manufacturing (Panel C) and export value (Panel D). This latter results could be attributed to comparative advantage in those industries.

Table 13, at the industry level, shows no evidence of an increase in industry concentration. Although most point estimates are negative and large in magnitude, suggesting an increase in concentration compatible with the idea that some pro-competitive shocks work in this

Table 11: FTAs and Markups. Chile

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.004^{**}	-0.003^{*}	-0.004^{**}	-0.003^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	33831	33847	33844	32513	33266
Panel B: Industry concentration					
Tariff US	0.001	0.002	0.000	-0.003	-0.000
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Tariff US x CR1	-0.000	-0.000^{*}	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25258	25259	25267	24642	25174
Panel C: Industry share					
Tariff US	-0.003	-0.001	-0.005^{*}	-0.004^{**}	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Tariff US x Share	-0.095	-0.176	0.088	0.078	-0.078
	(0.166)	(0.170)	(0.168)	(0.125)	(0.129)
Observations	25258	25259	25267	24642	25174
Panel D: Industry exports					
Tariff US	-0.005^{***}	-0.004^{**}	-0.005^{***}	-0.004^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Tariff US x Exports	0.019^{**}	0.020^{**}	0.020^{***}	0.007	0.014^{*}
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Observations	33821	33837	33834	32502	33255
Panel E: Firm exporter dummy					
Tariff US	-0.004^{***}	-0.004^{**}	-0.005^{***}	-0.004^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Tariff US x Exporter	0.006^{**}	0.006^{**}	0.004	0.005^{**}	0.004^{*}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	33831	33847	33844	32513	33266

Notes: FE regressions at the firm level. Dependent variables and controls are analogous to Table 5. The main regressor is the average US import tariff at the 4-digit industry. Panels B to E incluse several interactions of the shock variable: the industry level CR1 concentration ratio (B); the initial year industry share in total manufacturing output (C); the initial year industry value of exports (D); a dummy for exporting firms in the initial year (E). Time periods 1995–2007.

direction, confidence intervals are very large and none of the coefficients are statistically significant.

Table 12: FTAs and Markups. Colombia

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.004^{***}	-0.002^{*}	-0.003^{***}	-0.001^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	79525	79525	79502	78588	80440
Panel B: Industry concentration					
Tariff US	-0.010^{***}	-0.009^{***}	-0.008^{***}	-0.002^{**}	-0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Tariff US x CR1	0.001^{***}	0.001^{***}	0.001^{***}	0.000	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48077	48099	48108	47611	48572
Panel C: Industry share					
Tariff US	0.005^{**}	0.008^{***}	0.004^{**}	0.000	0.002
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Tariff US x Share	-0.196^{***}	-0.235^{***}	-0.170^{***}	-0.029	-0.118^{***}
	(0.039)	(0.051)	(0.038)	(0.026)	(0.036)
Observations	48077	48099	48108	47611	48572
Panel D: Industry exports					
Tariff US	0.001	0.004	0.002	0.000	0.001
	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Tariff US x Exports	-0.007	-0.009^{*}	-0.007^{**}	-0.002	-0.005^{**}
	(0.004)	(0.005)	(0.003)	(0.001)	(0.002)
Observations	79515	79513	79492	78576	80428

Notes: FE regressions at the firm level. Dependent variables and controls are analogous to Table 6. The main regressor is the average US import tariff at the 4-digit industry. Panels B to E incluse several interactions of the shock variable: the industry level CR1 concentration ratio (B); the initial year industry share in total manufacturing output (C); the initial year industry value of exports (D). Time periods 2001–2016.

5 Conclusion

This study provides detailed empirical evidence on how robot automation and globalization, specifically import competition from China and export opportunites that arose due to the signature of free trade agreements, have influenced market concentration and market power in the manufacturing sectors of Chile and Colombia, over recent decades.

We uncover several interesting findings. Regarding automation, on average, the increase in industry-level robot exposure has contributed to reduce firm-level markups. However,

Table 13: FTAs and Industry concentration

	CR1	CR2	CR3
Chile			
Tariff US	−0.289	−0.276	−0.205
	(0.216)	(0.237)	(0.273)
Observations	675	675	675
Colombia			
Tariff US	0.177	−0.024	−0.082
	(0.279)	(0.300)	(0.271)
Observations	1101	1101	1101

Notes: FE regressions at the industry level. Industry-level dependent variables and controls are analogous to Table 8. The main regressor is is the average US import tariff at the 4-digit industry.

the opposite has occurred among top firms, with evidence of increase in markups and TFP as a response to robot exposure. We interpret these findings as top firms adopting global technology at a before or at a faster rate than their domestic competitors.

The paper also investigates the role of import competition, particularly from China. Results point out that the competitive shock induced by an increase in Chinese imports has a significant negative impacts on market power measures both for Chile and Colombia, both on average and for firms with largest market share in each industry.

Finally, our research shows that the reduction of bilateral import tariffs in the United States that resulted from the signature of FTAs had a positive effect on firm-level profitability, TFP, and markups. In the case of Chile, these results are concentrated on initial non-exporters, in line with existing research highlighting the extensive margin of exports as a critical driver of firms' performance. In contrast, in Colombia, the increase in markups was larger for firms in industries with higher market share and higher export values, implying that FTAs have been beneficial for firms in industries with natural or historical comparative advantage.

In summary, this study demonstrates how automation, import competition, and export opportunities interact to shape market power and productivity in Chile and Colombia. While automation generally reduces markups for most firms, top firms benefit from early technology adoption, consolidating or even increasing their market power. Import competition, especially from China, acts as a powerful force in reducing markups across the board, underscoring the competitive dynamics of global trade. Meanwhile, the expansion of export opportunities enhances firm profitability and productivity although it may also lead to increased market concentration among top firms.

These results offer important insights for policymakers, suggesting that support for small and medium-sized firms in adopting automation and other advanced technologies could help sustain their competitiveness against technologically advanced firms. Additionally, fostering import competition may serve as an effective tool to regulate domestic market power in favor of consumer welfare. Finally, while expanding export opportunities is key to driving productivity improvements, it must be carefully managed to avoid exacerbating market concentration.

