Globalización, Cambio Tecnológico y Poder de Mercado en América Latina: Evidencia para Colombia

Manuela Cerimelo

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Directora de tesis: Irene Brambilla

Co-director de tesis: Guillermo Falcone

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Globalization, technological change and market power in Latin America: Evidence for Colombia*

Manuela Cerimelo†

Abstract

This paper aims to study concentration and market power in Colombia and the role that globalization and automation have on the evolution of these two phenomena. First, we document how market concentration and markups have evolved through the last decades using firm-level data, as well as its link to other measures of industry and firm performance. Second, we define particular episodes within our sample in which we investigate the role of globalization and automation technology in the distribution of markups. We focus on the import competition generated by the entry of China in the WTO, and on changes in the availability of robotics. Our results show that markups decrease in response to the penetration of Chinese imports, both at the firm- and industry-level. Regarding the adoption of robots, we find a negative relationship between these two variables but with heterogeneous effects across different groups of firms. Specifically, there is a positive relationship for the largest firms, but not for the rest.

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†CEDLAS-Instituto de Investigaciones Económicas, Facultad de Ciencias Económicas, Universidad Nacional de La Plata, Argentina.

1 Introduction

Empirical evidence indicates a global rise in market concentration and corporate market power, especially in United States (U.S.) where average markups have risen mainly because highly profitable firms were able to grasp additional market shares (IMF, 2019; De Loecker and Eeckhout, 2018; De Loecker et al., 2020). Although most studies focus on the U.S. economy, the significant implications of market power for economic growth have sparked growing concern over the negative effects of reduced competition in Latin America and the Caribbean (LAC). In LAC countries, average markups are seemingly higher than OECD countries and economic rents tend to be concentrated among fewer shareholders, leading to greater business ownership concentration compared to the rest of the world (Eslava et al., 2021).

An important question is what factors are behind these observed trends in market power measures. Interestingly, changes in markups can arise from shifts within firms and alterations in the firm distribution. De Loecker et al. (2016) examine India's trade liberalization and find that while input tariff reductions lowered costs, firm-level markups increased. Their findings underscore substantial variation in markups over time and across firms. Autor et al. (2020) argue that globalization and technological advancements drive market shares towards the most productive firms in each sector, fostering the emergence of "superstar" firms with heightened product market concentration and increased sales-weighted average markups.[1] Historical data from the U.S. analyzed by De Loecker et al. (2020) reveals that while median markups have remained steady, upper percentiles of the markup distribution have risen, potentially leading to a decrease in the labor share (Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019). De Loecker and Eeckhout (2018) and Díez et al. (2021) document a global increase in markups, primarily attributed to a redistribution of market shares from low to high markup firms. This body of literature assumes that firms' markups correlate with their market shares, implying that the observed rise in markups indicates a rise in market concentration.

In this paper, we examine trends in market concentration and market power in one Latin American country and assess the role of two potential drivers of market power. We focus on Colombia's manufacturing sector for the period 2001-2016 and study how globalization and technology can affect the distribution of measures of market power. Both phenomena have the potential to significantly benefit economies by advancing the technological frontier through enhanced access to new

[1] Related research by Autor and Salomons (2018) and Autor et al. (2017), links these trends to the debate on the labor share, suggesting that the rise of capital-intensive superstar firms, particularly in digital and IT sectors, has contributed to declines in labor's share of income (Autor et al., 2020; Bauer and Lashkari, 2018). While superstar firms are predominantly observed in digital and service sectors benefiting from platform economies, similar albeit less pronounced trends are also observed among technology leaders in manufacturing (Andrews et al., 2016; Stiebale, 2016).

technologies, intermediate inputs, and intensified competition.

The objective of this paper is two-fold. First, we seek to document the evolution of market concentration and markups in Colombia, as well as its link to profitability, firm-size, the labor share, and average wages. To compute markups we rely on production-side methods based on estimated output elasticities and cost minimization first order conditions as in De Loecker and Warzynski (2012) and De Loecker et al. (2020).

Second, we define particular episodes within our samples in which we investigate the role of globalization and automation technology in the distribution of markups. We focus on two scenarios: 1) the import competition shock given by the penetration of Chinese imports in Colombia and, 2) the changes in availability of robotics. We combine data on the universe of Colombian manufacturing plants in 2001-2016 with data on trade flows and data on robot adoption from International Federation of Robotics (IFR), and exploit the fact that in Colombia different industries have been exposed to trade and automation shocks differentially during the last decades. We perform both an industry- and a firm-level analysis, in order to capture both within firm reactions and also aggregated phenomena that could also be explained by the role of reallocation within industry in response to the shocks.

During the period under study, China joined the World Trade Organization in December 2001, significantly impacting global trade. This remarkable growth of China in recent decades provides a unique opportunity to measure the causal effect of trade on relevant market power outcomes. For identification, we exploit the fact that in 2001-2006, Chinese import penetration (measured as the total value of imports from China relative to domestic absorption) increased sharply in Colombia but this expansion varied widely across manufacturing industries. To account for the endogenous nature of trade, we apply an instrumental variable (IV) strategy that is also used in other papers in the literature (Autor et al., 2013, 2014; Acemoglu et al., 2016; César and Falcone, 2020).

Automation and robotization are recent phenomena that may widen disparities among firms through scale-biased technological advancements. Although Latin American countries lag behind developed economies in the adoption of robotics, automation and robotization have significantly increased over the past two decades. Using data from the International Federation of Robotics (IFR), we analyze robot adoption as a proxy for automation's impact on market power across Colombian industries. Given Colombia's low adoption of robots, directly measuring their impact on market power is challenging. Therefore, this paper examines how automation trends in other countries indirectly shape market power dynamics in Colombia's industries over time.

Our analysis indicates that both phenomena have the potential to affect the distribution of markups. Specifically, we find that Chinese import competition reduces markups at both the firm- and industry-level. Further industry-level analysis reveals that Chinese import penetration has resulted in reduced markups even among larger firms. On average, a one percentage point increase in Chinese import penetration leads to a 1 percent decrease in a firm's markup. Moreover, our findings show that industries with greater exposure to automation tend to exhibit lower markups. Conversely, while larger firms benefit from automation potential, smaller firms demonstrate negative correlations between markups and automation potential. This reflects the complex market dynamics influenced by technological change.

We contribute to the literature in two aspects. We provide evidence on the evolution of market power measures in a Latin American country, Colombia, and we examine the relationship between globalization, technological change, and market power. This paper aims to determine whether the trade and technological scenarios lead to a reduction in aggregate markups, either through declines within firms or through the redistribution of sales among heterogeneous firms.

This paper is organized as follows. In Section 2 we briefly discuss the data from the firm survey. In Section 3 we explain how markups are obtained and provide estimates of markups and profitability. In Section 4 we describe the evolution of market power in Colombia. In Section 5 we give more details on the empirical strategy to estimate the causal impact of globalization and automation technology on concentration and market power, while in Section 6 we present the main results. Section 7 discuss limitations and robustness exercises, and Section 8 concludes.

2 Data

For our analysis, we use a yearly plant census, the Colombian Annual Manufacturing Survey (EAM, *Encuesta Anual Manufacturera* in spanish), spanning the years 1995 to 2016. This dataset covers all manufacturing plants with at least 10 employees or with revenue above a given threshold that is updated annually, and so contains about 6000 plants per year.[2] The census contains information on revenue, investment, capital[3], labor, wage bill, expenditures in materials and energy (electricity and fuels), other expenditures, industry affiliation, among other variables that we use to compute measures of market power in Colombia. Importantly, this data allows us to compute industry concentration measures, profit rates, and to rely on the production approach for measuring markups at the firm- and industry-level. We use capital, materials, and output deflators in order to construct consistent measures of inputs and outputs over time. Table 1 summarizes the structure of the dataset. Between 2000 and 2001 there is a change in the industry classification from International Standard Industrial Classification (ISIC) Revision 2 to ISIC Revision 3. We use all available years of data to estimate technology parameters and markups and a shorter panel from

[2]The unit of observation is an establishment (plant), but we refer to it as a firm.

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

2001 to 2016 for the regression analysis.[4] We follow firms from 2001 to 2016, including firms that enter and exit the sample during this period.

Table 1: Summary of firm survey

	Firm-year	Industry-year Rev.2	Industry-year Rev.3
	(1)	(2)	(3)
Panel 1995-2000	38714	360	0
Panel 2001-2011	72875	659	1187
Panel 2012-2016	39067	300	532

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.

Firm-level data is complemented with annual industry level information from two additional data sources. On the one hand, we use information on trade flows from the World Integrated Trade Solution (WITS) compiled by the World Bank from United Nations Commodity Trade Statistics Database (US COMTRADE) and Trade Analysis Information System (TRAINS) over the period 1995 - 2016. It contains information on import and export dollar values, quantities, partners, and product codes (at the 6-digit Harmonized System of tariff nomenclature) and can be matched with the firm panel at the 4-digit level of disaggregation of the ISIC classification. Thus, we can construct a measure of the penetration of Chinese imports in Colombia and other countries, which varies at the industry-year level (at the 4-digit level of ISIC Rev. 3). On the other hand, we use information on robot adoption from the IFR. IFR conducts annual surveys of the number of industrial robots shipped to firms worldwide by robot manufacturers, covering many countries including the U.S, Colombia, China and European adopting countries over the period 1995 - 2016.[5] The data from IFR is constructed at a higher level of aggregation for a total of 15 manufacturing sectors: 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 miscellaneous manufacturing. We complement this data with the OECD Industry Employment statistics to obtain information on the number of workers in other countries.

[4] We conduct the regression analysis using the available panels for the ISIC Revision 3 classification, as it allows for a higher level of disaggregation.

[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".

3 Empirical framework for estimating markups

The markup is usually defined as the price of the product divided by the marginal cost. Estimating markups in practice is challenging because data on marginal cost and prices are not always available. Two main methods have been adopted to recover markups: the demand approach, and the production approach.[6] We apply the production approach developed by De Loecker and Warzynski (2012) and De Loecker et al. (2020), which 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 to obtain markups. In contrast with the demand approach, this method does not require to impose a specific model of how firms compete; it only requires observing revenues and expenditures for each available input at the firm level and estimated production function parameters. Next, we introduce this empirical framework to compute markups.

3.1 The production approach

This section closely follows De Loecker and Warzynski (2012) and Raval (2023). We have a firm i at a time t that produces output with production function $Q_{it} = F_{it}(K_{it}, X_{it}^1, \ldots, X_{it}^V, \omega_{it})$, where K_{it} is capital and X_{it} are variable inputs. Note that the firm can rely on V variable inputs, such as labor, intermediate inputs and electricity. 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.

The firm receives price P_{it} for its output and faces input prices p_{it}^v for input v. Then a cost minimizing firm sets marginal products equal to input prices. This implies, for variable input X_{it}^v, that

$$P_{it} \frac{\partial F_{it}}{\partial X_{it}^v} = \frac{P_{it}}{\lambda_{it}} p_{it}^v, \quad \text{where } v = m, l. \tag{1}$$

where λ_{it} is the firm's marginal cost.[7] The left-hand side is the marginal revenue product of increasing input X_{it}^v. The right-hand side is the marginal cost of increasing X_{it}^v – its price, p_{it}^v –

[6] The demand approach consists of estimating price elasticities of demand that require to specify a demand system and to establish assumptions about how firms compete. However, we do not implement it because: firm-level data does not have information on prices and quantities at the product level; and, we do not want to make assumptions about the type of competition of firms operating in different industries. For a detailed discussion, see De Loecker et al. (2020)

[7] The Lagrange multiplier on the production function in the cost minimization problem.

multiplied by the markup $\frac{P_{it}}{\lambda_{it}}$. Next, we can rearrange terms and multiply each side by $\frac{X_{it}^{v}}{F_{it}}$ to obtain a expression that relates markups with the share of flexible inputs in revenue and the output elasticity of flexible inputs. That is, the first order condition of variable input v of firm i in 2-digit sector s and time t can be written as

$$\mu_{ist} = \frac{\theta_s^v}{S_{ist}^v}, \quad \text{where } v = m, l. \tag{2}$$

The markup 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.

