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An Empirical Exploration

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Abstract

While there is widespread evidence of increasing markups in the United States and other developed economies in the last several decades, little is known about that evolution in developing economies, particularly Latin American countries. Using a harmonized dataset on listed firms from 70 countries in the period 2000-2022, I document four stylized facts about market power—measured as price-cost markups—in the six largest Latin American economies from a worldwide perspective. First, average markups in LAC are high relative to other emerging and developed economies, although they have slightly declined from prevailing levels during the commodity boom period. Second, aggregate markup dynamics are primarily driven by already high-markup firms in the top decile of the markup distribution, with little changes in the market power measured for the remaining nine deciles. Third, in contrast to the prediction of most theories about endogenously variable markups, I document a nonlinear relationship between firm-level markups and size, which is significantly negative for most of the size distribution and significantly positive for very large corporations. Fourth, the relationship between markups and investment depends heavily on the markup level. For a typical firm with median market power, a 1% increase in its markup implies a 0.86% rise in the investment rate. In contrast, for firms at the 99th percentile of the markup distribution, a 1% increase in its markup implies a -0.44% reduction in investment.

JEL classifications: D22, D24, L11
Keywords: Market power, Pricing, Firm size, TFP

The views expressed here are strictly those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent. Contact author Rodrigo Heresi at rheresi@IADB.ORG.

1 Introduction

There is widespread empirical evidence of increasing market concentration and corporate market power in the United States and other developed economies since the 1980s (De Loecker and Eeckhout (2018); De Loecker et al. (2020); Díez et al. (2021)). These upward trends have raised concerns among academics and policymakers, as they have been accompanied by drops in investment, innovation, and productivity growth (Covarrubias et al. (2020); Díez et al. (2018)), entry rates, and business dynamism (Decker et al. (2016); Akcigit and Ates (2021, 2023)),and the labor share of income relative to the capital share of income (De Loecker et al. (2020); Barkai (2020)), as well as rising income inequality (Eslava et al. (2021, 2023)).

This paper provides an up-to-date picture of the distribution of markups—–defined as the ratio of a good's price over its marginal cost—–in the six largest Latin American countries (henceforth LAC) and compares the results against worldwide benchmarks. Unlike in the United States or other developed economies, in emerging economies, neither the rise of market power itself nor its macroeconomic implications have been studied using a standardized database. On the one hand, broad market concentration measures, such as Herfindahl-Hirschman indexes (HHI) or concentration ratios (the fraction of total sales accrued by the largest firms within an industry), while easy to compute, are generally not sufficient statistics to gauge the degree of market power or its welfare implications. On the other hand, better and more direct measures of firm-level market power, such as price markups, are hard to estimate homogeneously for a large set of firms and sectors in emerging economies, particularly in LAC.

To address this research gap, I have constructed a database of about forty thousand listed firms across 70 developed and emerging economies, spanning various economic sectors, from 2000 to 2022. I have applied a well-established methodology originally developed by Hall (1988) using data at the sector level and refined later by Loecker and Warzynski (2012), who apply it at the firm level. Equipped with the firm-level markup results over time by country group and economic sectors, this paper aims to address several key questions. Has market power increased in developing economies as much as in developed economies? How does market power vary across country groups and economic sectors? What is the correlation between firms' size and market power? What is the influence of market power on firm investment and growth?

The results show markup levels in LAC are relatively high from a worldwide perspective, compared to developed economies as well as emerging countries, although they have slightly declined from the levels observed during the commodity boom period between the early 2000s and 2012. For instance, the weighted *average* markup across firms in the six largest countries in the region is 1.34 (that is, a price 34% above the firm's marginal cost). This central tendency estimate is not driven by outlier observations, as the weighted *median* markup estimated for LAC is 1.30 over the sample, doubling the median markup in developed economies (1.15), almost tripling the median in other emerging economies (1.11), and quintupling the U.S. median (1.06). Peru and Brazil display the largest markups within LAC, with weighted averages of 1.40 and 1.39, respectively, followed by Mexico and Argentina with 1.35. In contrast, Chile (1.24) and Colombia (1.26) record the lowest markup levels and markup dispersion among the countries analyzed in the region.