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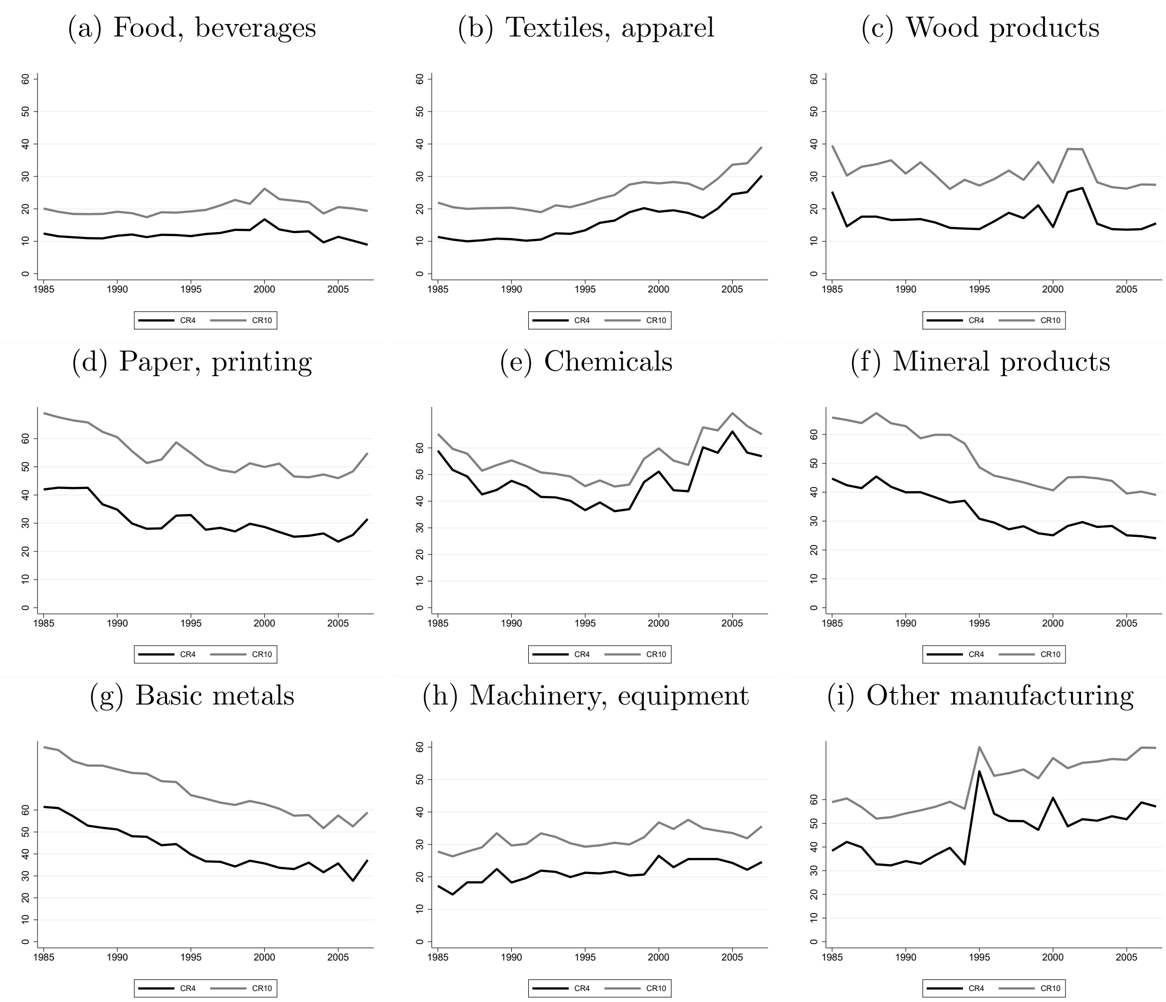
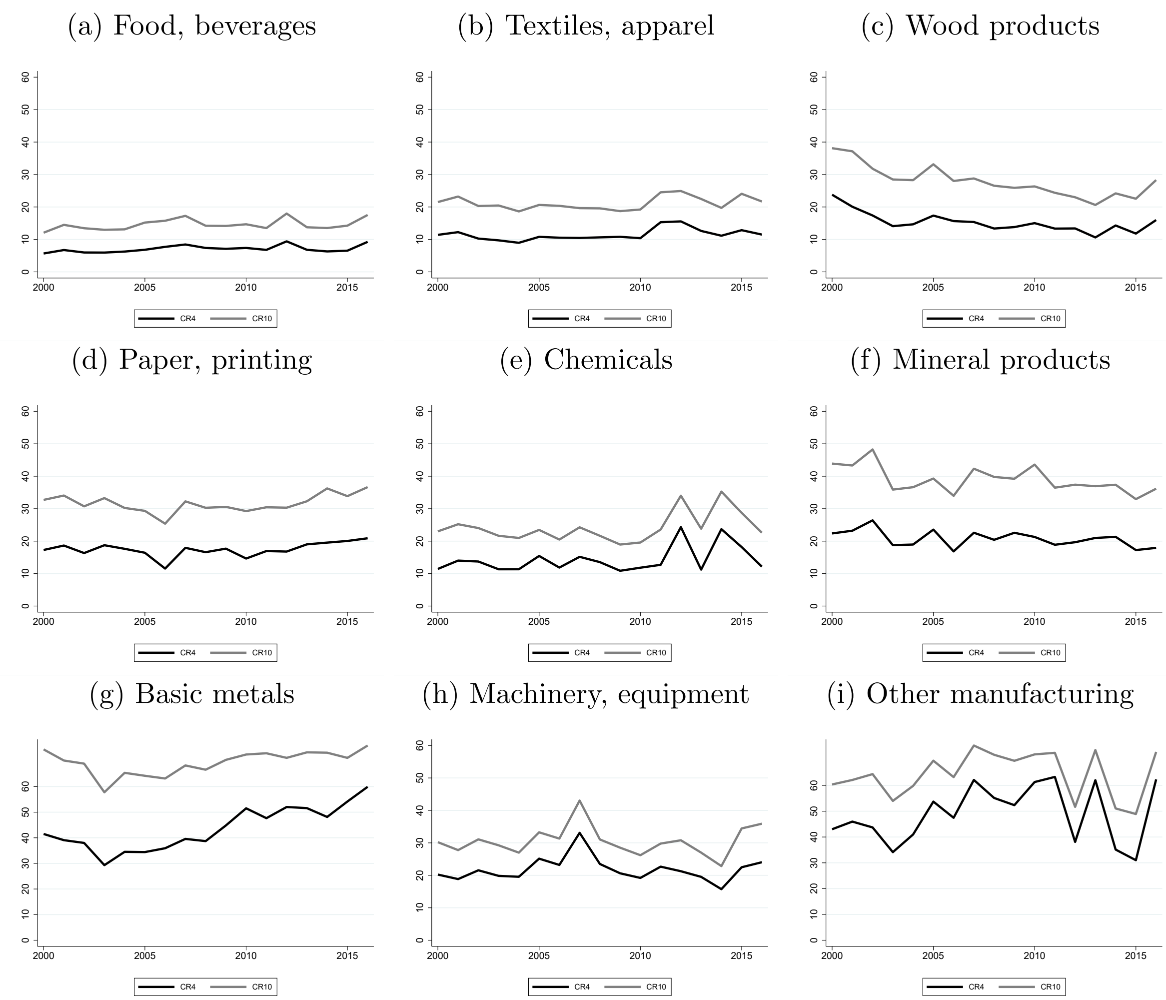
Appendix A: Additional figures and tables

Figure A1: Concentration by manufacturing sectors. Chile



Notes: Figure shows concentration ratios (CR4: solid black, CR10: solid gray) of 2 digit manufacturing sectors. Sectors correspond to codes 31 to 39 of the ISIC Rev 2 classification at 2 digits of aggregation.
Source: Annual Industrial Survey (ENIA).

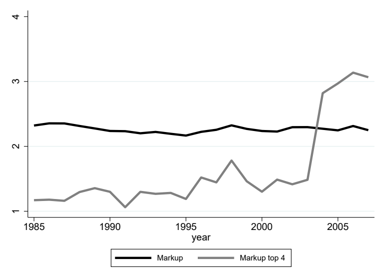
Figure A2: Concentration by manufacturing sectors. Colombia



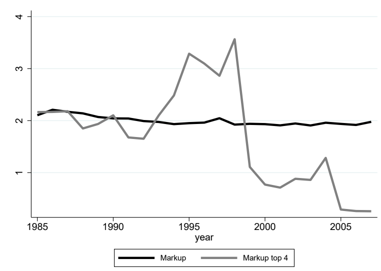
Notes: Figure shows concentration ratios (CR4: solid black, CR10: solid gray) of 2 digit manufacturing sectors. Sectors correspond to codes 31 to 39 of the ISIC Rev 2 classification at 2 digits of aggregation.
Source: Colombian Annual Manufacturing Survey (EAM).