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 (2) 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 (2) as

$$\widehat{\mu}_{ist}^A = \arg\min_{\mu} \begin{pmatrix} \mu - \widehat{\theta}_m^v / S_{ist}^m \\ \mu - \widehat{\theta}_l^v / S_{ist}^l \end{pmatrix} W \left(\mu - \widehat{\theta}_m^v / S_{ist}^m, \mu - \widehat{\theta}_l^v / S_{ist}^l \right) \tag{3}$$

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

$$\widehat{\mu}_{ist}^B = \widehat{\theta}_s^m / S_{ist}^m \tag{4}$$

$$\widehat{\mu}_{ist}^C = \widehat{\theta}_s^l / S_{ist}^l. \tag{5}$$

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

We explore robustness to three 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 et al. (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 below.

3.2 Estimation of output elasticities

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 (2 digit ISIC Rev. 2). 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.

3.2.1 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

$$\theta^m_{ist} = \frac{ExpM_{ist}}{ExpM_{ist} + ExpL_{ist} + r_t K_{ist}},\ \theta^l_{ist} = \frac{ExpL_{ist}}{ExpM_{ist} + ExpL_{ist} + r_t K_{ist}}, \tag{6}$$

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 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 0.199. The correlation between the firm-level cost shares computed with a fixed r and with a time varying r is 0.9899.

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

$$\widehat{\theta}^m_s = \frac{1}{T}\sum_t Med\left(\theta^m_{ist}\right),\ \widehat{\theta}^l_s = \frac{1}{T}\sum_t Med\left(\theta^l_{ist}\right), \tag{7}$$

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 Appendix B Tables B1 and B2, 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 (1995-2016) 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 (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 0.50 to 0.71, and elasticities of output for labor that range from 0.18 to 0.30. The correlation across columns is displayed in the top panel of Table B3. They range from 0.96 to 0.98 implying that using a fixed or time-varying real interest rate or a shorter sample do not have a large influence of the estimates of the elasticity of output. We use column (1) as our baseline estimate for the cost share approach.

3.2.2 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

$$y_{ist} = \theta_s^m m_{ist} + \theta_s^l l_{ist} + \theta_s^k k_{ist} + \omega_{ist} + \varepsilon_{ist}, \tag{8}$$

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

$$y_{ist} = \theta_s^m m_{ist} + \theta_s^l l_{ist} + \phi(k_{ist}, i_{ist}, z_{jt}) + \varepsilon_{ist}, \tag{9}$$

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 (9) can be estimated with cross sections of firms.

We estimate regression (9) 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 Appendix B Table B2, 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 B3. They range from 0.96 to 0.99. We use column (5) as our baseline estimate for the investment control approach.

3.2.3 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 et al. (2015) 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

$$y_{ist} = \phi(m_{ist}, l_{ist}, k_{ist}, z_{jt}) + \varepsilon_{ist} \tag{10}$$

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 Markov process given by $\omega_{ist} = g(\omega_{ist-1}) + \xi_{ist}$, where g is unknown. The innovation term can be written as

$$\xi_{ist} = \left(\phi_{ist} - \theta_s^m m_{ist} - \theta_s^l l_{ist} - \theta_s^k k_{ist}\right) - g\left(\phi_{ist-1} - \theta_s^m m_{ist-1} - \theta_s^l l_{ist-1} - \theta_s^k k_{ist-1}\right) \tag{11}$$

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.

Results are shown in Appendix B Tables B1 and B2, column (7) for the panel sample (analogous to samples in columns 2, 4, 6). In general, results are more similar to those obtained using the investment control approach (columns 5 and 6), than using the cost share approach (columns 1 to 4).

3.3 Markup estimation

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, cost share). While there are similarities across some estimates, there are also important differences.

Appendix B Table B4 reports summary statistics of the firm-level markups. Markups calculated using the minimum distance approach (μ^A) are shown in columns (1) to (3) which correspond to different estimates of the output elasticity (investment control, intermediate inputs control, cost share). Average markups are 77, 79, and 54 percent, whereas median markups are lower than average markups, at 67, 65, and 46 percent. In general sales-weighted-average markups are higher than a simple average counterpart, suggesting that larger firms charge larger markups. When we estimate markups using first order conditions solely based on intermediate inputs or labor results tend to be different. On the one hand, markups estimated using intermediate inputs (μ^B) are lower (columns 4 to 6): average markups are 39, 31, and 46 percent and median markups are only 22, 13 and 28 percent. On the other hand, markups estimated using labor (μ^C) are higher in general (columns 7 to 9): average markups are 101, 110 and 49 percent and median markups are only 77, 78 and 32 percent.

Additionally, we explore correlations across markups estimates. Appendix B Table B5 reports these results. First, we calculate how markups computed from the same first order conditions correlate; that is, we obtain correlation across estimates in columns (1,2,3); (4,5,6); (7,8,9) (Table B5 Panel A). In this case, correlations range from 0.83 to 0.98. Second, we calculate how markups computed from the same output elasticities correlate. Correlation across estimates in columns (1,4,7); (2,5,8); (3,6,9) range from 0.33 to 0.79 (Table B5 Panel B). This implies that when analyzing similarities across estimates in different columns, the definition of the first order conditions from which the markup is obtained is more relevant than the estimation method for the output elasticity.

Additionally, it can be useful to study correlations between markups and sales or profits.[8] Appendix B Table B6 reports these results. 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), whereas it is negative for estimates based on intermediate input first order

[8]The definition and construction of the profit rate is discussed in Section 4.

conditions (μ^B). 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 Loecker et al., 2016; Autor et al., 2020; De Loecker et al., 2020; Garcia-Marin and Voigtländer, 2019).[9]. Correlation with profit rate (revenue over costs) is positive for all estimates.

In summary, our baseline estimates are the ones obtained from the minimum distance and investment control approach (summarized in Table B4, 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, 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 higher in magnitude.

4 The evolution of market power in Colombia

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 are Food and beverages, Chemicals, Textiles and apparel and Machinery and equipment. The sectoral structure remains relatively stable over time, with the exception of the decrease in the share in Other manufacturing in 2012.

4.1 Market concentration

A key aspect to understanding the dynamics of market power in Colombia is the study of how concentrated a certain market is. In practice, various indicators are often used to elucidate how to measure and evaluate concentration. In this section we will refer to two commonly used indicators: the concentration ratio (CR) and the Herfindahl-Hirschman index (HHI).

The concentration ratios are defined as revenue market share held by the largest firms within the manufacturing sector. Note that a high concentration ratio indicates that a few companies dominate the market, which may suggest an oligopolistic market structure. Conversely, a low concentration ratio implies greater competition among a larger number of small firms. Formally,

[9] See Dhingra and Morrow (2019) for a discussion.

Table 2: Manufacturing sectors. Share in revenue

	2001 (1)	2006 (2)	2012 (3)	2016 (4)
Food, beverages	0.32	0.26	0.28	0.31
Textiles, apparel	0.13	0.12	0.10	0.09
Wood products	0.01	0.01	0.02	0.02
Paper, printing	0.08	0.08	0.05	0.05
Chemicals	0.18	0.20	0.30	0.25
Mineral products	0.03	0.04	0.04	0.05
Basic metals	0.02	0.04	0.04	0.04
Machinery, equipment	0.08	0.10	0.09	0.08
Other manufacturing	0.14	0.14	0.08	0.11

Notes: Participation of 2-digit sectors (ISIC Rev 2.) in total manufacturing revenue.

the K concentration ratio is defined as

$$\text{CR}_t^K = \frac{\sum_{i=1}^{K} \text{Revenue}_{it}}{\sum_{i=1}^{N} \text{Revenue}_{it}} \qquad \text{for K} = \{4, 10, 25\} \tag{12}$$

where i indexes firms, N is the total number of firms, and, in summing from 1 to K, firms are sorted from largest to smallest revenue. We compute three different measures of aggregate concentration ratios: CR_4, CR_{10} and CR_{25}.

The HHI is the sum of squares of the revenue market shares of all firms in the manufacturing sector The higher the HHI, the more concentrated the market is. Formally, the HHI in year t can be expressed as

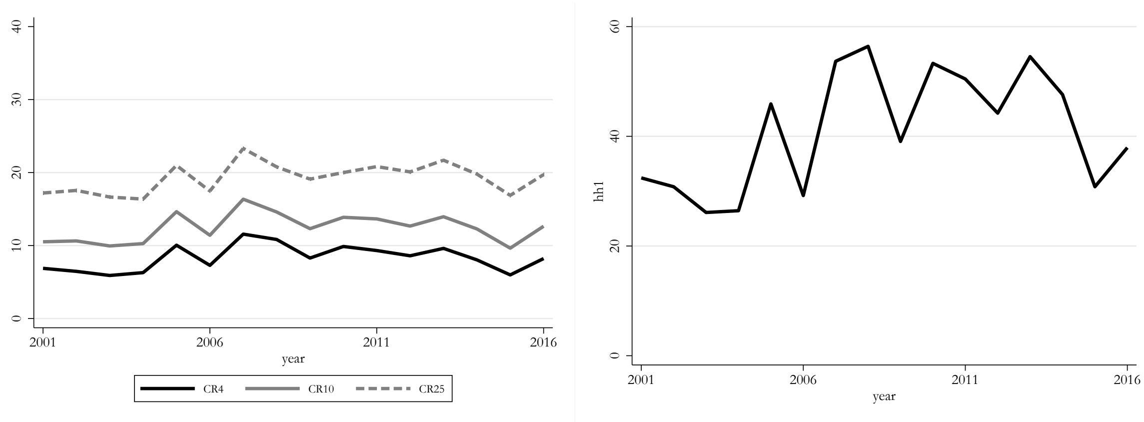
$$\text{HHI}_t = \sum_{i=1}^{N} \left(\frac{\text{Revenue}_{it}}{\sum_{i=1}^{N} \text{Revenue}_{it}} \right)^2 \tag{13}$$

Figure 1 shows the evolution of the aggregate concentration measures. Between 2001 and 2007 concentration shows a slight trend increase, whereas between 2008 and 2016 concentration fluctuates.[10] Aggregate concentration suggests that the largest 25 firms accounts for less than 25 percent of all manufacturing revenue over the period. The industry affiliation of the largest 25 firms is disperse. For example, in 2005, 10 out of 25 firms are 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 (See Appendix Table A1).

[10] Appendix Figure A1 shows the evolution of the CR4 and CR10 measures for each manufacturing sector.

Figure 1: Concentration in manufacturing

(a) Average CR4, CR10, CR15 (b) Average HHI



Notes: Figure shows measures of market concentration in the manufacturing sector. Panel (a): Average concentration ratios (CR4: solid black, CR10: solid grey, CR15: dashed grey). Panel (b): Average HHI.

4.2 Markups

Another important aspect when analyzing the dynamics of market power in Colombia is the study of markups and profitability. We first present descriptive statistics of the estimated markups at the firm level for two time periods, 2001-2008 and 2009-2016 (Table 3, top panel), and then evaluate markups across sectors. During 2001-2008, the average markup is 72 percent and increases to 76 percent during 2009-2016. Average profit rate also increases between periods. The median markups are stable and range from 56 to 59. The weighted average markup[11] is much higher, at 124 percent during 2001-2008 and at 139 percent over 2009-2016, 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 3 to 172 percent. There is also considerable variation across sectors. Markups are higher in Other manufacturing, Paper and printing and Mineral products. Between the two periods, markups sharply increase in Chemicals from 98 percent to 138 percent.