The aggregate markup dynamics hide a huge heterogeneity across the markup distribution. For instance, pooling all firms in the six largest LAC economies, while the median markup is estimated at 1.30, a firm in the 5th (95th) percentile of the markup distribution registers a markup of 0.98 (1.90). Similarly, firms in the 25th (75th) percentile of the markup distribution register a markup of 1.13 (1.47), yielding an interquartile range of 34%. On the other hand, the results also show a large disconnect between the evolution of markups for already high-markup firms (defined as firms in the top decile of the markup distribution), which increased dramatically between 2000 and 2022, and the rest of the firms (first nine deciles) which on average register no markup changes whatsoever.

Regarding the relationship between markups and firm size, most classic theories of heterogeneous markups predict a positive correlation, with large firms charging higher markups. For instance, Atkeson and Burstein (2008) and Edmond et al. (2015) show that the firm's size is a sufficient statistic to recover a firm's markup under Cournot competition. Similarly, Edmond et al. (2023) show that under monopolistic competition with (non-CES) Kimball (1995) demand, more productive firms grow larger, face less competition, and therefore can charge higher markups. The empirical results obtained in this paper show that these theoretical predictions are violated for a large range of the size distribution. On average, larger firms charge lower markups. However, the markup-size relationship is remarkably non-monotonic, becoming positive and consistent with the theory for firms at the very right tail of the size distribution. For instance, for a typical firm with a median size worldwide, a one percentage point increase in the firm's market share is associated with a -0.40% lower markup. In contrast, for a firm in the 99th percentile of the size distribution, a one percentage point increase in its market share is associated with a 0.42% increase in the markup. The analogous estimates for LAC are -0.46% for the median firm and 0.25% for firms in the 99th percentile.

Using a database of publicly listed corporations allows the collection of detailed firm characteristics related to investment decisions. In the paper's final section, I study the relationship between markups and investment. More specifically, I run "Tobin's Q" regressions relating investment rates against classic determinants of firm investment to investigate whether high-markup firms invest more or less than low-markup firms. The results strongly reveal that the relationship between markup and investment depends heavily on the markup level. For a firm with a median markup worldwide, a 1% increase in its markup implies a 0.86% increment in the investment rate. In contrast, for firms at the 99th percentile of the markup distribution, a 1% increase in its markup implies a -0.44% reduction in investment. The analogous figures for LAC are 1.24% for the median markup firm and -0.21% (not statistically significant) for firms at the 99th percentile of the markup distribution.

The remainder of the paper is organized as follows. Section 2 describes the data, and Section 3 presents the empirical framework. Section 4 presents the time evolution of the estimated firm-level markups aggregated by country groups, while Section 5 details the distribution of markups. Section 6 studies the correlation between markups and size, while section 7 documents the nonlinear relationship between firm market power and investment rates. Section 8 concludes.

2 Data

I build an annual panel of publicly listed firms from 70 countries for 2000-2022, sourced by Datastream Refinitiv. This dataset has the advantage of allowing cross-country comparisons using harmonized accounts for a long period of time and covering the vast majority of economic sectors. On the other hand, an obvious disadvantage of using publicly listed firms is that they are not representative of the universe of firms, therefore tilting the sample towards bigger and older companies.

The dataset includes 27 developed economies[1] besides the United States, 36 non-LAC emerging countries[2], and the six largest LAC countries (Argentina, Brazil, Chile, Colombia, Mexico, and Peru).