Figure A3: Markups by manufacturing sector. Chile

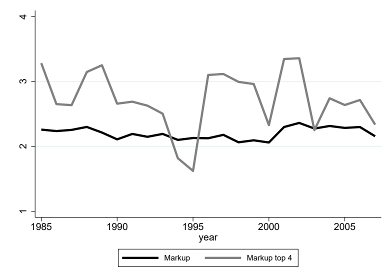
(a) Food, beverages



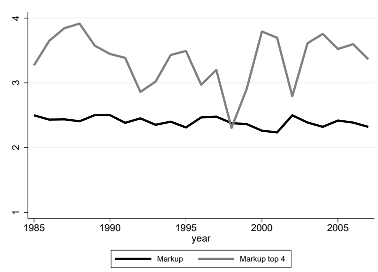
(b) Textiles, apparel



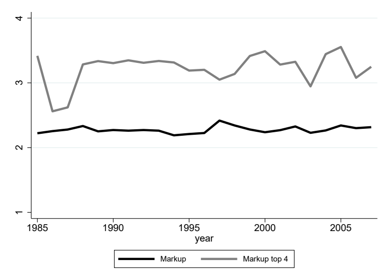
(c) Wood products



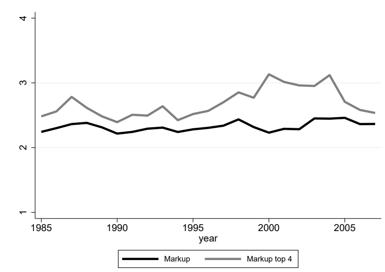
(d) Paper, printing



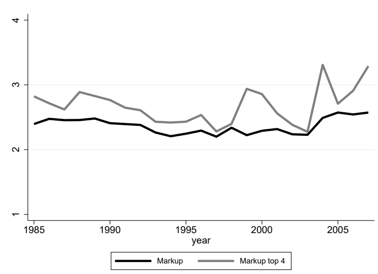
(e) Chemicals



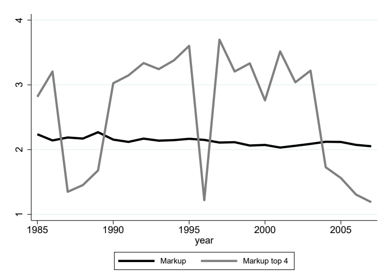
(f) Mineral products



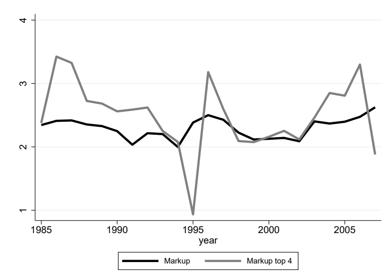
(g) Basic metals



(h) Machinery, equipment

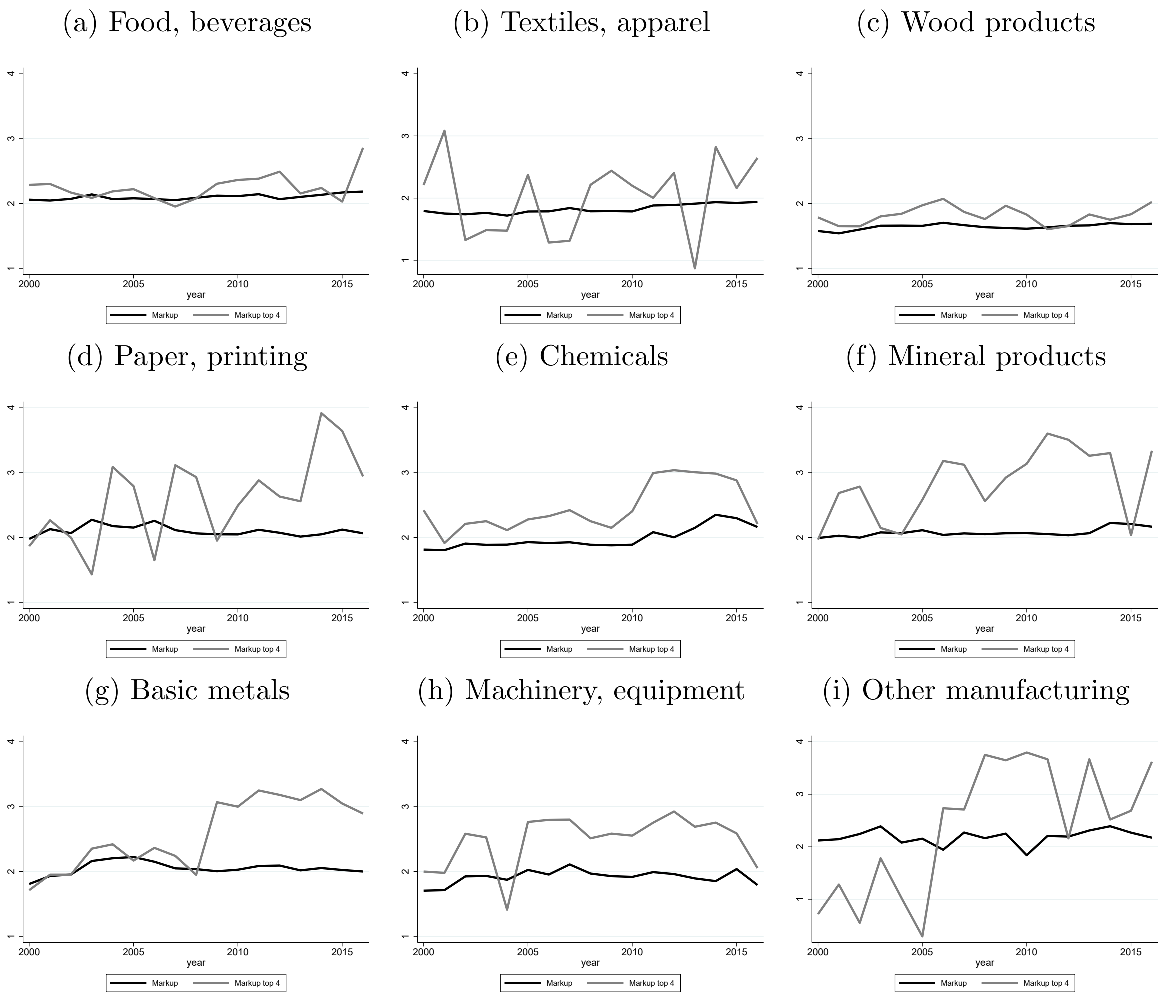


(i) Other manufacturing



Notes: Figure shows sales weighted average markups (all firms: solid black, top 4 firms: solid gray) of 2 digit manufacturing sectors. Sectors correspond to codes 31 to 39 of the ISIC Rev 2 classification at 2 digits of aggregation.
Source: Annual Industrial Survey (ENIA).

Figure A4: Markups by manufacturing sector. Colombia

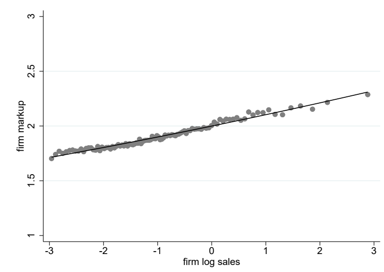


Notes: Figure shows sales weighted average markups (all firms: solid black, top 4 firms: solid gray) of 4 digit industries weighted by share of industry in total sector sales. Sectors correspond to codes 31 to 39 of the ISIC Rev 2 classification at 2 digits of aggregation.
Source: Colombian Annual Manufacturing Survey (EAM).

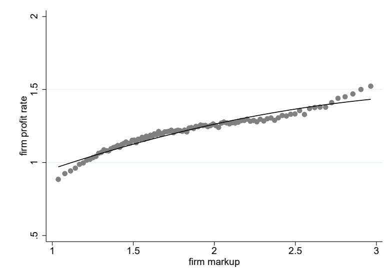
Figure A5: Firm characteristics

Chile

(a) Markups and sales

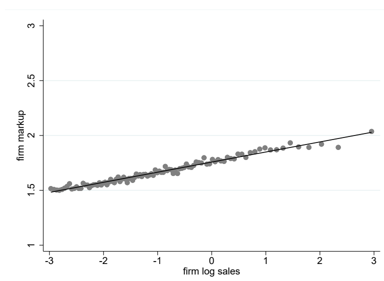


(b) Markups and profits

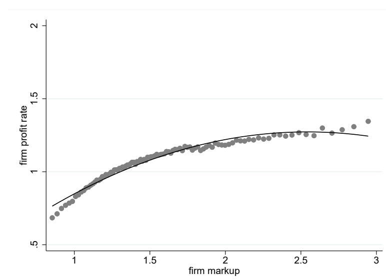


Colombia

(c) Markups and sales



(d) Markups and profits



Notes: Figure shows mean firm-level markup conditional on firm-level sales, and mean firm-level profit rate conditional on firm-level markup.
Source: Annual Industrial Survey (ENIA) for Chile and Colombian Annual Manufacturing Survey (EAM) for Colombia.

Table A1: Global automation and markups. Chile. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	-0.017^{***}	-0.015^{***}	-0.009^{**}	-0.009^{*}	-0.006
	(0.006)	(0.006)	(0.004)	(0.005)	(0.005)
Observations	66071	66270	66038	62216	63619
Panel B: Top firms					
RobotExp*	-0.020^{***}	-0.019^{***}	-0.012^{***}	-0.010^{*}	-0.007
	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)
RobotExp* × Top 1	0.048^{*}	0.047^{*}	0.022^{**}	0.026^{***}	0.023^{***}
	(0.027)	(0.025)	(0.009)	(0.007)	(0.004)
Observations	43613	43668	43653	41481	42330
Panel C: Imports of robots					
RobotExp* × Imports	0.002	0.003	0.002	-0.002	0.000
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Observations	66071	66270	66038	62216	63619
Panel D: Imports of robots and top firms					
RobotExp* × Imports	0.000	0.001	0.001	-0.003^{**}	-0.000
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
RobotExp* × Imports × Top 1	0.000^{*}	0.000^{*}	0.000	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43613	43668	43653	41481	42330

Notes: analogous to Table 5 with markups computed from labor first order conditions.

Table A2: Global automation and markups. Colombia. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	-0.007^{**}	-0.003	-0.007^{***}	-0.002^{***}	-0.004^{***}
	(0.003)	(0.004)	(0.002)	(0.000)	(0.001)
Observations	111970	111928	112010	109508	112044
Panel B: Top firms					
RobotExp*	-0.004	-0.001	-0.005^{**}	-0.002^{***}	-0.004^{**}
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)
RobotExp* $\times$ Top 1	-0.008	-0.003	-0.012	0.010	0.017^{***}
	(0.007)	(0.006)	(0.009)	(0.006)	(0.005)
Observations	58673	58717	58913	57849	58977
Panel C: Imports of robots					
RobotExp* $\times$ Imports	0.001	-0.000	0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	111970	111928	112010	109508	112044
Panel D: Imports of robots and top firms					
RobotExp* $\times$ Imports	-0.002	-0.001	-0.002^{*}	-0.002^{***}	-0.002^{***}
	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
RobotExp* $\times$ Imports $\times$ Top 1	-0.003	-0.000	-0.004	0.005^{**}	0.008^{***}
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
Observations	58673	58717	58913	57849	58977

Notes: analogous to Table 6 with markups computed from labor first order conditions.