Figure 2 shows weighted average and simple average markups (Panels (a) and (b)). There is an increasing trend in weighted average markups, while the simple average markup is more stable over time. This result in 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.[12] Panel (c) shows the weighted average markup of the top 10 (solid black) and top 25 (solid gray) firms relative to the

[11] We calculate the weighted average markup as follows: $\mu_t = \sum_i m_{it}\mu_{it}$ where m_{it} is the share of sales of each firm in year t.

[12] Appendix Figure A2 shows the evolution of markups for each manufacturing sector.

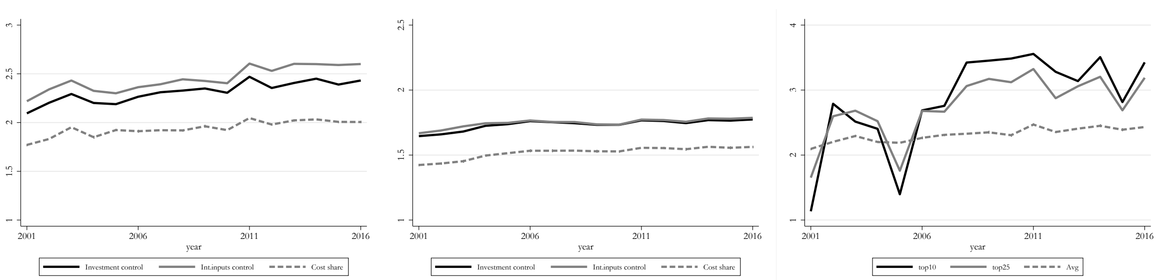
Table 3: Estimates of markups and profits

	Markup		Profit rate	
	2001-2008 (1)	2009-2016 (2)	2001-2008 (3)	2009-2016 (4)
Weightedaverage	2.24	2.39	1.14	1.18
Mean	1.72	1.76	1.06	1.09
Median	1.56	1.59	1.05	1.07
p10	1.05	1.03	0.72	0.70
p90	2.61	2.72	1.39	1.49
Food, beverages	2.20	2.24	1.11	1.17
Textiles, apparel	1.97	2.04	1.12	1.18
Wood products	1.69	1.69	1.13	1.14
Paper, printing	2.54	2.60	1.10	1.12
Chemicals	1.98	2.38	1.11	1.15
Mineral products	2.38	2.55	1.16	1.27
Basic metals	2.27	2.74	1.04	1.03
Machinery, equipment	2.01	2.01	1.11	1.14
Other manufacturing	2.90	3.12	1.37	1.36

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. The table trims observations with markups that are above and below the 1st and 99th percentiles of the markup distribution.

Figure 2: Markups in manufacturing

(a) Weighted avg. markup (b) Simple avg. markup (c) Avg. markup in large firms

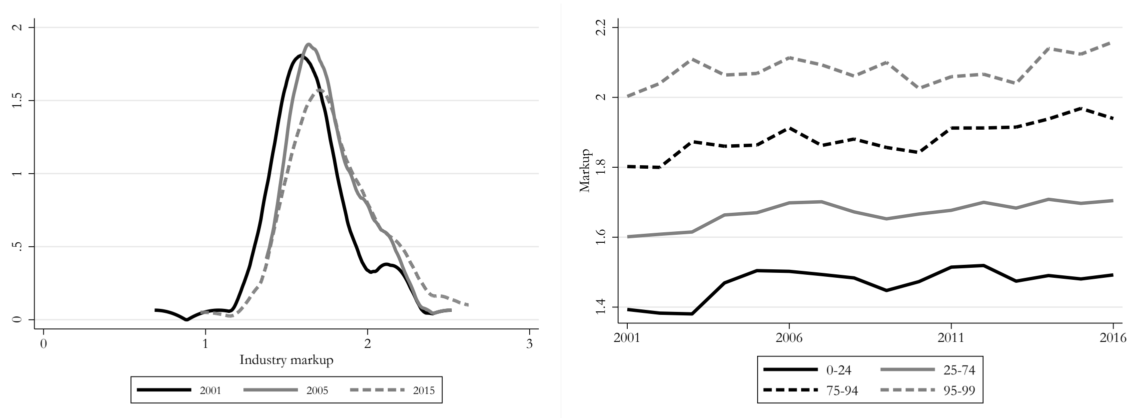


Notes: Figure shows sales weighted average markup (estimation based on investment control function: solid black, estimation based on intermediate inputs control function: solid gray, estimation based on cost shares: dashed gray), simple average markup, and sales weighted average markup for top 10 firms (solid black), for top 25 firms (solid gray), and all firms (dashed gray) from 2001 to 2016.

weighted average markup across all firms (dashed gray). Markups are indeed higher in the largest firms over the period, with the exception of 2005.

Figure 3: Distribution of markups

(a) Kernel density (b) Markups by firm-size percentile



Notes: Figure illustrates the distribution of markups in Colombia. Panel (a): Kernel density of unweighted markups (year 2001 solid black, year 2005 solid gray, year 2016 dashed gray). Panel (b): percentile markup distribution (sales weighted) (percentiles 1 to 24, 25 to 74, 75 to 94, 95 to 99). Firm size is computed relative to 4 digit industry mean.

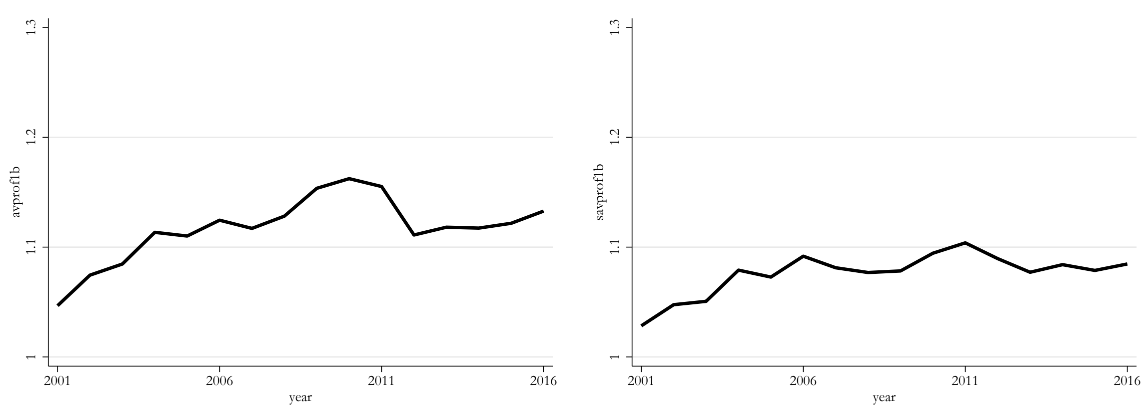
To gain further insight on the dynamics of firm markups over time, we study how the distribution of markups has changed. Figure 3 summarizes our findings. In Panel (a) we plot the kernel density of unweighted markups for 2001, 2005 and 2015. There seems to be a distributional change in markups since the densities have been shifting further to the right over the years, suggesting an increase in firm-level markups. We find an increase in the variance, especially in 2015. The greater dispersion of the 2015 curve suggests there is a greater difference between high and low markups in 2015 compared to previous years. Although Panel (a) shows how the distribution of average markups has been changing over the years, it does not provide information about the dynamics of the different firms. For that, Panel (b) shows the average markups by firm size groups. Firm size groups are determined based on each firm's sales as a proportion of the industry average (4 digits of ISIC Rev. 2). The groups are updated each year, so the firms at the top may be different each year. There is an increasing trend in markups for firms in the highest percentiles of the distribution.

4.3 Profitability

Price above marginal cost need not imply positive profits in the presence of fixed costs. In this section we analyze the evolution of profitability to get a more complete picture of the evolution of market power. 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 premiums, leases, communications, licenses, legal and technical advice, publicity and promotion, representation expenses, storage and refrigeration services, commissions

Figure 4: Profitability in manufacturing

(a) Weighted avg. markup (b) Simple avg. markup



Notes: Figure shows sales weighted average profit rate (revenue over costs) and simple average profit rate from 2001 to 2016.

to distributors, maintenance and repairs, leasing, commissions paid to sellers and other services. The profit rate is defined as revenue over costs.

The Figure 4 shows the evolution of the average weighted profit rate and the average simple profit rate. In both cases, a growing trend in the profit rate is observed. Similar to the figures for markups, the trend is more pronounced when considering weighted profits. This result aligns with what was found in the previous section regarding markup trends. While the profit trend is increasing, there is a decline between 2011 and 2012, which is more pronounced in Panel (a).

5 Empirical Strategy

In this section, we discuss the empirical strategies we use to evaluate the role of Chinese import penetration (as a phenomenon of globalization) and automation in forms of market power in Colombia. While each phenomenon has distinct characteristics that we discuss below, we estimate both firm- and industry-level regressions because the first type of regressions capture within-firm effects, and the latter capture a mix of within-firm and reallocation effects. Formally, the baseline estimation equations are as follows:

$$Y_{jt} = \gamma_1 R_{jt} + X'_{jt}\beta_1 + \delta_j + D_{1t} + \varepsilon_{1jt} \quad (14)$$

$$y_{ijt} = \gamma_2 R_{jt} + x'_{ijt}\beta_2 + \psi_i + D_{2t} + \varepsilon_{2ijt} \quad (15)$$

where j, i, and t index industries, firms, and time, respectively; δ_j and ψ_i represent industry- and firm-level fixed effects; D_{1t} and D_{2t} are time fixed effects; and ε_{1jt} and ε_{2ijt} are a mean-zero disturbance. Regression (14) is run at the industry level, where Y accounts for industry level outcomes such as concentration ratios, average profit rates, average weighted markups, and markups for size groups of firms (i.e., markups of firms that are at the top (or bottom) of the ranking (in terms of sales) within an industry). Regression (15) is run at the firm level, where the variable y refers to the firm-level markup or profit rate. We use our preferred definitions of markups, estimated by minimum distance, using the investment control function approach, the intermediates inputs control function approach, and the cost shares. The variable R is a treatment variable at the industry level that takes two different forms (described below). Additionally, the preferred specification controls for preexisting industry trends.[13] For firm-level estimates, we control for initial differences in firm characteristics. For these regression analyses, we define industries at the 4-digit level of aggregation of the ISIC Rev. 3 classification because it allows for a higher level of disaggregation than Rev. 2.

In what follows, we briefly describe our empirical strategy based on two shocks that occurred during our sample period: (i) increased import competition driven mainly by the entrance of China to the WTO and more generally on world export markets, and (ii) increased automation and robotization originated on the emergence of a new industrial revolution.

5.1 Chinese import penetration

China's entry into the World Trade Organization in December 2001 significantly impacted global trade. Since then, Colombia has been exposed to the increase of low-price Chinese imports, creating competitive pressure for local producers. This pressure may affect firms differently based on their productivity and size, potentially reshaping market concentration, markups, and profitability. Chinese imports to Colombia skyrocketed from 93 million dollars in 1995 to 5,400 million dollars in 2016, representing an increase of approximately 5,700 percent.