The Refinitiv data contains comprehensive balance sheet information at the firm-year level, including total sales, cost of goods sold (COGS, a bundle of variable expenses directly attributable to the production process, including materials, intermediate inputs, labor costs, and energy costs), capital stock, and detailed NAICS-based industry classification. The data source also contains a measure of overhead cost, including selling, general, and administrative expenses (SGA), which is useful for computing total costs and firm-level profits. To compute the cost of capital, I multiply the value of the capital stock by a proxy of the user cost of capital obtained as in De Loecker et al. (2020). In the final sections of the paper, I use additional financial variables, such as firms' market capitalization, capital expenditures, assets, leverage, and cash on hand, to study the relationship between firm-level market power and investment rates.

Table 1 reports summary statistics for the key variables in the analysis broken down by country groups. Median sales over the worldwide sample amount to 125 million (2016 real) dollars, ranging from 88 million in non-LAC emerging countries to 377 million in the United States. Analogously, the median COGS is 81 million worldwide, ranging from 60 million in non-LAC emerging countries to almost 200 million in the United States and LAC. As is usually the case with firm-level data, all variables are significantly skewed, as all means are significantly higher than the median.

Table 1: Summary Statistics

Variable	Countries	N. obs	mean	sd	p25	p50	p75
SALES	USA	42,466	2,118	4,279	36	377	1,945
	Developed	199,721	1,040	2,953	39	143	567
	Emerging	171,056	517	1,713	25	88	300
	LAC	10,247	1,357	3,136	71	295	1,052
	Worldwide	423,490	945	2,756	32	125	505
COGS	USA	42,500	1,324	2,801	19	199	1,163
	Developed	200,243	697	1,999	23	92	379
	Emerging	170,530	371	1,241	16	60	211
	LAC	10,216	898	2,122	46	188	681
	Worldwide	423,489	634	1,867	19	81	338
CAPITAL	USA	42,671	1,275	3,106	12	135	883
	Developed	200,161	742	2,383	14	70	329
	Emerging	170,465	401	1,519	12	50	189
	LAC	10,193	1,241	2,803	49	221	926
	Worldwide	423,490	670	2,203	13	65	296

Notes: All monetary statistics are expressed in millions of 2016 U.S. dollars. All variables are winsorized with trimming at the 1% and 99% levels.

[1] Developed countries (27): Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, South Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, Taiwan, United Kingdom.

[2] Emerging countries (36): Bangladesh, Bosnia and Herzegovina, Bulgaria, China, Croatia, Egypt, Hungary, India, Indonesia, Iraq, Jordan, Kazakhstan, Kenya, Kuwait, Macedonia, Malaysia, Mauritius, Morocco, Nigeria, Oman, Pakistan, Philippines, Poland, Qatar, Republic of Serbia, Russia, Saudi Arabia, Slovenia, South Africa, Sri Lanka, Thailand, Tunisia, Turkey, Ukraine, United Arab Emirates, Vietnam.

3 Empirical Framework

Firm i in period t produce output (Q_{it}) using the following firm-specific technology:

$$Q_{it} = Q_{it}(X_{it}, K_{it}; \omega_{it}) \tag{1}$$

where X_{it} denotes a bundle of variable inputs (including labor, intermediates, materials, etc), K_{it} is the capital stock, and ω_{it} is the firm's productivity level. The timing assumptions are as follows: (a) K_{it} is predetermined, chosen optimally in $t-1$, and (b) X_{it} is fully flexible (not subject to adjustment costs) and optimally chosen in t *after* the firm observes its productivity level ω_{it} (unobserved by the econometrician). The firm purchases inputs in perfectly competitive markets, taking factor prices P^x_{it} and r^k_{it} as given. Instead, the firm has market power with respect to the goods it sells, facing an inverse demand schedule $P_{it}(Q_{it})$.