Table A3: Global automation and markups. Chile. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	−0.014	−0.016	−0.017	−0.009*	−0.006
	(0.011)	(0.011)	(0.013)	(0.005)	(0.005)
Observations	65572	65737	65563	62216	63619
Panel B: Top firms					
RobotExp*	−0.012	−0.014	−0.015	−0.010*	−0.007
	(0.009)	(0.010)	(0.011)	(0.006)	(0.005)
RobotExp* × Top 1	0.032***	0.035***	0.037***	0.026***	0.023***
	(0.009)	(0.011)	(0.011)	(0.007)	(0.004)
Observations	43276	43378	43304	41481	42330
Panel C: Imports of robots					
RobotExp* × Imports	−0.005	−0.006*	−0.005	−0.002	0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Observations	65572	65737	65563	62216	63619
Panel D: Imports of robots and top firms					
RobotExp* × Imports	−0.005	−0.005	−0.005	−0.003**	−0.000
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
RobotExp* × Imports × Top 1	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43276	43378	43304	41481	42330

Notes: analogous to Table 5 with markups computed from intermediate inputs first order conditions.

Table A4: Global automation and markups. Colombia. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp*	−0.003	−0.001	−0.004**	−0.002***	−0.004***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Observations	111714	111710	111681	109508	112044
Panel B: Top firms					
RobotExp*	−0.005*	−0.003	−0.006**	−0.002***	−0.004**
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
RobotExp* × Top 1	0.020***	0.025***	0.021***	0.010	0.017***
	(0.008)	(0.009)	(0.008)	(0.006)	(0.005)
Observations	58996	58920	59024	57849	58977
Panel C: Imports of robots					
RobotExp* × Imports	−0.003**	−0.004***	−0.003**	−0.001	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	111714	111710	111681	109508	112044
Panel D: Imports of robots and top firms					
RobotExp* × Imports	−0.003**	−0.002	−0.004***	−0.002***	−0.002***
	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
RobotExp* × Imports × Top 1	0.008***	0.009***	0.008***	0.005**	0.008***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	58996	58920	59024	57849	58977

Notes: analogous to Table 6 with markups computed from intermediate inputs first order conditions.

Table A5: Domestic automation and markups. Colombia. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp	-0.173^{***}	-0.074	-0.188^{***}	-0.060^{***}	-0.093^{**}
	(0.064)	(0.061)	(0.056)	(0.019)	(0.036)
KP F-stat	36.6	37.5	36.1	34.8	31.6
Observations	111970	111928	112010	109508	112044
Panel B: Top firms					
RobotExp	-0.111	-0.034	-0.148^{**}	-0.068^{***}	-0.106^{**}
	(0.076)	(0.074)	(0.071)	(0.025)	(0.042)
RobotExp × Top 1	-0.183	-0.061	-0.278	0.257	0.462^{**}
	(0.385)	(0.279)	(0.355)	(0.185)	(0.225)
KP F-stat	10.4	10.7	10.2	9.9	9.7
Observations	58673	58717	58913	57849	58977

Notes: analogous to Table 7 with markups computed from labor first order conditions.

Table A6: Domestic automation and markups. Colombia. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
RobotExp	-0.083^{*}	-0.036	-0.102^{**}	-0.060^{***}	-0.093^{**}
	(0.044)	(0.046)	(0.047)	(0.019)	(0.036)
KP F-stat	31.9	31.7	31.2	34.8	31.6
Observations	111714	111710	111681	109508	112044
Panel B: Top firms					
RobotExp	-0.125^{**}	-0.078	-0.154^{**}	-0.068^{***}	-0.106^{**}
	(0.056)	(0.068)	(0.061)	(0.025)	(0.042)
RobotExp × Top 1	0.547	0.664	0.558	0.257	0.462^{**}
	(0.378)	(0.452)	(0.376)	(0.185)	(0.225)
KP F-stat	9.4	9.4	9.2	9.9	9.7
Observations	58996	58920	59024	57849	58977

Notes: analogous to Table 7 with markups computed from intermediate inputs first order conditions.

Table A7: Import penetration and markups. Chile and Colombia. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Chile					
Panel A: Average effect					
Import penetration	-0.008^{***}	-0.010^{***}	-0.005^{***}	0.000	0.000
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
KP F-stat	62.5	67.2	64.5	60.6	63.8
Observations	66007	66206	65975	62152	63555
Panel B: Top firms					
Import penetration	-0.007^{***}	-0.010^{***}	-0.004^{***}	0.000	0.000
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Import penetration x Top 1	0.001	0.000	-0.001	-0.002	0.001
	(0.009)	(0.008)	(0.006)	(0.004)	(0.004)
KP F-stat	25.6	25.6	27.3	23.7	26.6
Observations	43583	43638	43624	41451	42300
Colombia					
Panel C: Average effect					
Import penetration	-0.033^{***}	-0.030^{***}	-0.027^{***}	-0.006^{***}	-0.007^{*}
	(0.008)	(0.008)	(0.006)	(0.002)	(0.004)
KP F-stat	20.8	18.3	20.3	21.2	21.1
Observations	110289	110247	110329	107872	110385
Panel D: Top firms					
Import penetration	-0.032^{***}	-0.030^{***}	-0.027^{***}	-0.004^{***}	-0.004
	(0.008)	(0.008)	(0.007)	(0.002)	(0.003)
Import penetration x Top 1	0.001	0.003	-0.000	0.003	0.006^{*}
	(0.007)	(0.008)	(0.006)	(0.003)	(0.003)
KP F-stat	9.0	7.9	8.8	9.4	9.3
Observations	57928	57973	58168	57111	58232

Notes: analogous to Table 9 with markups computed from labor first order conditions.

Table A8: Import penetration and markups. Chile and Colombia. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Chile					
Panel A: Average effect					
Import penetration	0.006***	0.006***	0.006***	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
KP F-stat	61.3	58.0	63.3	60.6	63.8
Observations	65508	65676	65499	62152	63555
Panel B: Top firms					
Import penetration	0.005***	0.005***	0.005***	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Import penetration x Top 1	0.003	0.004	0.003	−0.002	0.001
	(0.010)	(0.011)	(0.011)	(0.004)	(0.004)
KP F-stat	21.4	21.9	21.3	23.7	26.6
Observations	43246	43349	43274	41451	42300
Colombia					
Panel C: Average effect					
Import penetration	0.007	0.005	0.008*	−0.006***	−0.007*
	(0.004)	(0.004)	(0.005)	(0.002)	(0.004)
KP F-stat	20.1	19.9	20.1	21.2	21.1
Observations	110058	110045	110039	107872	110385
Panel D: Top firms					
Import penetration	0.006	0.004	0.007*	−0.004***	−0.004
	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)
Import penetration x Top 1	0.006	0.009	0.007	0.003	0.006*
	(0.007)	(0.007)	(0.007)	(0.003)	(0.003)
KP F-stat	8.5	8.2	8.6	9.4	9.3
Observations	58247	58171	58279	57111	58232

Notes: analogous to Table 9 with markups computed from intermediate inputs first order conditions.

Table A9: FTAs and Markups. Chile. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.001	0.000	-0.000	-0.003^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	34166	34316	34156	32513	33266
Panel B: Industry concentration					
Tariff US	-0.003	-0.002	-0.002	-0.003	-0.000
	(0.006)	(0.006)	(0.004)	(0.002)	(0.003)
Tariff US x CR1	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25449	25568	25441	24642	25174
Panel C: Industry share					
Tariff US	0.003	0.004	0.002	-0.004^{**}	-0.003
	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)
Tariff US x Share	-0.284	-0.261	-0.187	0.078	-0.078
	(0.252)	(0.291)	(0.166)	(0.125)	(0.129)
Observations	25449	25568	25441	24642	25174
Panel D: Industry exports					
Tariff US	-0.001	-0.001	-0.001	-0.004^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Tariff US x Exports	0.017	0.020	0.010	0.007	0.014^{*}
	(0.016)	(0.014)	(0.011)	(0.007)	(0.008)
Observations	34155	34305	34145	32502	33255
Panel E: Firm exporter dummy					
Tariff US	-0.002	-0.001	-0.001	-0.004^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Tariff US x Exporter	0.011^{***}	0.010^{***}	0.007^{***}	0.005^{**}	0.004^{*}
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	34166	34316	34156	32513	33266

Notes: analogous to Table 11 with markups computed from labor first order conditions.