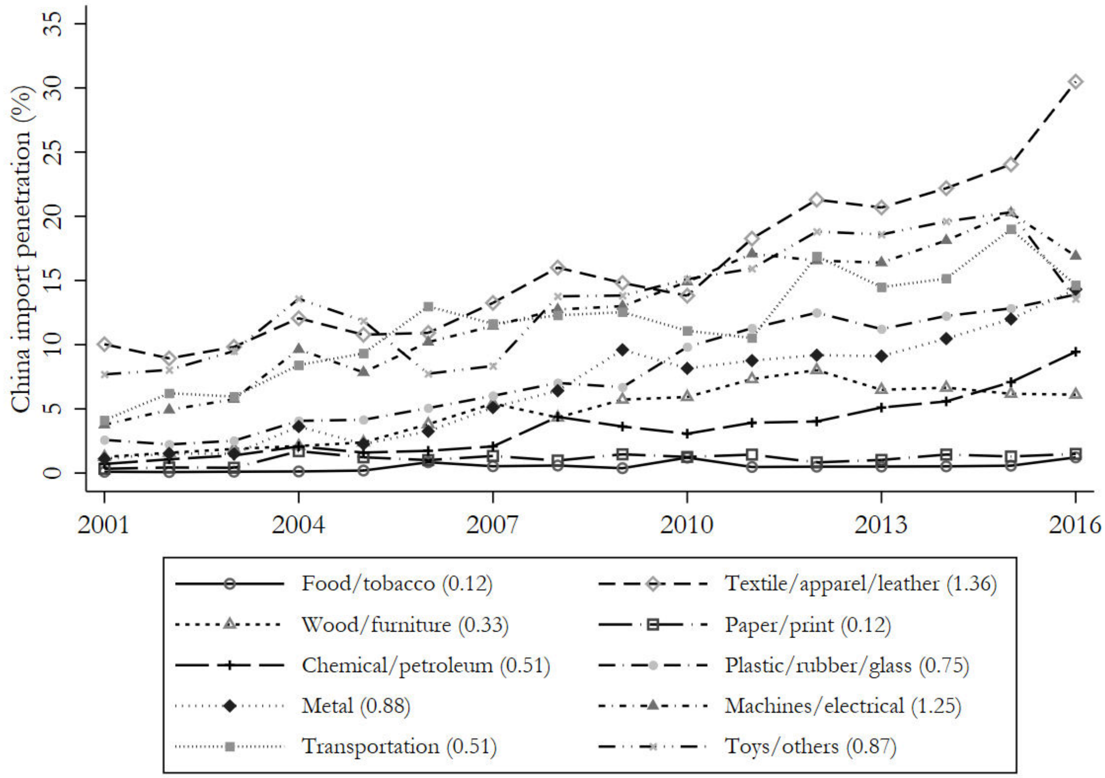
To estimate the causal impact of this trade shock, we exploit the variability in industry exposure to imports of Chinese origin. We define the China import penetration ratio (CIP) as the total value of imports from China relative to domestic absorption, given by

$$CIP_{jt} = \frac{M_{jt}^{China}}{[Q_{jt} + M_{jt} - X_{jt}]} \tag{16}$$

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 production Q_{jt} by

[13] These trends corresponds to a 5-year change in log industry revenue, log industry employment, and median industry markup.

Figure 5: Evolution of Chinese Import Penetration



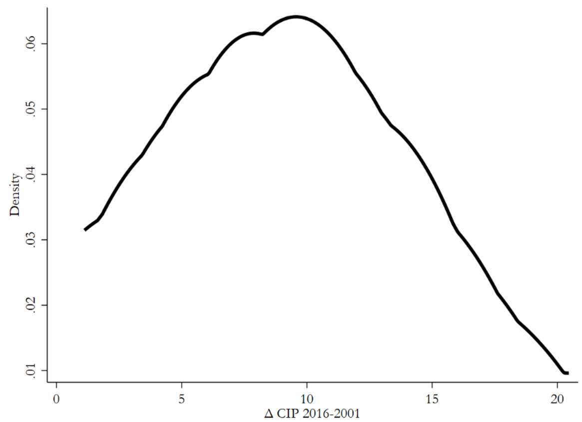
Notes: Figure shows the evolution of Chinese Import Penetration in Colombia. Manufacturing industries are defined at the 4-digit ISIC rev. 3 level and are grouped into ten broad sectors comprising similar industries. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption (production minus net exports) and varies at industry-year level. The sectoral average annual change (in percentage points) in Chinese import penetration is given in parentheses.

aggregating over plant level information from the firm survey (EAM).

Figure 5 plots changes in exposure to China in Colombia (2001 to 2016). Sectors such as Textiles, apparel and leather and Machines and electrical show the highest rates of exposure to Chinese import competition, while sectors such as Food, beverages and tobacco, and Paper and print remain barely exposed. On average Chinese import penetration increased from 3.18 percent to 12.21 percent. Figure 6 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 follow Autor et al. (2013, 2014) and Acemoglu et al. (2016) and apply an instrumental variable approach. That is, we instrument Chinese import penetration with the share of Chinese imports in total imports in all countries (as in César and Falcone (2020)). This

Figure 6: Distribution of Chinese Import Penetration



Notes: Figure shows the distribution of the change in import penetration across industries in Colombia (2001 to 2016).

identification strategy 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 of China's industry import share across all countries in the world given by

$$CIP^{Z}_{jt} = \frac{1}{N}\sum_{c=1}^{N}\frac{M^{China}_{cjt}}{M_{cjt}} \tag{17}$$

where M_{cjt} are total imports of country c, industry j, M^{China}_{cjt} are Chinese imports of country c, industry j, and N is the number of countries.[14] This variable aims to capture supply-driven shocks inherent to Chinese economy, that allowed the country to gain market share within specific industries over time all over the world (or specifically, in Latin America). Therefore we rely on this variable to predict China import penetration in Colombian manufacturing industries. First-stage unconditional (conditional) correlation shows a strong predictive power of the instrument, with a coefficient of 0.49 (0.5), robust standard error of 0.11 (0.13) and R-squared of 0.93 (0.94). See Appendix Table A2. The identifying assumptions are that: (i) China's export growth is exogenous (driven by TFP, infrastructure, migration, etc.), and (ii) industry demand shocks affecting product demand are uncorrelated between Colombia and the rest of the world (or Latin America). We then estimate equations (14) and (15) by two-stage least squares (2SLS) regression analysis.

5.2 Automation potential

The recent phenomena of automation and robotization is a factor that may exacerbate differences across firms through scale-biased technological change, as larger more productive firms are able

[14] We also test the robustness of our results to alternative groups of countries (namely, a subset of selected high-income countries and Latin American countries).

to invest in robots and sophisticated ICT further increasing their productivity and size advantage (Autor et al., 2020; Unger, 2022). We use robotization data from the IFR as a proxy for automation technology and define a treatment variable for our second set of regressions that is robot penetration across industries from other countries.

IFR conducts annual surveys of the number of industrial robots shipped to firms worldwide by robot manufacturers. The IFR uses its own industry classification, which closely follows the ISIC revision 4 classification, with fifteen manufacturing sectors. Figure 7 displays the evolution of the stock of robots for Colombia from 1994 to 2016. The stock of robots grew significantly between 2006 and 2016, from values close to zero to 124. Figure Figure 8 shows that the increase has been heterogeneous across industries, and show the stock of robots by industry for the year 2016. Note that IFR data suggests that the adoption of robots in Colombia is minimal compared to the adoption in the U.S. [15].

Due to the low adoption of robots in Colombia, it is difficult to capture the direct effect of this phenomenon on market power measures. For this reason, we focus on studying the indirect effect of automation in other countries in order to characterize different trends in market power for industries exposed to varying degrees of automation possibilities over time. As discussed in Kugler et al. (2020), Colombia could be indirectly affected by changes in automation technology through shifts in trade patterns of more advanced countries.

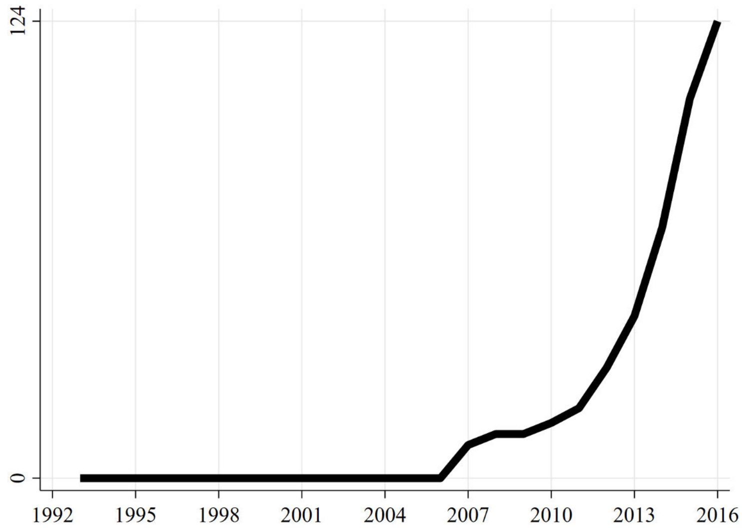
We construct a measure of automation potential and study its effects on markups and profits. First, we define industry-level robot penetration as the number of robots (*Robots*) relative to the number of workers (*Workers*) in a given industry and country, expressed as

$$RP_{jt} = \frac{Robots_{jt}}{Workers_{jt}}. \tag{18}$$

The number of robots is computed from the IFR data and the number of workers OECD Industry Employment statistics. We define automation potential as the average industry stock of robots per thousand workers in 1995 (the average across 54 countries with complete and comparable data from the IFR). The evolution of this variable represents an approximation to the automation potential existing in each industry. We perform reduced-form regressions as in Acemoglu and Restrepo (2020) using industry-level robot adoption across all countries in order to obtain correlations between measures of market power and automation. Given that domestic robots are scarce in Colombia they are, therefore, unlikely to have large economy-wide effects on the Colombian labor market, alleviating concerns about domestic automation confounding the effects of automation potential (Kugler et al., 2020). The main variable of interest is Automation potential (AP_{jt}), which varies at 2-digit industry-year level. Figure 9 compares the robot penetration in Colombia (Panel

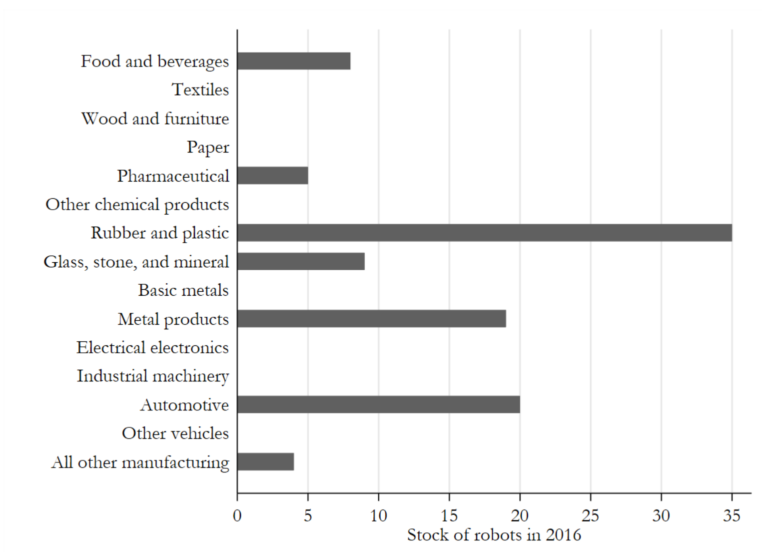
[15] The stock of robots in U.S. in 2016 was 250479 (of Robotics, 2020)

Figure 7: Manufacturing robots



Notes: Number of manufacturing robots. Source: International Federation of Robotics.