In this framework, the markup of firm i at time t, μ_{it}, is the ratio of the firm's price P_{it} over its marginal cost λ_{it}. To see this, note the profit maximization problem can be written as:

$$\Pi_{it} = \max_{Q_{it}} P_{it}(Q_{it})Q_{it} - C_{it}(Q_{it}),$$

where $C_{it}(Q_{it})$ is the firm cost function defined by the cost minimization problem:

$$C_{it}(Q_{it}) = \min_{\{X_{it}, K_{it}\}} P^x_{it}X_{it} + r^k_{it}K_{it} \quad \text{subject to (1), with Lagrange multiplier } \lambda_{it}.$$

The first-order condition for profit maximization yields:

$$\frac{\partial C_{it}}{\partial Q_{it}} = P_{it} + \frac{\partial P_{it}}{\partial Q_{it}}Q_{it} = \lambda_{it}$$

where the last equality follows from the envelope condition in the cost minimization problem. Dividing both sides by P_{it} and rearranging yields:

$$P_{it} = \mu_{it}\lambda_{it} \quad \text{and} \quad \mu_{it} = \frac{1}{1+\varepsilon_{P,Q}} \geq 1 \quad \text{with} \quad \varepsilon_{P,Q} \equiv \frac{\partial P_{it}}{\partial Q_{it}}\frac{Q_{it}}{P_{it}} \leq 0 \tag{2}$$

Under monopolistic competition, firms set prices P_{it} equal to a markup μ_{it} over the marginal cost λ_{it}. The markup is a function of the inverse elasticity of demand $\varepsilon_{P,Q}$: the lower the inverse elasticity, the lower the competition, and the larger the markup. Equation (2) shows markups can be estimated from demand elasticities, which gave rise to the demand approach to markup estimation (see Berry et al. (1995)). However, the latter approach requires detailed information on prices and quantities, only available for a small set of goods, industries, and countries.

On the other hand, the production approach to markup estimation, originally developed by Hall (1988) and applied to firm-level datasets by Loecker and Warzynski (2012), relies on the optimality condition for the cost minimization problem, given by:

$$\mathcal{L} = P^x_{it}X_{it} + r^k_{it}K_{it} + F_{it} - \lambda_{it}[Q_{it}(X_{it}, K_{it}; \omega_{it}) - \overline{Q}]$$

where F_{it} is a fixed (overhead) cost and $\overline{Q}$ is a scalar. The first-order condition for the variable input is given by:

$$\frac{\partial \mathcal{L}}{\partial X_{it}} = P_{it}^x - \lambda_{it} \frac{\partial Q_{it}}{\partial X_{it}} = 0.$$

Multiplying both sides by $\frac{X_{it}}{Q_{it}}$ and using the key result from profit maximization (equation (2)) yields:

$$\mu_{it} = \frac{\frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}}{\frac{P_{it}^x X_{it}}{P_{it} Q_{it}}} \equiv \frac{\beta_{it}^x}{\alpha_{it}^x}, \tag{3}$$

where β_{it}^x is the firm's output elasticity of the variable input, and α_{it}^x is the share of expenditures on the variable input ($P_{it}^x X_{it}$) in total sales ($P_{it} Q_{it}$). While the expenditure shares, α_{it}^x, can be directly computed from the data (more details below), the output elasticity, β_{it}^x, is not observable and thus has to be estimated using (production function) proxy methods addressing endogenous factors. That is the goal of the next subsections.

3.1 Estimating the Production Function: Cobb-Douglas Case

Consider a Cobb-Douglas production function for gross output (Q_{it}) with one variable input, X_{it} (call it COGS), and one predetermined input, K_{it} (call it capital):

$$Q_{it} = K_{it}^{\beta_{it}^k} X_{it}^{\beta_{it}^x} \exp(\omega_{it}). \tag{4}$$