Table A10: FTAs and Markups. Colombia. MuL

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.003	-0.002	-0.002	-0.001^{***}	-0.003^{***}
	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
Observations	80244	80178	80208	78588	80440
Panel B: Industry concentration					
Tariff US	-0.011^{***}	-0.010^{***}	-0.008^{***}	-0.002^{**}	-0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Tariff US x CR1	0.001^{***}	0.001^{***}	0.001^{**}	0.000	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48332	48349	48500	47611	48572
Panel C: Industry share					
Tariff US	0.007	0.009^{*}	0.005	0.000	0.002
	(0.005)	(0.005)	(0.004)	(0.001)	(0.002)
Tariff US x Share	-0.240^{***}	-0.261^{***}	-0.184^{**}	-0.029	-0.118^{***}
	(0.092)	(0.092)	(0.074)	(0.026)	(0.036)
Observations	48332	48349	48500	47611	48572
Panel D: Industry exports					
Tariff US	-0.001	0.003	-0.001	0.000	0.001
	(0.007)	(0.007)	(0.005)	(0.001)	(0.002)
Tariff US x Exports	-0.003	-0.006	-0.001	-0.002	-0.005^{**}
	(0.008)	(0.008)	(0.006)	(0.001)	(0.002)
Observations	80236	80170	80201	78576	80428

Notes: analogous to Table 12 with markups computed from labor first order conditions.

Table A11: FTAs and Markups. Chile. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.007^{***}	-0.008^{***}	-0.008^{***}	-0.003^{***}	-0.004^{***}
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Observations	33919	34011	33900	32513	33266
Panel B: Industry concentration					
Tariff US	0.000	-0.002	-0.002	-0.003	-0.000
	(0.005)	(0.006)	(0.006)	(0.002)	(0.003)
Tariff US x CR1	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25319	25357	25311	24642	25174
Panel C: Industry share					
Tariff US	-0.010^{***}	-0.011^{***}	-0.012^{***}	-0.004^{**}	-0.003
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Tariff US x Share	0.234	0.280	0.364	0.078	-0.078
	(0.238)	(0.233)	(0.255)	(0.125)	(0.129)
Observations	25319	25357	25311	24642	25174
Panel D: Industry exports					
Tariff US	-0.009^{***}	-0.009^{***}	-0.009^{***}	-0.004^{***}	-0.004^{***}
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Tariff US x Exports	0.029^{***}	0.032^{***}	0.033^{***}	0.007	0.014^{*}
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Observations	33908	34000	33889	32502	33255
Panel E: Firm exporter dummy					
Tariff US	-0.008^{***}	-0.008^{***}	-0.008^{***}	-0.004^{***}	-0.004^{***}
	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Tariff US x Exporter	0.002	0.004	0.000	0.005^{**}	0.004^{*}
	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)
Observations	33919	34011	33900	32513	33266

Notes: analogous to Table 11 with markups computed from intermediate inputs first order conditions.

Table A12: FTAs and Markups. Colombia. MuI

	Markup			Profitability	TFP
	μ_{inv}	μ_{inp}	μ_{cs}		
	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
Tariff US	-0.003	-0.002	-0.003	-0.001^{***}	-0.003^{***}
	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Observations	80002	79976	79955	78588	80440
Panel B: Industry concentration					
Tariff US	-0.005^{**}	-0.004^{*}	-0.006^{**}	-0.002^{**}	-0.006^{***}
	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
Tariff US x CR1	0.000	0.000	0.000	0.000	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48326	48295	48362	47611	48572
Panel C: Industry share					
Tariff US	0.002	0.003	0.003	0.000	0.002
	(0.004)	(0.004)	(0.005)	(0.001)	(0.002)
Tariff US x Share	-0.104	-0.110	-0.132	-0.029	-0.118^{***}
	(0.078)	(0.070)	(0.088)	(0.026)	(0.036)
Observations	48326	48295	48362	47611	48572
Panel D: Industry exports					
Tariff US	0.002	0.003	0.003	0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)
Tariff US x Exports	-0.007^{*}	-0.008^{*}	-0.008^{**}	-0.002	-0.005^{**}
	(0.003)	(0.004)	(0.004)	(0.001)	(0.002)
Observations	79990	79964	79943	78576	80428

Notes: analogous to Table 12 with markups computed from intermediate inputs first order conditions.

Appendix B: Estimation of markups

To estimate markups we apply the production method of De Loecker and Warzynski (2012) and De Loecker, Eeckhout and Unger (2020). The method relies on the first order conditions of the cost minimization problem in variable inputs of a firm that faces exogenous and constant unit prices in input markets. Operating, the first order condition of variable input v of firm i in 2-digit sector s and time t can be written as

$$\mu_{ist} = \theta_s^v / S_{ist}^v, \ v = m, l. \tag{6}$$

The mark-up μ, defined as output price over marginal cost, is the ratio of the output elasticity of variable input v, θ^v, and the share of variable input v in firm revenue, S^v. The share of input v in firm revenue is computed from the firm survey data in a straightforward manner, whereas the output elasticity θ^v is an estimable parameter that represents technology in sector s.

An input is variable when it is flexible enough that the optimal input quantity is the solution of a static optimization problem. Intermediate inputs such as materials and energy are typically considered static inputs. Labor is a flexible input but not as flexible as materials and energy due to potential hiring, training, and firing costs. Capital is a much less flexible factor of production subject to costs of adjustment, time to build and depreciation, and it is usually thought to be obtained as the solution of a dynamic optimization problem. In our context, we consider that flexible inputs are intermediate inputs, m, defined as the sum of expenditures on materials and energy, and labor, l, defined as the number of workers.

Under the assumption that the firm can adjust flexible input quantities freely at a given input price, and when evaluated at the true parameters θ_s^v, equation (6) holds for all flexible inputs simultaneously. Let $\widehat{\theta}_s^m$ and $\widehat{\theta}_s^l$ denote previously obtained sector-level estimates of the output elasticities of intermediate inputs and labor. An estimator of the firm-level markup, $\widehat{\mu}_{ist}^A$, is given by the minimum distance solution to overidentified system (6) as

$$\widehat{\mu}_{ist}^A = \arg\min_{\mu} \begin{pmatrix} \mu - \widehat{\theta}_m^v / S_{ist}^m \\ \mu - \widehat{\theta}_l^v / S_{ist}^l \end{pmatrix} W \left(\mu - \widehat{\theta}_m^v / S_{ist}^m, \mu - \widehat{\theta}_l^v / S_{ist}^l \right) \tag{7}$$

where W is a 2×2 weighting matrix. Alternatively, markups can be estimated from only one first order condition, based solely on intermediate inputs m, or solely on labor l, as

$$\widehat{\mu}_{ist}^B = \widehat{\theta}_s^m / S_{ist}^m \tag{8}$$

$$\widehat{\mu}_{ist}^C = \widehat{\theta}_s^l / S_{ist}^l. \tag{9}$$

In the empirical implementation we compute estimates of markups based on the three alternatives , $\widehat{\mu}^A_{ist}$, $\widehat{\mu}^B_{ist}$, $\widehat{\mu}^C_{ist}$. We refer to these estimates as minimum distance, intermediate input first order conditions, and labor first order conditions.

Estimation of the elasticities of output

As noted above, the estimation of markups requires estimates of the output elasticities of intermediate inputs and labor. The output elasticities can be calibrated or estimated econometrically in the context of a production function. For comparison purposes we estimate θ^m and θ^l using three estimation methods that we discuss below. Under the three discussed methods, we estimate a time-invariant output elasticity that varies at the sector level. There are 9 sectors and therefore 9 parameters: (1) Food and beverages; (2) Textiles and apparel; (3) Wood and wood products; (4) Paper and printing; (5) Chemicals; (6) Minerals and mineral products; (7) Basic metals and metal products; (8) Machinery and equipment; (9) Other manufacturing. Notice that in this context a sector is defined at the two digit level and it is not the same as an industry, which we define at the 4 digit level. An industry represents a finer level of disaggregation.

The cost share approach

Under the assumption of constant returns to scale, the firm-level cost share of input v in total variable cost is equal to the output elasticity. The firm-level cost share of intermediate inputs and labor can be written as

$$\theta^m_{ist} = \frac{ExpM_{ist}}{ExpM_{ist} + ExpL_{ist} + r_t K_{ist}},\ \theta^l_{ist} = \frac{ExpL_{ist}}{ExpM_{ist} + ExpL_{ist} + r_t K_{ist}}, \tag{10}$$

where $ExpM$ is expenditure in intermediate inputs, $ExpL$ is expenditure in labor, and rK is the cost of using the installed capital stock. The user cost of capital r is the same across firms and is defined as the sum of the real interest rate and the capital depreciation rate. The firm level variables $ExpM$, $ExpL$ and K are from the firm surveys. The rate r is computed from the real interest rate for Chile and Colombia from the World Development Indicators and the depreciation rate is set at 10 percent. We work under two scenarios: a time varying real interest rate, and a fixed real interest rate computed as the average over the time period 1995-2015. The average user cost of capital is 0.158 in Chile and 0.199 in Colombia. The correlation between the firm-level cost shares computed with a fixed r and with a time varying r is 0.9915 for Chile and 0.9899 for Colombia.