Figure 8: Manufacturing robots by sector, 2016

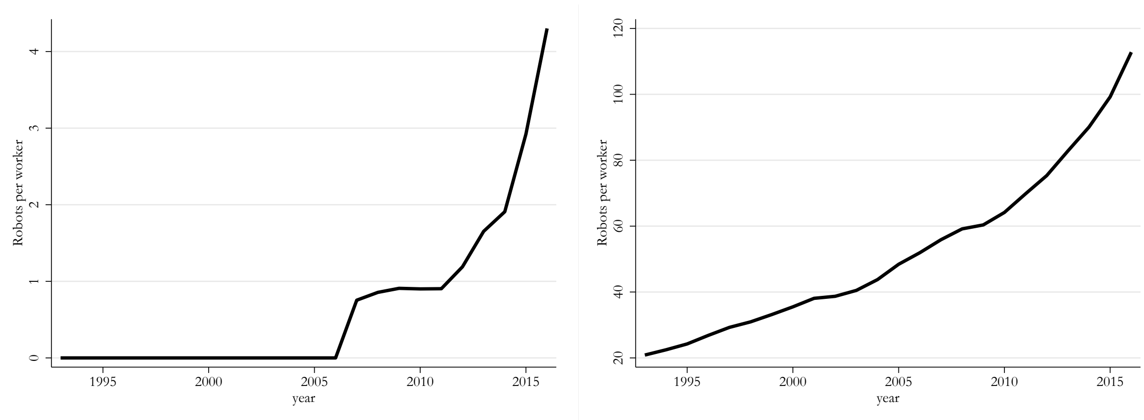


Notes: Manufacturing robots by 2-digit sector of the ISIC Revision 4 classification, year 2016. Source: International Federation of Robotics.

(a)) versus the robot penetration in all countries (Panel (b)).

Figure 9: Manufacturing robots by worker

(a) Colombia (b) All countries



Notes: Number of manufacturing robots per worker in Colombia (Panel (a)) and in all countries (Panel (b)). Source: International Federation of Robotics.

6 Results

In this section, we present the results of the role of globalization and automation technology on measures of concentration and market power.

6.1 Chinese import competition

As detailed in section 5, we begin with estimates of how the penetration of Chinese imports has impacted firm-level measures of market power. We then proceed to examine the effects on industry-level outcomes. This approach allows us to provide a comprehensive view of the trade shock's impact on market power.

Table 4 presents the firm-level estimates of equation (15) with our preferred specification. Dependent variables are different measures of markups by minimum distance approach (investment control, inputs control and cost share) and profit rate. China import penetration is instrumented with the China's supply shock calculated for all countries in the world. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) present the 2SLS one. We control for industry preexisting trends (1995-2000 changes in log industry revenue, log industry employment, and median of the corresponding dependent variable) interacted with year dummies, and for firm initial characteristics interacted with year dummies (log revenue, log employment and log wage). In all specifications, robust standard errors are clustered at industry level (4-digit ISIC rev. 3 classification).

The penetration of Chinese imports has a significantly negative impact on market power measures, leading to decreases in both markups and profits. This result holds across all three calculated markup measures. Specifically, our findings indicate that a one percentage point increase in Chinese import penetration reduces a firm's markup by between 0.7 percent and 1.3 percent, ceteris paribus. Additionally, the profit rate decreases by 0.6 percent. Notably, the OLS estimates yield slightly lower coefficients compared to the 2SLS estimates. This discrepancy aligns with the positive correlation between Colombia's industry import demand shocks and its industry revenue/labor/capital demand shocks, introducing a bias towards zero in the OLS estimates.

Table 4: Firm-level effects of Chinese import competition on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China IP	-0.003^{***}	-0.010^{***}	-0.004^{***}	-0.013^{***}	-0.002^{**}	-0.007^{*}	-0.002^{***}	-0.006^{***}
	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.004)	(0.000)	(0.002)
KP F-stat		24.8		22.9		15.4		16.1
Observations	109327	109327	109289	109289	109244	109244	107994	107994
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on firm-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across all countries in the world. Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. Industry preexisting trends (PT) are defined as the change in log industry revenue, log industry employment and in the corresponding dependent variable in the five-year period before the start of the sample (1995-2000) interacted with year dummies. Firm initial characteristics (PT) are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

We present the industry-level estimates of equation (14) in Tables 5 and 6. Table 5 displays the aggregated results for the three markup estimates and the profit rate. The industry-level markups are weighted by each firm's revenue share in the total industry revenue. The results remain consistent at the industry level: markups and profits decline with an increase in Chinese import penetration. Unlike the firm-level estimates, the industry-level estimates indicate a somewhat greater impact of CIP. This aligns with the within-industry reallocation of productive factors, which dampens the estimated coefficients at the firm level. A one percentage increase in CIP decrease markups, on average, by between 0.9 percent and 1.4 percent.

Table 6 explores the heterogeneous effects of CIP on industry-level markups of leading firms in the industry. Leading firms are defined as those ranked highest in industry revenue share; that is, they belong to the top 1, 2, 3, or 5 of the industry revenue share distribution. Our findings show that this trade shock has also negatively impacted the markups of larger firms, with effects ranging from 1 percent to 2 percent. Similarly, the markups for firms that do not belong to the top group also decline (see Appendix Table A3).

Our results are 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).

Table 5: Industry-level effects of Chinese import competition on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China IP	-0.009^{***}	-0.009^{*}	-0.009^{***}	-0.014^{***}	-0.007^{***}	-0.007	-0.002^{**}	-0.005^{*}
	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.005)	(0.001)	(0.003)
KP F-stat		87.9		75.9		84.3		68.0
Observations	1674	1674	1669	1669	1672	1672	1663	1663
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across all countries in the world. Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. Industry initial characteristics (PT) are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

6.2 Automation potential

Table 7 presents the firm-level results of equation (15), which characterizes the relationship between automation potential on market power measures. We estimate a reduced form of equation (15). The dependent variables are the same as those defined for the trade scenario studied in previous section. Columns (1), (3), (5), and (7) include year and firm fixed effects, while columns (2), (4), (6), and (8) control for industry preexisting trends (1995-2000 changes in log industry revenue, log industry employment, and median of the corresponding dependent variable) interacted with year dummies, and for firm initial characteristics interacted with year dummies (log revenue, log employment and log wage) The specification in these latter columns represents our preferred specification. Robust standard errors are clustered at the IFR sector level.

Our results suggests that firms in industries more exposed to automation potential exhibit lower markups. The coefficient of the automation potential is negative and statistically significant in all specifications and indicates a clearly negative trend in markups for firms in industries highly exposed to the automation possibilities. These results are also 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. Although our estimates cannot establish a causal effect, we can

Table 6: Industry-level effects of Chinese import competition on markups of top firms

	Top 1		Top 2		Top 3		Top 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	-0.013^{***}	-0.018^{**}	-0.010^{***}	-0.014^{**}	-0.010^{***}	-0.012^{**}	-0.011^{***}	-0.012^{**}
	(0.003)	(0.007)	(0.002)	(0.006)	(0.002)	(0.006)	(0.003)	(0.006)
KP F-stat		89.0		95.7		85.7		90.7
Observations	1591	1591	1638	1638	1659	1659	1673	1673
Panel B: markup inputs control (min. distance)								
China IP	-0.013^{***}	-0.020^{***}	-0.010^{***}	-0.015^{***}	-0.010^{***}	-0.016^{***}	-0.011^{***}	-0.019^{***}
	(0.003)	(0.007)	(0.002)	(0.006)	(0.002)	(0.005)	(0.003)	(0.005)
KP F-stat		75.9		83.2		78.6		79.0
Observations	1575	1575	1624	1624	1645	1645	1660	1660
Panel C: markup cost share (min. distance)								
China IP	-0.009^{***}	-0.015^{**}	-0.007^{***}	-0.011^{**}	-0.007^{***}	-0.010^{**}	-0.008^{***}	-0.010^{**}
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)
KP F-stat		85.8		92.6		90.5		89.1
Observations	1597	1597	1651	1651	1654	1654	1669	1669
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across all countries in the world. Outcome variables are weighted markups of firms that are in the highest ranking of the share of revenue at the industry level in each year (top 1, top 2, top 3, and top 5). Industry initial characteristics (PT) are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

identify a negative relationship between markups and the potential for automation given the trends in automation in other countries. Nevertheless, we cannot establish a relationship between profits and automation potential at the firm-level.

Next, we present the industry-level estimates of equation (14) in Table 8. The results consistently align with those observed at the firm level, showing a clear negative relationship between markups and the potential for automation. However, the relationship is not significant for the markups estimates using the input control method.

As with the analysis of the trade shock (captured by the Chinese import penetration), it is possible to study heterogeneities at the industry level for different groups of firms. In particular, we are interested in examining whether the aggregated industry-level effects differ for firms at the top of the sales distribution (i.e., the largest firms). Table 9 calculates the industry-level, annual weighted markups of firms at the top of the sales share ranking (a proxy for firm size). The table shows that the potential for automation is positively correlated with the markups of the largest firms, which have the highest sales shares in each industry. For firms in the top 3 or top 5, while the sign is positive, the correlations are not significant. The results suggest that the largest firms in Colombia would benefit from the potential for automation in more exposed industries.

Table 7: Firm-level effects of automation potential on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation pot.	-0.004^{**}	-0.005^{**}	-0.005^{***}	-0.005^{**}	-0.004^{***}	-0.004^{**}	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	109747	109747	109705	109705	109663	109663	109631	109631
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE		✓		✓		✓		✓
Firm PT x Year FE		✓		✓		✓		✓

Notes: The table presents OLS estimates of the correlation between automation potential and firm-level outcomes for Colombia during 2001-2016. Automation potential is the average industry stock of robots per thousand workers in 1995 (the average across all countries in the world with comparable data from the IFR). Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. All specifications control for log capital. Industry preexisting trends (PT) are defined as the change in log industry revenue, log industry employment and in the corresponding dependent variable in the five-year period before the start of the sample (1995-2000) interacted with year dummies. Firm initial characteristics (PT) are defined as the value at 2001 of log revenue, log employment, log wage and log capital interacted with year dummies. Robust standard errors (in parentheses) are clustered by 2-digit IFR industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

To determine if this phenomenon is exclusive to the largest firms, we also calculate, at the industry level and by year, the weighted markups of firms that are below the top firms. Similar to the markups of the top firms, we calculate the markups for the "below" firms based on their ranking in the sales share each year. Thus, we can construct a "markup below 1" measure that calculates the industry-level weighted markups of all firms excluding the one ranked first in sales. We do this in order to obtain a full picture of the distributional effects of automation. Table 10 report the results. We find that the markups of firms not at the top of the sales ranking (i.e., not the largest firms) are negatively associated with automation potential. This means there is a negative correlation between markups and the potential for automation, which aligns with the aggregate industry-level results.

Overall, these findings are consistent with Autor et al. (2017, 2020), who demonstrate that the rise in markups is driven by "superstar" firms. Additionally, a recent study by Stiebale et al. (2024) using a similar framework find no average effect of automation on markups for manufacturing firms, but do observe an increase for firms in the highest quintile.