Under a Cobb-Douglas production function, factor elasticities are time-invariant. Moreover, I estimate one production function for each industry and country group, meaning that $\beta_{it}^j = \beta^j$, $j \in \{k, x\}$, for all firms i in the same industry and country group.[3] These assumptions are relaxed later under a trans-log production function. Let lowercase letters denote the $\log$ of uppercase letters, and let $y_{it} = q_{it} + \varepsilon_{it}$ be the $\log$ of **observed** gross output, with ε_{it} denoting a zero-mean measurement error. Then, we can write (4) as:

$$y_{it} = \beta^k k_{it} + \beta^x x_{it} + \omega_{it} + \varepsilon_{it}. \tag{5}$$

As is well-known, OLS estimation of (5) yields biased estimates of the output elasticities because of the likely correlation between the firm's input choices and its current productivity: intuitively, firms experiencing a large positive productivity shock may respond using more inputs. The "control function" approach, pioneered by Olley and Pakes (1996) and developed further by Levinsohn and Petrin (2003) and Ackerberg et al. (2015), exploits the fact that, given the timing assumptions, the variable input's demand function can be written as:

$$x_{it} = x(k_{it}, \omega_{it}).$$

Assuming monotonicity of the function $x(.)$, one can invert to write productivity as an (unknown) "control function" of observables: $\omega_{it} = x^{-1}(k_{it}, x_{it})$. Plugging the control function back

[3] I work with the NAICS at two digits of disaggregation and define four country groups: United States (USA), Latin America (LAC), non-USA developed countries (DEV), and non-LAC emerging countries (EME).

into the production function (5) yields:

$$y_{it} = \phi(k_{it}, x_{it}) + \varepsilon_{it} \quad \text{with} \quad \phi(k_{it}, x_{it}) = \beta^k k_{it} + \beta^x x_{it} + x^{-1}(k_{it}, x_{it}) \equiv \phi_{it}$$

The first stage of the procedure consists of removing the measurement error by approximating the function $\phi(k_{it}, x_{it})$ with a n-order polynomial. In practice, I set $n = 2$ and run OLS on:

$$y_{it} = \delta + \delta^k k_{it} + \delta^x x_{it} + \delta^{kk} k_{it}^2 + \delta^{xx} x_{it}^2 + \delta^{kx} k_{it} x_{it} + \varepsilon_{it},$$

to obtain and estimate of projected output $\hat{\phi}_{it} = y_{it} - \hat{\varepsilon}_{it}$. Then, for any vector $\beta = (\beta^k, \beta^x)$, we can write unobserved firm-level productivity ω_{it} as a function of observables and the vector of coefficients to be estimated:

$$\omega_{it} = x^{-1}(k_{it}, x_{it}) = \hat{\phi}_{it} - \beta^k k_{it} - \beta^x x_{it} = \omega_{it}(\beta)$$

The next step relies on assuming that firm-level productivity follows a 1^{st} order Markov process of the form:

$$\omega_{it} = g(\omega_{it-1}) + \eta_{it}.$$

where η_{it} denotes unanticipated idiosyncratic productivity shocks. It is common practice in the literature to approximate $g(.)$ using a 3^{rd} order polynomial, running OLS on:

$$\omega_{it} = \rho_0 + \rho_1 \omega_{it-1} + \rho_2 \omega_{it-1}^2 + \rho_3 \omega_{it-1}^3 + \eta_{it}$$

to obtain an estimate of $\hat{\eta}_{it}(\beta)$, which by assumption, should be uncorrelated with $\big(k_{it}, x_{it-1}\big)$. Therefore, the orthogonality condition to identify $\beta = (\beta^k, \beta^x)$ is given by:

$$E\Bigg[\hat{\eta}_{it}(\beta) | k_{it}, x_{it-1}\Bigg] = 0.$$

3.2 Estimating the Production Function: Trans-Log Case

Consider now a second-order trans-log production function for gross output (Q_{it}) with one variable input, X_{it} (COGS), and one predetermined input, K_{it} (capital):

$$y_{it} = \gamma^k k_{it} + \gamma^x x_{it} + \gamma^{kk} k_{it}^2 + \gamma^{xx} x_{it}^2 + \gamma^{kx} k_{it} x_{it} + \omega_{it} + \varepsilon_{it} \tag{6}$$