The estimator for the sector-level output elasticities are defined as

$$\widehat{\theta}_s^m = \frac{1}{T}\sum_t Med\left(\theta_{ist}^m\right), \ \widehat{\theta}_s^l = \frac{1}{T}\sum_t Med\left(\theta_{ist}^l\right), \tag{11}$$

where T is the number of time periods. For each sector s, we first compute the median across firms, for each year, and we then compute the average across years.

Results are shown in Tables B1 to B4, columns (1) to (4). In columns (1) and (3) the user cost of capital r varies across years, whereas in columns (2) and (4) the user cost of capital is time invariant. Columns (1) and (2) use all available years of data (Chile: 1985-2011, Colombia: 1995-2021) whereas columns (3) and (4) restrict the sample to a shorter time span of firm panel samples with low attrition and the Revision 3 industry classification (Chile: 1995-2007, Colombia: 2001-2011). The horizontal panels (1) to (9) correspond to the nine manufacturing 2-digit sectors. Results are very similar across the four columns, with elasticities of output for intermediate inputs that range from 0.56 to 0.75 in Chile, and 0.50 to 0.71 in Colombia, and elasticities of output for labor that range from 0.14 to 0.32 in Chile, and 0.18 to 0.30 in Colombia. The correlation across columns is displayed in the top panel of Table B5. They range from 0.97 to 0.999 implying that using a fixed or time-varying real interest rate or a shorter sample does not have a large influence on the estimates of the elasticity of output. We use column (1) as our baseline estimate for the cost share approach.

The control function approach based on investment

The control function approach, also referred to as the investment proxy approach, was developed by Olley and Pakes (1996) motivated by endogeneity concerns in the econometric estimation of regression functions of output on inputs. The technology of firm i in sector s is given by

$$y_{ist} = \theta_s^m m_{ist} + \theta_s^l l_{ist} + \theta_s^k k_{ist} + \omega_{ist} + \epsilon_{ist}, \tag{12}$$

where y is log output, m, l, k are log intermediate inputs, labor and capital, ω is unobserved productivity that affects firm input decisions, and ϵ is measurement error in output. The estimation of θ^m and θ^l is based on the assumption that invesment decisions are dynamic and depend monotonically on unobserved ω and on the predetermined capital stock. By inverting the decision function, investment can be used to non-parametrically control for ω. The regression equation is given by

$$y_{ist} = \theta_s^m m_{ist} + \theta_s^l l_{ist} + \phi(k_{ist}, i_{ist}, z_{jt}) + \epsilon_{ist}, \tag{13}$$

where i is investment and z are 4-digit industry level investment demand shifters. The coefficient θ^k is recovered in a second estimation stage that requires panel data. In our context, however, we only need $\widehat{\theta}^m$ and $\widehat{\theta}^l$ and the second stage is not necessary. First stage regression (13) can be estimated with cross sections of firms.[13]

We estimate regression (13) separately for each of the 9 manufacturing sectors. Coefficients vary across sectors but are fixed over time. We approximate the function ϕ with a second degree polynomial in capital and investment, 4-digit industry-year effects, and 4-digit industry effects interacted with investment.

Results are shown in Tables B1 to B4, columns (5) and (6), for the full sample and the shorter time span panel sample. The estimates are in general smaller than the ones based on cost shares (columns 1 to 4) in the case of intermediate inputs, and larger in the case of labor. The correlation across columns (5) and (6) is displayed in the bottom panel of Table B5. They range from 0.95 to 0.99. We use column (5) as our baseline estimate for the investment control approach.

The control function approach based on intermediate inputs

The Olley and Pakes method relies on observing strictly positive investment rates, however, in firm surveys reported investment is often zero, which may substantially reduce the number of observations. Levinsohn and Petrin (2003) and Ackerberg, Caves and Frazer (2016) notice that intermediate inputs are also a function of unobserved productivity ω and are typically reported as strictly positive in firm data. They propose methods that rely on using intermediate inputs as a control for unobserved productivity. These methods do require panel data to estimate all coefficients. The specifics of the estimation method depend on the model assumptions.

We assume that intermediate inputs are a function of unobserved productivity, predetermined capital, previously determined labor, and 4-digit industry-level input demand shifters z_{jt}. The input decision function is inverted to non-parametrically control for unobserved ω in the production function equation. The first-stage regression equation becomes

$$y_{ist} = \phi(m_{ist}, l_{ist}, k_{ist}, z_{jt}) + \epsilon_{ist} \tag{14}$$

and yields estimates of the value of the non-parametric function ϕ for each data point ($\widehat{\phi}_{ist}$).

The second stage of the estimation is based on the assumption that ω follows a first-order

[13]In the empirical implementation we do run the second stage and estimate θ^k in order to compute total factor productivity, which we use in the later regression analysis. The second stage, however, does not affect estimates of markups.

Markov process given by $\omega_{ist} = g(\omega_{ist-1}, h_{jt-1}) + \xi_{ist}$, where g is unknown and h are 4-digit industry level shifters such as trade and technology shocks. The innovation term can be written as

$$\xi_{ist} = \left(\phi_{ist} - \theta_s^m m_{ist} - \theta_s^l l_{ist} - \theta_s^k k_{ist}\right) - g\left(\phi_{ist-1} - \theta_s^m m_{ist-1} - \theta_s^l l_{ist-1} - \theta_s^k k_{ist-1}, h_{jt-1}\right) \tag{15}$$

Under the assumption that capital is predetermined and that labor is determined after the realization of ξ_{ist}, the output elasticity coefficients are jointly estimated from the moment conditions $E(k_{ist}\xi_{ist}) = 0$, $E(l_{ist-1}\xi_{ist}) = 0$, $E(m_{ist-1}\xi_{ist}) = 0$, with a polynomial approximation to g.

We estimate the first stage with a second degree polynomial with full interaction terms for intermediate inputs, labor and capital, 4-digit industry-year effects, and interactions of intermediate inputs and 4-digit industry effects. In the second stage we use a second-degree polynomial to approximate the function g and 4-digit industry-year effects that capture industry level shocks to the stochastic evolution of ω in a non-parametric manner. Results are shown in Tables B1 to B4, column (7) for the panel samples (analogous to samples in columns 2, 4, 6).

Estimates of markups

For comparison purposes, we compute nine alternative firm-level markups, corresponding to pairwise combinations of the three approaches to the cost minimization first order conditions (minimum distance based on both intermediate inputs and labor, μ^A, based only on intermediate inputs, μ^B, based only on labor, μ^C) and the three approaches to the estimation of the output elasticities (investment control, intermediate inputs control, share in cost). While there are similarities across some estimates, there are also important differences. The main conclusions are the following:

- When using the minimum distance approach (μ^A), average markups are 83, 85 and 52 percent in Chile and 62, 57, and 44 percent in Colombia. These results are reported in Table B6, columns (1) to (3). The three columns correspond to different estimates of the output elasticity (investment control, intermediate inputs control, cost share).

- Median markups are lower than average markups, at 75, 76, and 46 percent in Chile, and 51, 46 and 36 percent in Colombia.

- Estimated markups tend to be lower when we use first order conditions solely based on intermediate inputs (columns 4 to 6), and higher when we use first order conditions solely based on labor (columns 7 to 9).

- Sales-weighted-average markups are higher than their simple average counterpart (except for columns 4 to 6), suggesting that larger firms charge larger markups.

- Table B7 reports correlations across markups. Correlation across estimates computed from the same first order conditions range from 0.88 to 0.99 (Panel A). Correlation across estimates computed from the same output elasticities range from 0.19 to 0.86 (Panel B). This implies that when analyzing similarities across estimates of markups, the definition of the first order conditions from which the markup is obtained is more relevant than the estimation method for the output elasticity.

- Correlation with sales (normalized by year and 4 digit industry mean) is positive for minimum distance estimates (μ^A), and estimates based on labor first order conditions (μ^C), and it is negative for estimates based on intermediate input first order conditions (μ^B). They are reported in Table B8. A positive correlation between markups and sales has been found by studies that use different approaches to markup estimation (Nevo, 2001; Atkin et al, 2015; De Locker et al, 2016; Autor et al, 2020; De Loecker et al, 2020; García-Marín and Voigtländer, 2019. See Dinghra and Morrow, 2019, for a discussion).

- Correlation with profit rate is positive for all estimates. They are reported in Table B8.

Our baseline estimates are the ones obtained from the minimum distance and investment control approach (summarized in Table B6, column 1). In our empirical analysis we further explore robustness to using estimates summarized in columns 2 and 3. These estimates yield plausible mean and median markups and correlate positively with sales. From a conceptual point of view, the minimum distance estimates (μ^A) take into consideration the two first order conditions of the cost minimization problem in flexible inputs. Estimates based solely on first order conditions of intermediate inputs (columns 4 to 6) do not show a clear positive correlation with sales, while estimates based solely on first conditions of labor (columns 7 to 9) are high in magnitude.