7 Discussion and Robustness

We discuss two simple robustness exercises to check the sensitivity of our results. First, we test our China Shock results using other instruments. To capture the effect of Chinese import penetration on various measures of market power, we have instrumented this variable with China's average

Table 8: Industry-level effects of automation potential on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation pot.	-0.003	-0.006^{**}	-0.002	-0.004	-0.004^{**}	-0.005^{**}	0.000	-0.001
	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	1694	1689	1691	1686	1694	1689	1708	1692
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE		✓		✓		✓		✓

Notes: The table presents OLS estimates of the correlation between automation potential and industry-level outcomes for Colombia during 2001-2016. Automation potential is the average industry stock of robots per thousand workers in 1995 (the average across all countries in the world with comparable data from the IFR). Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. All specifications control for log capital. Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and the corresponding dependent variable interacted with year dummies. Robust standard errors (in parentheses) are clustered by 2-digit IFR industries classification. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table 9: Industry-level effects of automation potential on markups for top firms

	Top 1		Top 2		Top 3		Top 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
Automation pot.	0.020^{***}	0.019^{**}	0.010^{**}	0.008	0.006	0.002	0.002	-0.002
	(0.007)	(0.009)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	1664	1634	1707	1681	1713	1702	1716	1716
Panel B: markup inputs control (min. distance)								
Automation pot.	0.015^{***}	0.017^{**}	0.009^{***}	0.008^{**}	0.006	0.004	0.003	-0.001
	(0.005)	(0.007)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	1643	1619	1688	1668	1694	1689	1704	1704
Panel C: markup cost share (min. distance)								
Automation pot.	0.018^{***}	0.019^{**}	0.010^{**}	0.010^{**}	0.006	0.006	0.004	0.003
	(0.006)	(0.008)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Observations	1666	1640	1700	1694	1703	1697	1712	1712
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE		✓		✓		✓		✓

Notes: The table presents OLS estimates of the correlation between automation potential and firm-level outcomes for Colombia during 2001-2016. Automation potential is the average industry stock of robots per thousand workers in 1995 (the average across all countries in the world with comparable data from the IFR). Outcome variables are weighted markups of firms that are in the highest ranking of the share of revenue at the industry level in each year (top 1, top 2, top 3, and top 5). All specifications control for log capital. Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and the corresponding dependent variable interacted with year dummies. Robust standard errors (in parentheses) are clustered by 2-digit IFR industries classification. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

industry import share for all countries. To test our results of the China Shock and confirm that our instrument is indeed capturing a supply-driven shock in China that caused this country to increase its share in the imports of many countries and regions worldwide, we re-run all regressions with two additional instruments: a subset of selected high-income countries (used in Autor et al. (2013,

Table 10: Industry-level effects of automation potential on markups for below firms

	Below 1		Below 2		Below 3		Below 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
Automation pot.	-0.013^{**}	-0.016^{***}	-0.007^{*}	-0.010^{***}	-0.012^{**}	-0.013^{***}	-0.007	-0.011^{***}
	(0.006)	(0.003)	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)
Observations	1617	1574	1543	1413	1475	1346	1337	1232
Panel B: markup inputs control (min. distance)								
Automation pot.	-0.009	-0.015^{***}	-0.006	-0.008^{***}	-0.011^{**}	-0.010^{***}	-0.007	-0.009^{**}
	(0.006)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)
Observations	1615	1572	1541	1410	1475	1346	1337	1232
Panel C: markup cost share (min. distance)								
Automation pot.	-0.009	-0.010^{***}	-0.005	-0.007^{***}	-0.009^{*}	-0.008^{***}	-0.007^{*}	-0.008^{***}
	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.004)	(0.002)
Observations	1616	1573	1543	1412	1475	1346	1337	1232

Notes: The table presents OLS estimates of the correlation between automation potential and firm-level outcomes for Colombia during 2001-2016. Automation potential is the average industry stock of robots per thousand workers in 1995 (the average across all countries in the world with comparable data from the IFR). Outcome variables are weighted markups of firms that are below the highest ranking of the share of revenue at the industry level in each year (below 1, below 2, below 3, and below 5). All specifications control for log capital. Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and the corresponding dependent variable interacted with year dummies. Robust standard errors (in parentheses) are clustered by 2-digit IFR industries classification. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

2014))[16]; and all Latin American countries.[17] Tables C1 and C2 present the results at the firm- and industry-level. In all cases, regressions pass the weak IV test, and the estimated coefficients in the second stage have the same sign and are statistically significant.[18]

Second, a limitation of the EAM database is its incomplete identification of firm entry and exit. For example, when a firm appears in the sample in a given year, it is unclear if this is also the year the firm entered the market. This issue can affect the distribution of firm performance within industries, as there are different responses from incumbent firms compared to those entering or exiting the market. To ensure the robustness of our previous results, we follow Stiebale et al. (2024) and run the regressions at the firm level for both scenarios using only incumbent firms that are present in both the first and last years of the sample. Tables C7 and C8 show that the effects persist for both shocks and, in general, are of similar magnitude.

8 Concluding Remarks

This study has centered on documenting trends in market concentration and market power within Colombia's manufacturing sector. We aimed to investigate the impacts of international trade dynamics and technological advancements on these trends, providing empirical insights at both the

[16] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[17] Brazil, Argentina, Chile, Uruguay, Paraguay, Ecuador, Peru, Colombia, Bolivia, Mexico, Venezuela, Costa Rica, El Salvador, Guatemala, Haiti, Honduras, Nicaragua, Panama, and the Dominican Republic.

[18] Appendix Tables C3 - C6 display the results at the industry level for top and below firms.

firm and industry levels.

Trade liberalization and rapid technological progress are two phenomena that promise substantial economic benefits through technological advancement, enhanced access to innovations, and intensified competitive pressures. However, they also exert profound influences on market dynamics, including concentration and market power within firms and industries.

In Colombia, our examination of market concentration and markups from a longitudinal perspective underscores the relationship between globalization, technological change, and economic outcomes. Specifically, our research delves into two pivotal scenarios: the impact of Chinese import competition and the dynamics of automation technology adoption. Our findings show that Chinese import penetration has reduced markups across industries, even affecting larger firms. Concurrently, while automation technology remains underutilized in Latin America compared to developed economies, its potential effects on market power measures, particularly among larger firms in automation-exposed industries, indicate a positive correlation with markups.

In conclusion, this study contributes to the broader understanding of how trade dynamics and technological shifts shape market concentration and corporate market power in emerging economies like Colombia. By examining both firm-level responses and industry-level dynamics, we provide nuanced insights into the drivers of economic performance amidst global economic shifts.

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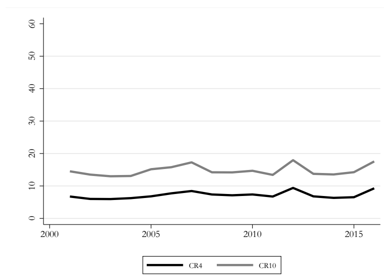
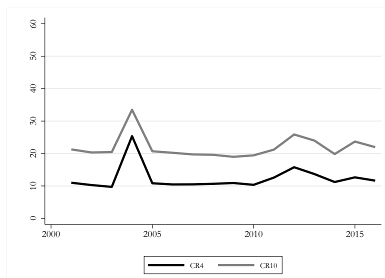
Appendix A: Additional figures and tables

Figure A1: Concentration by manufacturing sectors.

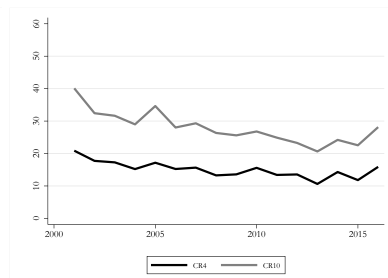
(a) Food, beverages



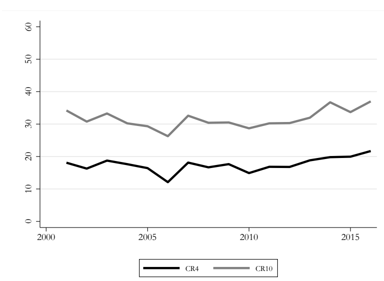
(b) Textiles, apparel



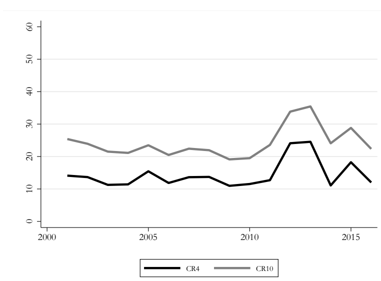
(c) Wood products



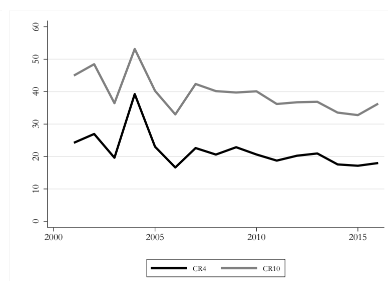
(d) Paper, printing



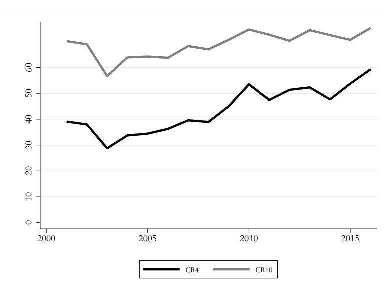
(e) Chemicals



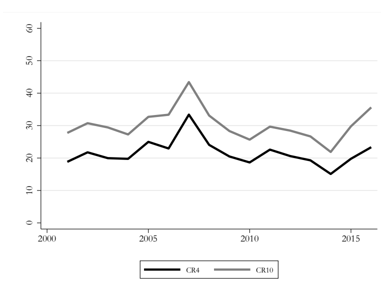
(f) Mineral products



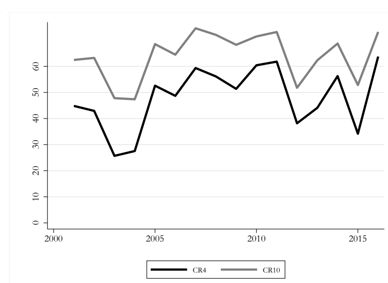
(g) Basic metals



(h) Machinery, equipment



(i) Other manufacturing



Notes: Figure shows 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.

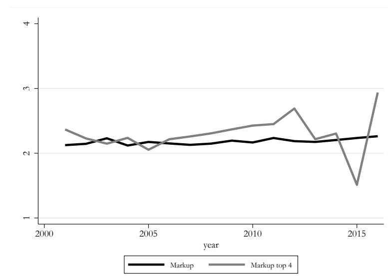
Table A1: Distribution of top 25 firms

	2000		2005		2015	
Ranking	2 digits	4 digits	2 digits	4 digits	2 digits	4 digits
1	39	3909	39	3909	35	3540
2	39	3909	39	3909	35	3540
3	38	3843	38	3843	37	3720
4	35	3523	35	3513	39	3909
5	35	3513	39	3909	35	3523
6	39	3909	35	3513	35	3523
7	31	3118	39	3909	39	3909
8	38	3843	38	3843	35	3540
9	39	3909	39	3909	35	3540
10	31	3121	35	3523	39	3909
11	35	3513	39	3909	35	3540
12	39	3909	31	3134	35	3540
13	39	3909	39	3909	35	3540
14	35	3523	31	3112	31	3121
15	35	3512	37	3710	35	3540
16	35	3512	39	3909	35	3513
17	35	3523	31	3118	31	3121
18	32	3220	39	3909	38	3839
19	31	3112	39	3909	31	3118
20	31	3121	31	3119	39	3909
21	39	3909	31	3115	31	3112
22	34	3411	32	3220	31	3118
23	35	3523	31	3121	38	3849
24	35	3523	31	3121	31	3118
25	35	3522	31	3112	38	3849

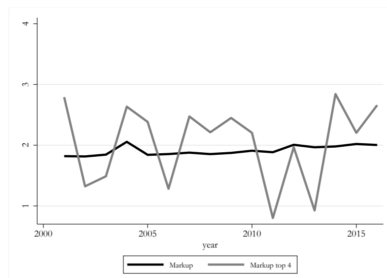
Notes: Sector and industry affiliation of top 25 firms (ISIC Rev. 2).

Figure A2: Markups by manufacturing sector.