This trans-log specification is more flexible than the basic Cobb-Douglas case as it allows for potential nonlinearities in the relationship between inputs and output as well as complementarities between inputs. Moreover, this specification delivers time-varying and firm-specific output elasticities. To see this, note that the elasticities in the trans-log case are by definition:

$$\begin{aligned} \beta_{it}^k &\equiv \frac{\partial y_{it}}{\partial k_{it}} = \gamma^k + 2\gamma^{kk} k_{it} + \gamma^{kx} x_{it} \\ \beta_{it}^x &\equiv \frac{\partial y_{it}}{\partial x_{it}} = \gamma^x + 2\gamma^{xx} x_{it} + \gamma^{kx} k_{it}. \end{aligned} \tag{7}$$

Thus, another advantage of this specification is that it allows for technology changes over time and heterogeneity across firms within the same industry and country.

As in the Cobb-Douglas case, given the timing assumptions, the variable input's demand function can be written as $x_{it} = x(k_{it}, \omega_{it})$, so that, assuming monotonicity of the function $x(.)$, one can invert to write $\omega_{it} = x^{-1}(k_{it}, x_{it})$. Plugging the control function back into (6) yields $y_{it} = \phi(k_{it}, x_{it}) + \varepsilon_{it}$, with:

$$\phi(k_{it}, x_{it}) = \gamma^k k_{it} + \gamma^x x_{it} + \gamma^{kk} k_{it}^2 + \gamma^{xx} x_{it}^2 + \gamma^{kx} k_{it} x_{it} + x^{-1}(k_{it}, x_{it}) \equiv \phi_{it}$$

As before, I approximate $\phi(k_{it}, x_{it})$ non-parametrically to obtain an estimate of projected output, $\hat{\phi}_{it} = y_{it} - \hat{\varepsilon}_{it}$. Then, for any vector $\gamma = (\gamma^k, \gamma^x, \gamma^{kk}, \gamma^{xx}, \gamma^{kx})$, we can write ω_{it} as a function of observables and the vector of parameters to be estimated:

$$\omega_{it} = x^{-1}(k_{it}, x_{it}) = \hat{\phi}_{it} - \gamma^k k_{it} - \gamma^x x_{it} - \gamma^{kk} k_{it}^2 - \gamma^{xx} x_{it}^2 - \gamma^{kx} k_{it} x_{it} = \omega_{it}(\gamma)$$

Assuming that the firm's productivity follows a first-order Markov process $\omega_{it} = g(\omega_{it-1}) + \eta_{it}$, and approximating $g(.)$ with a 3^{rd} order polynomial to obtain an estimate of $\hat{\eta}_{it}(\gamma)$, the orthogonality condition to identify $\gamma = (\gamma^k, \gamma^x, \gamma^{kk}, \gamma^{xx}, \gamma^{kx})$ is given by:

$$E\left[\hat{\eta}_{it}(\gamma) | k_{it}, x_{it-1}, k_{it}^2, x_{it-1}^2, k_{it} x_{it-1}\right] = 0$$

Finally, after obtaining an estimate of $\hat{\gamma}$, I recover the output elasticities using (7).

Table 2 summarizes the estimated production function elasticities for each economic sector and country group using the Trans-Log specification. Since these coefficients are firm-specific and time-varying, for each $j \in \{k, x\}$, I report $\overline{\beta}^j = \frac{1}{T} \sum_t \sum_i m_{it} \beta_{it}^j$, that is, the weighted averages across firms with SALES-based weights m_{it}, and then simple averaging across years.