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Table B1: Output elasticity of intermediate inputs θ^m. Chile

	Cost share				Control function		
	Variable r (1)	Fixed r (2)	Variable r (3)	Fixed r (4)	Investment control (5)	Investment control (6)	Inputs control (7)
(1)	0.75***	0.75***	0.72***	0.72***	0.69***	0.66***	0.73***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.012)	(0.012)
	n= 36085	*n= 36085*	*n= 19296*	*n= 19296*	*n= 20391*	*n= 10781*	*n= 19294*
(2)	0.68***	0.68***	0.65***	0.65***	0.54***	0.50***	0.51***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.016)	(0.020)	(0.014)
	n= 18287	*n= 18287*	*n= 9476*	*n= 9476*	*n= 9597*	*n= 4639*	*n= 9476*
(3)	0.70***	0.69***	0.69***	0.69***	0.61***	0.59***	0.61***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.020)	(0.025)	(0.018)
	n= 12084	*n= 12084*	*n= 7033*	*n= 7033*	*n= 6975*	*n= 4005*	*n= 7032*
(4)	0.59***	0.59***	0.59***	0.60***	0.58***	0.55***	0.62***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.015)	(0.022)	(0.109)
	n= 8293	*n= 8293*	*n= 4860*	*n= 4860*	*n= 5131*	*n= 2929*	*n= 4859*
(5)	0.68***	0.68***	0.69***	0.69***	0.57***	0.54***	0.63***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.014)	(0.020)	(0.030)
	n= 14623	*n= 14623*	*n= 7860*	*n= 7860*	*n= 10360*	*n= 5482*	*n= 7859*
(6)	0.65***	0.65***	0.65***	0.65***	0.62***	0.59***	0.76***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.032)	(0.040)	(0.019)
	n= 4993	*n= 4993*	*n= 2883*	*n= 2883*	*n= 2968*	*n= 1710*	*n= 2883*
(7)	0.72***	0.72***	0.70***	0.70***	0.63***	0.55***	0.71***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.022)	(0.033)	(0.217)
	n= 2755	*n= 2755*	*n= 1741*	*n= 1741*	*n= 1900*	*n= 1192*	*n= 1740*
(8)	0.62***	0.62***	0.61***	0.61***	0.52***	0.48***	0.53***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.013)	(0.012)
	n= 20848	*n= 20848*	*n= 11860*	*n= 11860*	*n= 12512*	*n= 6722*	*n= 11853*
(9)	0.59***	0.58***	0.56***	0.56***	0.44***	0.40***	0.42***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.047)	(0.064)	(0.110)
	n= 1312	*n= 1312*	*n= 762*	*n= 762*	*n= 675*	*n= 393*	*n= 762*

Notes: Horizontal panels correspond to sectors: (1) Food and beverages; (2) Textiles and apparel; (3) Wood and wood products; (4) Paper and printing; (5) Chemicals; (6) Minerals and mineral products; (7) Basic metals and metal products; (8) Machinery and equipment; (9) Other manufacturing. Columns (1), (2), (5) display estimates from sample years 1985-2011. Columns (3), (4), (6), (7), (8) display estimates from sample years 1995-2007. Standard errors are computed with 1000 bootstrap replications.

Table B2: Output elasticity of labor θ^l. Chile

	Cost share				Control function		
	Variable r (1)	Fixed r (2)	Variable r (3)	Fixed r (4)	Investment control (5)	Investment control (6)	Inputs control (7)
(1)	0.18***	0.18***	0.21***	0.21***	0.27***	0.28***	0.25***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.013)	(0.010)
	n= 36085	*n= 36085*	*n= 19296*	*n= 19296*	*n= 20391*	*n= 10781*	*n= 19294*
(2)	0.23***	0.23***	0.26***	0.26***	0.36***	0.40***	0.43***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.018)	(0.022)	(0.020)
	n= 18287	*n= 18287*	*n= 9476*	*n= 9476*	*n= 9597*	*n= 4639*	*n= 9476*
(3)	0.20***	0.20***	0.22***	0.22***	0.33***	0.32***	0.35***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.031)	(0.025)	(0.023)
	n= 12084	*n= 12084*	*n= 7033*	*n= 7033*	*n= 6975*	*n= 4005*	*n= 7032*
(4)	0.27***	0.27***	0.30***	0.30***	0.39***	0.41***	0.36***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.017)	(0.025)	(0.117)
	n= 8293	*n= 8293*	*n= 4860*	*n= 4860*	*n= 5131*	*n= 2929*	*n= 4859*
(5)	0.19***	0.20***	0.21***	0.21***	0.33***	0.35***	0.30***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.013)	(0.019)	(0.157)
	n= 14623	*n= 14623*	*n= 7860*	*n= 7860*	*n= 10360*	*n= 5482*	*n= 7859*
(6)	0.22***	0.22***	0.24***	0.24***	0.31***	0.30***	0.19***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.025)	(0.035)	(0.059)
	n= 4993	*n= 4993*	*n= 2883*	*n= 2883*	*n= 2968*	*n= 1710*	*n= 2883*
(7)	0.14***	0.14***	0.17***	0.17***	0.23***	0.24***	0.18
	(0.004)	(0.004)	(0.005)	(0.005)	(0.025)	(0.036)	(0.175)
	n= 2755	*n= 2755*	*n= 1741*	*n= 1741*	*n= 1900*	*n= 1192*	*n= 1740*
(8)	0.27***	0.27***	0.30***	0.30***	0.41***	0.44***	0.43***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.010)	(0.014)	(0.014)
	n= 20848	*n= 20848*	*n= 11860*	*n= 11860*	*n= 12512*	*n= 6722*	*n= 11853*
(9)	0.29***	0.29***	0.32***	0.32***	0.51***	0.55***	0.55***
	(0.008)	(0.007)	(0.010)	(0.009)	(0.070)	(0.101)	(0.097)
	n= 1312	*n= 1312*	*n= 762*	*n= 762*	*n= 675*	*n= 393*	*n= 762*

Notes: Horizontal panels correspond to sectors: (1) Food and beverages; (2) Textiles and apparel; (3) Wood and wood products; (4) Paper and printing; (5) Chemicals; (6) Minerals and mineral products; (7) Basic metals and metal products; (8) Machinery and equipment; (9) Other manufacturing. Columns (1), (2), (5) display estimates from sample years 1985-2011. Columns (3), (4), (6), (7), (8) display estimates from sample years 1995-2007. Standard errors are computed with 1000 bootstrap replications.

Table B3: Output elasticity of intermediate inputs θ^m. Colombia

	Cost share				Control function		
	Variable r (1)	Fixed r (2)	Variable r (3)	Fixed r (4)	Investment control (5)	Investment control (6)	Inputs control (7)
(1)	0.68***	0.68***	0.70***	0.69***	0.70***	0.67***	0.85***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.013)	(0.021)	(0.016)
	n= 35214	*n= 35214*	*n= 13988*	*n= 13988*	*n= 23722*	*n= 9489*	*n= 13841*
(2)	0.57***	0.57***	0.60***	0.59***	0.55***	0.55***	0.47***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.013)	(0.013)
	n= 37015	*n= 37015*	*n= 14910*	*n= 14910*	*n= 20681*	*n= 8746*	*n= 14430*
(3)	0.58***	0.58***	0.62***	0.61***	0.63***	0.65***	0.71***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.017)	(0.019)	(0.022)
	n= 11414	*n= 11414*	*n= 4362*	*n= 4362*	*n= 6482*	*n= 2571*	*n= 4360*
(4)	0.54***	0.54***	0.55***	0.54***	0.34***	0.25***	0.29***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.032)	(0.044)	(0.042)
	n= 14725	*n= 14725*	*n= 6400*	*n= 6400*	*n= 9814*	*n= 4385*	*n= 6273*
(5)	0.62***	0.62***	0.64***	0.63***	0.62***	0.61***	0.78***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.017)	(0.020)	(0.015)
	n= 31583	*n= 31583*	*n= 12549*	*n= 12549*	*n= 23603*	*n= 9664*	*n= 12500*
(6)	0.50***	0.49***	0.50***	0.50***	0.60***	0.53***	0.54***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.023)	(0.048)	(0.025)
	n= 8631	*n= 8631*	*n= 3175*	*n= 3175*	*n= 6251*	*n= 2355*	*n= 3162*
(7)	0.53***	0.53***	0.57***	0.57***	0.64***	0.66***	0.45***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.026)	(0.028)	(0.042)
	n= 4250	*n= 4250*	*n= 1763*	*n= 1763*	*n= 2549*	*n= 1139*	*n= 1753*
(8)	0.55***	0.55***	0.59***	0.59***	0.57***	0.59***	0.67***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.015)	(0.012)	(0.010)
	n= 30992	*n= 30992*	*n= 12082*	*n= 12082*	*n= 19982*	*n= 8053*	*n= 12040*
(9)	0.56***	0.56***	0.59***	0.59***	0.56***	0.54***	0.54***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.022)	(0.036)	(0.030)
	n= 12479	*n= 12479*	*n= 5248*	*n= 5248*	*n= 8129*	*n= 3526*	*n= 5219*

Notes: Horizontal panels correspond to sectors: (1) Food and beverages; (2) Textiles and apparel; (3) Wood and wood products; (4) Paper and printing; (5) Chemicals; (6) Minerals and mineral products; (7) Basic metals and metal products; (8) Machinery and equipment; (9) Other manufacturing. Columns (1), (2), (5) display estimates from sample years 1995-2021. Columns (3), (4), (6), (7), (8) display estimates from sample years 2001-2016. Standard errors are computed with 1000 bootstrap replications.