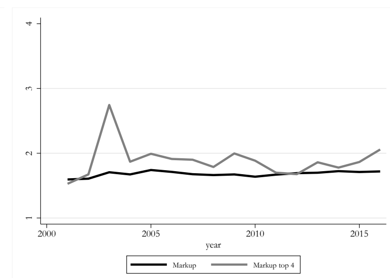
(a) Food, beverages



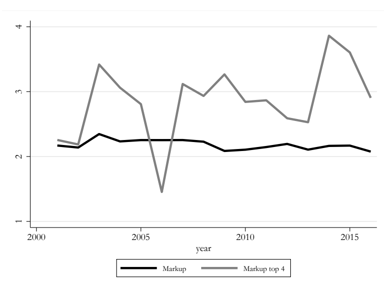
(b) Textiles, apparel



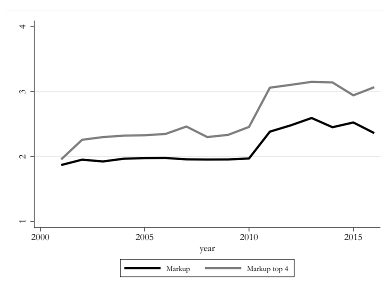
(c) Wood products



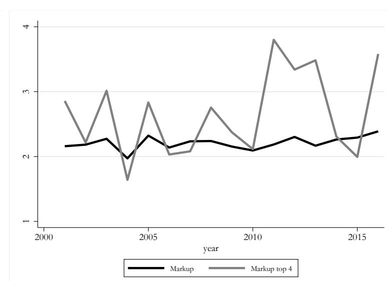
(d) Paper, printing



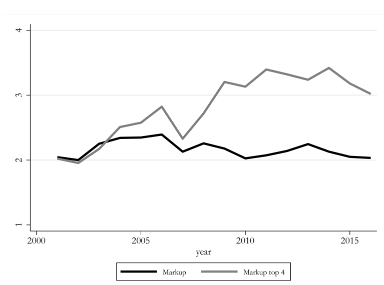
(e) Chemicals



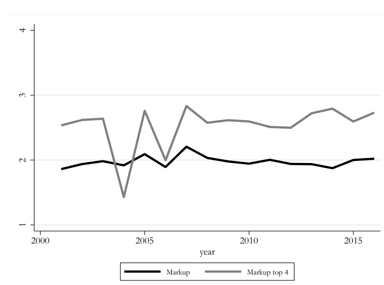
(f) Mineral products



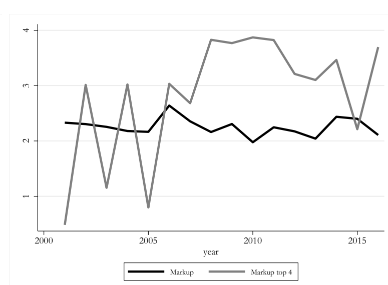
(g) Basic metals



(h) Machinery, equipment



(i) Other manufacturing



Notes: Figure shows sales weighted average markups (all firms: solid black, top 4 firms: solid gray) of 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.

Table A2: First stage regressions

(a) Firm-level

	CIP
	(1)
China IP in all countries	0.556***
	(0.110)
Observations	114492
R squared	0.940

(b) Industry-level

	CIP
	(1)
China IP in all countries	0.951***
	(0.097)
Observations	736
R squared	0.977

Notes: The table presents the first stage estimates at the firm- (Panel (a)) and industry-level (Panel (b). The dependent variable is chinese import penetration (measured as the total value of imports from China divided by domestic absorption) in Colombia. China IP in all countries is China's industry import share across all countries in the world. Both variable vary at the 4-digit industry-level. Specification in Panel (a) includes firm and year fixed effects, firm initial characteristics interacted with year dummies, and industry-level preexisting trends interacted with year dummies (log revenue, log employment and log markup). Specification in Panel (b) includes industry and year fixed effects, the industry initial characteristics interacted with year dummies (log revenue, log employment and log markup). Robust standard errors (in parentheses) are clustered by 4-digit ISIC Rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table A3: Industry-level effects of Chinese import competition on markups of below firms

	Below 1		Below 2		Below 3		Below 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	−0.004**	−0.005	−0.002	−0.007*	−0.003	−0.006*	−0.004**	−0.008*
	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
KP F-stat		50.5		64.9		71.9		37.9
Observations	1542	1542	1381	1381	1314	1314	1200	1200
Panel B: markup inputs control (min. distance)								
China IP	−0.004*	−0.014***	−0.001	−0.013***	−0.002	−0.011***	−0.004	−0.012**
	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)
KP F-stat		55.6		57.5		59.1		36.1
Observations	1540	1540	1378	1378	1314	1314	1200	1200
Panel C: markup cost share (min. distance)								
China IP	−0.002	−0.005	−0.001	−0.008*	−0.003	−0.006*	−0.003*	−0.009**
	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
KP F-stat		49.6		61.9		63.8		36.5
Observations	1541	1541	1380	1380	1314	1314	1200	1200
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across all countries in the world. Outcome variables are weighted markups of firms that are not in the highest ranking of the share of revenue at the industry level in each year (below 1, below 2, below 3, and below 5). Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Appendix B: Estimation of markups

Table B1: Output elasticity of intermediate inputs θ^m

	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)	0.71***	0.70***	0.70***	0.69***	0.69***	0.67***	0.55***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)	(0.019)	(0.016)
	n= 34946	*n= 34946*	*n= 13965*	*n= 13965*	*n= 23626*	*n= 9482*	*n= 13832*
(2)	0.60***	0.60***	0.60***	0.59***	0.56***	0.55***	0.39***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.013)	(0.013)
	n= 36705	*n= 36705*	*n= 14896*	*n= 14896*	*n= 20552*	*n= 8737*	*n= 14417*
(3)	0.61***	0.61***	0.62***	0.61***	0.64***	0.65***	0.26***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.017)	(0.020)	(0.023)
	n= 11312	*n= 11312*	*n= 4367*	*n= 4367*	*n= 6445*	*n= 2575*	*n= 4365*
(4)	0.57***	0.57***	0.55***	0.54***	0.37***	0.26***	0.80***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.032)	(0.045)	(0.045)
	n= 14658	*n= 14658*	*n= 6382*	*n= 6382*	*n= 9759*	*n= 4363*	*n= 6255*
(5)	0.65***	0.64***	0.64***	0.63***	0.63***	0.61***	0.54***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.017)	(0.020)	(0.014)
	n= 31496	*n= 31496*	*n= 12554*	*n= 12554*	*n= 23558*	*n= 9671*	*n= 12505*
(6)	0.53***	0.52***	0.50***	0.50***	0.58***	0.53***	0.59***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.022)	(0.047)	(0.025)
	n= 8575	*n= 8575*	*n= 3178*	*n= 3178*	*n= 6221*	*n= 2358*	*n= 3165*
(7)	0.57***	0.56***	0.57***	0.57***	0.64***	0.66***	0.47***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.027)	(0.028)	(0.048)
	n= 4213	*n= 4213*	*n= 1757*	*n= 1757*	*n= 2524*	*n= 1133*	*n= 1747*
(8)	0.58***	0.58***	0.59***	0.59***	0.58***	0.60***	0.61***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.015)	(0.012)	(0.010)
	n= 30824	*n= 30824*	*n= 12075*	*n= 12075*	*n= 19889*	*n= 8046*	*n= 12033*
(9)	0.59***	0.59***	0.59***	0.59***	0.56***	0.54***	0.60***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.022)	(0.037)	(0.032)
	n= 12412	*n= 12412*	*n= 5254*	*n= 5254*	*n= 8104*	*n= 3532*	*n= 5226*

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 1995-2016. Columns (3), (4), (6), (7), (8) display estimates from sample years 2001-2011. Standard errors are computed with 1000 bootstrap replications.

Table B2: Output elasticity of labor θ^l

	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)	0.19***	0.18***	0.19***	0.19***	0.27***	0.27***	0.37***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)	(0.020)	(0.015)
	n= 34946	*n= 34946*	*n= 13965*	*n= 13965*	*n= 23626*	*n= 9482*	*n= 13832*
(2)	0.29***	0.29***	0.30***	0.30***	0.38***	0.39***	0.45***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)	(0.015)	(0.012)
	n= 36705	*n= 36705*	*n= 14896*	*n= 14896*	*n= 20552*	*n= 8737*	*n= 14417*
(3)	0.28***	0.27***	0.28***	0.28***	0.32***	0.29***	0.49***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.017)	(0.018)	(0.021)
	n= 11312	*n= 11312*	*n= 4367*	*n= 4367*	*n= 6445*	*n= 2575*	*n= 4365*
(4)	0.28***	0.27***	0.29***	0.29***	0.53***	0.60***	0.20***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.028)	(0.038)	(0.038)
	n= 14658	*n= 14658*	*n= 6382*	*n= 6382*	*n= 9759*	*n= 4363*	*n= 6255*
(5)	0.23***	0.23***	0.24***	0.24***	0.29***	0.30***	0.35***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.016)	(0.019)	(0.014)
	n= 31496	*n= 31496*	*n= 12554*	*n= 12554*	*n= 23558*	*n= 9671*	*n= 12505*
(6)	0.27***	0.26***	0.27***	0.27***	0.37***	0.35***	0.34***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.022)	(0.041)	(0.027)
	n= 8575	*n= 8575*	*n= 3178*	*n= 3178*	*n= 6221*	*n= 2358*	*n= 3165*
(7)	0.29***	0.28***	0.29***	0.28***	0.30***	0.30***	0.51***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.027)	(0.035)	(0.045)
	n= 4213	*n= 4213*	*n= 1757*	*n= 1757*	*n= 2524*	*n= 1133*	*n= 1747*
(8)	0.30***	0.29***	0.29***	0.28***	0.36***	0.31***	0.32***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.013)	(0.013)	(0.011)
	n= 30824	*n= 30824*	*n= 12075*	*n= 12075*	*n= 19889*	*n= 8046*	*n= 12033*
(9)	0.26***	0.26***	0.26***	0.26***	0.38***	0.35***	0.36***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.018)	(0.023)	(0.024)
	n= 12412	*n= 12412*	*n= 5254*	*n= 5254*	*n= 8104*	*n= 3532*	*n= 5226*

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 1995-2016. Columns (3), (4), (6), (7), (8) display estimates from sample years 2001-2011. Standard errors are computed with 1000 bootstrap replications.

Table B3: Correlation of sector-level estimates of output elasticities

Baseline: Cost share, variable r (1)		
Cost share, fixed r (2)	1.00	1.00
Cost share, variable r, shorter sample (3)	0.97	0.98
Cost share, fixed r, shorter sample (4)	0.97	0.98

Baseline: Investment control (5)		
Investment control, shorter sample (6)	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 and B2. The bottom panel reports correlations between columns (5) and (6) in those same tables.

Table B4: Firm-level markups

	Min. distance			FOCs.Int.inputs			FOCs. Labor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean	1.77	1.79	1.54	1.39	1.31	1.46	2.01	2.10	1.49
Median	1.67	1.65	1.46	1.22	1.13	1.28	1.77	1.78	1.32
Weightedaverage	2.20	2.25	1.85	1.33	1.20	1.39	2.79	3.05	2.05
p10	1.12	1.10	1.01	0.82	0.71	0.86	0.85	0.82	0.65
p90	2.61	2.74	2.18	2.22	2.19	2.31	3.60	3.99	2.65

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 B5: 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			
Investment control	(1)	(2)	(3)	Min distance	(4)	(5)	(6)
Int.inputs control	0.89	0.86	0.83	Int.inputs	0.48	0.33	0.68
Cost share	0.95	0.98	0.96	Labor	0.72	0.79	0.55

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.