The results show that Latin American countries (LAC) have low capital intensity, measured by the estimated capital elasticity $\overline{\beta}^k$, relative to emerging and, especially, developed economies. For instance, the cross-sector simple average capital elasticity in LAC is 0.11 compared to 0.12 in other emerging economies, 0.17 in non-United States developed economies, and 0.19 in the United States. The LAC sectors with the largest capital intensity gaps relative to the United States are mining and quarrying (NAICS code 21), manufacturing of wood, paper, and chemicals (NAICS code 32), transportation and warehousing (NAICS code 48), professional, scientific, and technological services (NAICS code 54), health care (NAICS code 62), and arts, entertainment, and recreation (NAICS code 71).

Consequently, the COGS elasticity $\overline{\beta}^x$ tends to be larger in LAC than in other countries, especially relative to developed countries and the United States. The cross-sector simple average COGS elasticity in LAC is 0.91 compared to 0.87 in the non-LAC emerging economies, 0.84 in non-United States developed economies, and 0.78 in the United States. All manufacturing, agriculture, education, and health care are the LAC sectors with the largest COGS elasticity. In contrast, the sectors in the region with the lowest COGS share are information and utilities.

Finally, the results from the translog method deliver estimates that are on average, very close to constant returns to scale ($\overline{\beta}^k + \overline{\beta}^x$), with a cross-sector simple average of 1.02 in LAC, 1.00 in non-LAC emerging countries, 1.01 in non-USA developed economies, and 0.97 in the USA.

Table 2: Production Function: Output Elasticities

NAICS	Sector Description	USA	Developed	Emerging	LAC
	$\overline{\beta}^k$, Output Elasticity, K				
11	Agriculture, Forestry, Fishing	0.00	0.06	0.09	0.03
21	Mining, Quarrying	0.38	0.18	0.33	0.16
22	Utilities	0.13	0.26	0.26	0.24
23	Construction	0.03	0.10	0.03	0.08
31	Manuf1, Food, Textile, Apparel	0.15	0.16	0.05	0.10
32	Manuf2, Wood, Paper, Chemicals	0.23	0.18	0.09	0.02
33	Manuf3, Metals, Machinery	0.09	0.03	0.03	0.01
42	Wholesale Trade	0.11	0.06	0.05	0.06
44	Retail Trade	0.20	0.17	0.08	0.14
48	Transportation and Warehousing	0.23	0.19	0.16	0.07
51	Information	0.14	0.25	0.24	0.34
54	Prof., Scient., Tech. Services	0.40	0.23	0.10	0.01
55	Management of Companies	0.19	0.17	0.04	0.16
61	Education Services	0.14	0.01	0.09	0.14
62	Health Care	0.39	0.49	0.14	0.00
71	Arts, Entertainment, Recreation	0.39	0.22	0.11	0.10
72	Accomodation and Food Services	0.11	0.18	0.22	0.20
	$\overline{\beta}^x$, Output Elasticity, COGS				
11	Agriculture, Forestry, Fishing	1.10	0.96	0.93	1.00
21	Mining, Quarrying	0.61	0.88	0.70	0.84
22	Utilities	0.67	0.74	0.70	0.76
23	Construction	0.96	0.96	1.00	0.90
31	Manuf1, Food, Textile, Apparel	0.85	0.85	0.97	1.02
32	Manuf2, Wood, Paper, Chemicals	0.74	0.84	0.87	0.96
33	Manuf3, Metals, Machinery	0.90	1.00	0.94	1.01
42	Wholesale Trade	0.85	0.94	0.92	0.92
44	Retail Trade	0.74	0.78	0.88	0.80
48	Transportation and Warehousing	0.79	0.86	0.88	0.96
51	Information	0.78	0.67	0.78	0.68
54	Prof., Scient., Tech. Services	0.60	0.76	0.89	0.96
55	Management of Companies	0.63	0.81	1.04	0.87
61	Education Services	0.77	1.13	0.85	1.00
62	Health Care	0.66	0.49	0.84	1.02
71	Arts, Entertainment, Recreation	0.64	0.72	0.94	0.91
72	Accomodation and Food Services	0.89	0.84	0.73	0.85
	$\overline{\beta}^k + \overline{\beta}^x$, Returns To Scale				
11	Agriculture, Forestry, Fishing	1.10	1.02	1.02	1.03
21	Mining, Quarrying	0.99	1.06	1.03	0.99
22	Utilities	0.80	0.99	0.95	1.00
23	Construction	1.00	1.06	1.03	0.97
31	Manuf1, Food, Textile, Apparel	1.00	1.01	1.03	1.11
32	Manuf2, Wood, Paper, Chemicals	0.97	1.02	0.96	0.98
33	Manuf3, Metals, Machinery	0.99	1.03	0.97	1.02
42	Wholesale Trade	0.95	1.00	0.97	0.98
44	Retail Trade	0.94	0.95	0.96	0.94
48	Transportation and Warehousing	1.02	1.05	1.03	1.03
51	Information	0.92	0.92	1.01	1.02
54	Prof., Scient., Tech. Services	1.00	0.99	1.00	0.97
55	Management of Companies	0.82	0.98	1.08	1.03
61	Education Services	0.91	1.14	0.94	1.13
62	Health Care	1.06	0.98	0.98	1.02
71	Arts, Entertainment, Recreation	1.02	0.94	1.06	1.01
72	Accomodation and Food Services	0.99	1.02	0.95	1.05