Table B4: Output elasticity of labor θ^l. Colombia

	Cost share				Control function		
	Variable r (1)	Fixed r (2)	Variable r (3)	Fixed r (4)	Investment control (5)	Investment control (6)	Inputs control (7)
(1)	0.20***	0.20***	0.19***	0.19***	0.26***	0.27***	0.18***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)	(0.019)	(0.015)
	n= 35214	*n= 35214*	*n= 13988*	*n= 13988*	*n= 23722*	*n= 9489*	*n= 13841*
(2)	0.31***	0.31***	0.30***	0.30***	0.38***	0.38***	0.41***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)	(0.015)	(0.012)
	n= 37015	*n= 37015*	*n= 14910*	*n= 14910*	*n= 20681*	*n= 8746*	*n= 14430*
(3)	0.30***	0.29***	0.28***	0.28***	0.31***	0.29***	0.22***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.017)	(0.018)	(0.020)
	n= 11414	*n= 11414*	*n= 4362*	*n= 4362*	*n= 6482*	*n= 2571*	*n= 4360*
(4)	0.29***	0.29***	0.29***	0.29***	0.55***	0.61***	0.57***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.029)	(0.038)	(0.037)
	n= 14725	*n= 14725*	*n= 6400*	*n= 6400*	*n= 9814*	*n= 4385*	*n= 6273*
(5)	0.25***	0.24***	0.24***	0.24***	0.28***	0.30***	0.19***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.016)	(0.019)	(0.014)
	n= 31583	*n= 31583*	*n= 12549*	*n= 12549*	*n= 23603*	*n= 9664*	*n= 12500*
(6)	0.28***	0.28***	0.27***	0.27***	0.33***	0.35***	0.41***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.022)	(0.041)	(0.028)
	n= 8631	*n= 8631*	*n= 3175*	*n= 3175*	*n= 6251*	*n= 2355*	*n= 3162*
(7)	0.30***	0.30***	0.29***	0.29***	0.29***	0.30***	0.56***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.027)	(0.034)	(0.034)
	n= 4250	*n= 4250*	*n= 1763*	*n= 1763*	*n= 2549*	*n= 1139*	*n= 1753*
(8)	0.31***	0.31***	0.29***	0.28***	0.36***	0.31***	0.27***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.014)	(0.013)	(0.011)
	n= 30992	*n= 30992*	*n= 12082*	*n= 12082*	*n= 19982*	*n= 8053*	*n= 12040*
(9)	0.28***	0.28***	0.26***	0.26***	0.37***	0.35***	0.40***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.018)	(0.023)	(0.023)
	n= 12479	*n= 12479*	*n= 5248*	*n= 5248*	*n= 8129*	*n= 3526*	*n= 5219*

Notes: Horizontal panels correspond to sectors: (1) Food and beverages; (2) Textiles and apparel; (3) Wood and wood products; (4) Paper and printing; (5) Chemicals; (6) Minerals and mineral products; (7) Basic metals and metal products; (8) Machinery and equipment; (9) Other manufacturing. Columns (1), (2), (5) display estimates from sample years 1995-2021. Columns (3), (4), (6), (7), (8) display estimates from sample years 2001-2016. Standard errors are computed with 1000 bootstrap replications.

Table B5: Correlation of sector-level estimates of output elasticities

Baseline: Cost share, variable r (1)	**Chile** θ^m	**Chile** θ^l	**Colombia** θ^m	**Colombia** θ^l
Cost share, fixed r (2)	1.00	1.00	1.00	1.00
Cost share, variable r, shorter sample (3)	0.98	0.99	0.97	0.98
Cost share, fixed r, shorter sample (4)	0.97	0.99	0.97	0.98
	Chile		**Colombia**	
Baseline: Investment control (5)	θ^m	θ^l	θ^m	θ^l
Investment control, shorter sample (6)	0.97	0.99	0.97	0.96

Notes: Table shows correlations between different estimates of output elasticities. The top panel reports correlations between columns (1) to (4) in Tables B1 to B4. The bottom panel reports correlations between columns (5) and (6) in those same tables. Correlations above or equal to 0.995 are rounded up to 1.

Table B6: Firm-level markups

	Min. distance			FOCs.Int.inputs			FOCs. Labor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Chile									
Mean	1.83	1.85	1.52	1.32	1.38	1.50	2.24	2.19	1.45
Median	1.75	1.76	1.46	1.18	1.24	1.35	2.06	2.01	1.34
Weightedaverage	2.13	2.10	1.74	1.30	1.38	1.48	2.87	2.63	1.82
p10	1.23	1.24	1.08	0.82	0.85	0.93	1.07	1.02	0.70
p90	2.58	2.61	2.06	2.04	2.16	2.33	3.73	3.68	2.41
Colombia									
Mean	1.62	1.57	1.44	1.35	1.46	1.36	1.74	1.53	1.40
Median	1.51	1.46	1.36	1.18	1.28	1.20	1.51	1.32	1.23
Weightedaverage	2.00	1.84	1.74	1.30	1.46	1.31	2.45	2.12	1.95
p10	1.05	1.03	0.95	0.80	0.80	0.81	0.77	0.62	0.64
p90	2.37	2.28	2.07	2.16	2.38	2.16	3.14	2.79	2.49

Notes: Table shows descriptive statistics of estimes of markups at the firm level. Columns (1) to (3): definition of markup based on minimum distance of FOCs. Columns (4) to (6): definition of markup based on FOCs on intermediate inputs. Columns (7) to (9): definition of markup based on FOCs on labor. Columns (1), (4), (7): procedure to estimate output elasticities based on investment control function. Columns (2), (5), (8): procedure to estimate output elasticity based on intermediate input control function. Columns (3), (6), (9): output elasticity estimated from cost shares.

Table B7: Correlation of firm-level estimates of markups

Panel A: Estimates based on different procedures to estimate output elasticities				**Panel B:** Estimates based on different cost minimization FOC			
Chile							
Investment control	(1)	(2)	(3)	Min distance	(4)	(5)	(6)
Int.inputs control	0.96	0.99	0.95	Int.inputs	0.19	0.21	0.52
Cost share	0.91	0.98	0.99	Labor	0.86	0.85	0.64
Colombia							
Investment control	(1)	(2)	(3)	Min distance	(4)	(5)	(6)
Int.inputs control	0.93	0.92	0.88	Int.inputs	0.33	0.41	0.48
Cost share	0.96	0.95	0.95	Labor	0.79	0.69	0.70

Notes: Table shows correlations in estimates of markups computed at the firm level. Panel A shows the correlation across markups computed from different estimates of output elasticities (investment control function–the baseline,– intermediate inputs control function, cost shares). Panel B shows the correlation across markups computed from cost minimization first order conditions based on different flexible inputs (minimum distance–the baseline,– intermediate inputs, labor). Columns (1) to (3): definition of markup based on minimum distance of FOCs, FOCs based on intermediate inputs, FOCs based on labor. Columns (4) to (6): procedures to estimate output elasticities based on investment control function, intermediate inputs control function, cost shares. Correlations above or equal to 0.995 are rounded up to 1.

Table B8: Correlation of firm-level estimates of markups and sales

	Chile			**Colombia**		
	Min.distance (1)	Int.inputs (2)	Labor (3)	Min.distance (4)	Int.inputs (5)	Labor (6)
Log sales						
Investment control	0.26	-0.06	0.27	0.25	-0.02	0.27
Int.inputs control	0.24	-0.07	0.26	0.18	-0.00	0.19
Cost shares	0.19	-0.05	0.27	0.23	-0.02	0.29
Profitability						
Investment control	0.36	0.52	0.15	0.46	0.34	0.23
Int.inputs control	0.35	0.51	0.13	0.45	0.31	0.19
Cost shares	0.51	0.53	0.15	0.49	0.35	0.25

Notes: Table shows correlations between different estimates of markups and firm sales and firm profits. Columns (1) to (3), and (4) to (6): definition of markup based on minimum distance of FOCs, FOCs based on intermediate inputs, FOCs based on labor. Across lines the procedures to estimate the output elasticities are based on investment control function, intermediate inputs control function, cost shares.