Table B6: Correlation of firm-level estimates of markups and sales

	Min.distance (1)	Int.inputs (2)	Labor (3)
Log sales			
Investment control	0.22	-0.02	0.24
Int.inputs control	0.21	-0.04	0.21
Cost shares	0.20	-0.02	0.27
Profitability			
Investment control	0.49	0.35	0.28
Int.inputs control	0.43	0.31	0.25
Cost shares	0.53	0.37	0.29

Notes: Table shows correlations between different estimates of markups and firm sales and profits. The profit rate is defined as revenue over costs, where costs include the cost of production (materials, energy, labor, and the user cost of capital), and other expenditures. 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.

Appendix C: Robustness exercises

Table C1: Firm-level effects of Chinese import competition on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: China's supply shock (High-income countries)								
China IP	-0.003^{***}	-0.012^{***}	-0.004^{***}	-0.014^{***}	-0.002^{**}	-0.010^{**}	-0.002^{***}	-0.006^{***}
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.000)	(0.002)
KP F-stat		25.8		22.0		12.5		13.4
Observations	109327	109327	109289	109289	109244	109244	107994	107994
Panel B: China's supply shock (Latin American countries)								
China IP	-0.003^{***}	-0.009^{***}	-0.004^{***}	-0.011^{***}	-0.002^{**}	-0.006^{**}	-0.002^{***}	-0.005^{***}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.000)	(0.001)
KP F-stat		35.8		35.9		25.4		26.0
Observations	109327	109327	109289	109289	109244	109244	107994	107994
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on firm-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across across selected high-income (used in Autor et al. (2013, 2014)) and Latin American countries. Outcome variables are markups (investment control - INV, inputs control - INP-, and cost share - CS) and profit rate. Industry preexisting trends (PT) are defined as the change in log industry revenue, log industry employment and in the corresponding dependent variable in the five-year period before the start of the sample (1995-2000) interacted with year dummies. Firm initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C2: Industry-level effects of Chinese import competition on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: China's supply shock (High-income countries)								
China IP	-0.009^{***}	-0.017^{***}	-0.009^{***}	-0.019^{***}	-0.007^{***}	-0.017^{***}	-0.002^{**}	-0.005^{*}
	(0.002)	(0.005)	(0.002)	(0.006)	(0.002)	(0.005)	(0.001)	(0.003)
KP F-stat		78.5		60.4		71.6		59.0
Observations	1674	1674	1669	1669	1672	1672	1663	1663
Panel B: China's supply shock (Latin American countries)								
China IP	-0.009^{***}	-0.008^{**}	-0.009^{***}	-0.009^{**}	-0.007^{***}	-0.005	-0.002^{**}	-0.004^{*}
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)
KP F-stat		53.5		51.2		54.6		47.8
Observations	1674	1674	1669	1669	1672	1672	1663	1663
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across across selected high-income (used in Autor et al. (2013, 2014)) and Latin American countries. Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profit rate. Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C3: Industry-level effects of Chinese import competition on markups of top firms

	Top 1		Top 2		Top 3		Top 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	-0.013^{***}	-0.025^{***}	-0.010^{***}	-0.020^{***}	-0.010^{***}	-0.017^{***}	-0.011^{***}	-0.019^{***}
	(0.003)	(0.008)	(0.002)	(0.006)	(0.002)	(0.006)	(0.003)	(0.006)
KP F-stat		76.1		83.1		75.9		84.0
Observations	1591	1591	1638	1638	1659	1659	1673	1673
Panel B: markup inputs control (min. distance)								
China IP	-0.013^{***}	-0.026^{***}	-0.010^{***}	-0.018^{***}	-0.010^{***}	-0.017^{***}	-0.011^{***}	-0.022^{***}
	(0.003)	(0.008)	(0.002)	(0.006)	(0.002)	(0.006)	(0.003)	(0.006)
KP F-stat		61.7		65.7		60.4		63.9
Observations	1575	1575	1624	1624	1645	1645	1660	1660
Panel C: markup cost share (min. distance)								
China IP	-0.009^{***}	-0.024^{***}	-0.007^{***}	-0.018^{***}	-0.007^{***}	-0.016^{***}	-0.008^{***}	-0.019^{***}
	(0.003)	(0.007)	(0.002)	(0.006)	(0.002)	(0.006)	(0.002)	(0.006)
KP F-stat		71.2		74.9		72.1		75.5
Observations	1597	1597	1651	1651	1654	1654	1669	1669
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) present 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the four-digit industry-year level. This variable is instrumented with the average China's industry import share across selected high income countries (used in Autor et al. (2013, 2014)). Outcome variables are weighted markups of firms that are in the highest ranking of the share of revenue at the industry level in each year (top 1, top 2, top 3, and top 5). Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C4: Industry-level effects of Chinese import competition on markups of below firms

	Below 1		Below 2		Below 3		Below 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	-0.004^{**}	-0.009^{*}	-0.002	-0.012^{**}	-0.003	-0.009^{*}	-0.004^{**}	-0.008
	(0.002)	(0.005)	(0.003)	(0.005)	(0.002)	(0.004)	(0.002)	(0.005)
KP F-stat		51.2		46.2		43.5		21.4
Observations	1542	1542	1381	1381	1314	1314	1200	1200
Panel B: markup inputs control (min. distance)								
China IP	-0.004^{*}	-0.016^{**}	-0.001	-0.018^{**}	-0.002	-0.015^{**}	-0.004	-0.013^{**}
	(0.002)	(0.006)	(0.003)	(0.007)	(0.002)	(0.006)	(0.002)	(0.006)
KP F-stat		45.8		38.5		35.9		20.3
Observations	1540	1540	1378	1378	1314	1314	1200	1200
Panel C: markup cost share (min. distance)								
China IP	-0.002	-0.011^{**}	-0.001	-0.014^{**}	-0.003	-0.010^{**}	-0.003^{*}	-0.009^{*}
	(0.001)	(0.005)	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)
KP F-stat		47.1		44.3		39.8		20.4
Observations	1541	1541	1380	1380	1314	1314	1200	1200
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) present OLS estimates and columns (2), (4), (6) and (8) present 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the four-digit industry-year level. This variable is instrumented with the average China's industry import share across selected high income countries (used in Autor et al. (2013, 2014)). Outcome variables are weighted markups of firms that are below the highest ranking of the share of revenue at the industry level in each year (below 1, below 2, below 3, and below 5). Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C5: Industry-level effects of Chinese import competition on markups of top firms

	Top 1		Top 2		Top 3		Top 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	-0.013^{***}	-0.014^{**}	-0.010^{***}	-0.010^{**}	-0.010^{***}	-0.009^{**}	-0.011^{***}	-0.011^{**}
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.003)	(0.005)
KP F-stat		51.4		54.4		52.3		54.1
Observations	1591	1591	1638	1638	1659	1659	1673	1673
Panel B: markup inputs control (min. distance)								
China IP	-0.013^{***}	-0.013^{**}	-0.010^{***}	-0.010^{**}	-0.010^{***}	-0.011^{***}	-0.011^{***}	-0.013^{***}
	(0.003)	(0.006)	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.004)
KP F-stat		47.7		51.8		50.9		51.3
Observations	1575	1575	1624	1624	1645	1645	1660	1660
Panel C: markup cost share (min. distance)								
China IP	-0.009^{***}	-0.011^{**}	-0.007^{***}	-0.007	-0.007^{***}	-0.007^{*}	-0.008^{***}	-0.007^{*}
	(0.003)	(0.005)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
KP F-stat		51.8		55.7		55.4		55.8
Observations	1597	1597	1651	1651	1654	1654	1669	1669
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) present OLS estimates and columns (2), (4), (6) and (8) present 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the four-digit industry-year level. This variable is instrumented with the average China's industry import share across Latin American countries. Outcome variables are weighted markups of firms that are in the highest ranking of the share of revenue at the industry level in each year (top 1, top 2, top 3, and top 5). Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C6: Industry-level effects of Chinese import competition on markups of below firms

	Below 1		Below 2		Below 3		Below 5	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: markup investment control (min. distance)								
China IP	-0.004^{**}	-0.005	-0.002	-0.007^{*}	-0.003	-0.007^{**}	-0.004^{**}	-0.009^{**}
	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
KP F-stat		36.6		80.1		91.2		58.4
Observations	1542	1542	1381	1381	1314	1314	1200	1200
Panel B: markup inputs control (min. distance)								
China IP	-0.004^{*}	-0.010^{**}	-0.001	-0.010^{**}	-0.002	-0.009^{***}	-0.004	-0.010^{**}
	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)
KP F-stat		42.8		80.3		87.5		58.5
Observations	1540	1540	1378	1378	1314	1314	1200	1200
Panel C: markup cost share (min. distance)								
China IP	-0.002	-0.003	-0.001	-0.006	-0.003	-0.006^{**}	-0.003^{*}	-0.008^{**}
	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
KP F-stat		36.0		80.9		88.7		58.6
Observations	1541	1541	1380	1380	1314	1314	1200	1200
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on industry-level outcomes for Colombia during 2001-2016. Columns (1), (3), (5) and (7) present OLS estimates and columns (2), (4), (6) and (8) present 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the four-digit industry-year level. This variable is instrumented with the average China's industry import share across Latin American countries. Outcome variables are weighted markups of firms that are below the highest ranking of the share of revenue at the industry level in each year (below 1, below 2, below 3, and below 5). Industry initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C7: Firm-level effects of Chinese import competition on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China IP	-0.003^{***}	-0.009^{**}	-0.004^{***}	-0.011^{**}	-0.002^{*}	-0.004	-0.002^{***}	-0.004^{***}
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.002)
KP F-stat		27.3		26.4		16.9		18.0
Observations	35916	35916	35975	35975	35936	35936	35557	35557
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm PT x Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents estimates of the effects of Chinese import competition on firm-level outcomes for Colombia during 2001-2016. Panel of incumbent firms. Columns (1), (3), (5) and (7) report OLS estimates and columns (2), (4), (6) and (8) report 2SLS estimates. Chinese import penetration is measured as the total value of imports from China divided by domestic absorption and varies at the 4-digit industry-year level. This variable is instrumented with the average China's industry import share across all countries in the world. Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. Industry preexisting trends (PT) are defined as the change in log industry revenue, log industry employment and in the corresponding dependent variable in the five-year period before the start of the sample (1995-2000) interacted with year dummies. Firm initial characteristics are defined as the value at 2001 of log revenue, log employment and log wage interacted with year dummies. Weak IV F statistic is the Kleibergen-Paap weak instrument F statistic. Robust standard errors (in parentheses) are clustered by 4-digit ISIC rev. 3 industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

Table C8: Firm-level effects of automation potential on markups and profits

	Markup INV		Markup INP		Markup CS		Profitability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Automation pot.	-0.003^{*}	-0.006^{***}	-0.004^{**}	-0.005^{**}	-0.004^{***}	-0.004^{**}	-0.001^{**}	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Observations	36102	36102	36162	36162	36122	36122	36067	36067
Covariates:								
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry PT x Year FE		✓		✓		✓		✓
Firm PT x Year FE		✓		✓		✓		✓

Notes: The table presents OLS estimates of the correlation between automation potential and firm-level outcomes for Colombia during 2001-2016. Panel of incumbent firms. Automation potential is the average industry stock of robots per thousand workers in 1995 (the average across all countries in the world with comparable data from the IFR). Outcome variables are weighted average markups (investment control - INV, inputs control - INP-, and cost share - CS) and profitability. All specifications control for log capital. Industry preexisting trends (PT) are defined as the change in log industry revenue, log industry employment and in the corresponding dependent variable in the five-year period before the start of the sample (1995-2000) interacted with year dummies. Firm initial characteristics are defined as the value at 2001 of log revenue, log employment, log wage and log capital interacted with year dummies. Robust standard errors (in parentheses) are clustered by 2-digit IFR industries. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.