Notes: The table reports $\overline{\beta}^j = \frac{1}{T}\sum_t \sum_i m_{it}\beta^j_{it}$, for each $j \in \{k, x\}$, that is, weighted averages across firms with SALES-based weights m_{it}, and then simple averaging across years for each NAICS two-digit sector (rows) and country group (columns).

3.3 Variable Input Expenditure Shares

Unlike the output elasticities, the expenditure shares, α_{it}^{x}, can be directly computed from the data. Typical choices for the variable input X used in the literature are intermediate inputs, materials, and labor. However, the cross-country database used here only provides information for the "Cost of Goods Sold" (COGS), which bundles expenses directly attributable to production, including materials, intermediate inputs, wage bill, electricity, etc. Therefore, following De Loecker et al. (2020) (who use Compustat data) and Díez et al. (2021) (who use Orbis data), I compute the sales share of the variable input as:

$$\alpha_{it}^{x} = \frac{P_{it}^{x} X_{it}}{P_{it} Q_{it}} = \frac{\text{COGS}_{it}}{\text{SALES}_{it}} \tag{8}$$

Table 3 reports the weighted average α_{it}^{x} by economic sector and country groups. The simple average COGS share across sectors is 0.67 in LAC, 0.70 in other emerging economies, 0.66 in non-United States developed countries, and 0.63 in the United States.

The sectors with the largest variable input (COGS) expenditure shares in LAC are agriculture, construction, manufacturing of metals and machinery, wholesale trade, transportation, and professional services. Analogously, the region's sectors with the lowest expenditure shares are mining and quarrying, information, education, accommodation, and food services. At a country group level, it is generally the case that emerging economies, including LAC, display larger variable input expenditure shares than developed economies, including the United States.

Table 3: Average COGS Expenditure Shares in Total Sales ($\overline{\alpha}^{x}$)

NAICS	Sector Description	USA	Developed	Emerging	LAC
11	Agriculture, Forestry, Fishing	0.94	0.74	0.76	0.76
21	Mining, Quarrying	0.65	0.68	0.51	0.54
22	Utilities	0.36	0.69	0.69	0.63
23	Construction	0.80	0.67	0.81	0.75
31	Manuf1, Food, Textile, Apparel	0.64	0.59	0.72	0.64
32	Manuf2, Wood, Paper, Chemicals	0.63	0.67	0.77	0.68
33	Manuf3, Metals, Machinery	0.70	0.76	0.80	0.78
42	Wholesale Trade	0.90	0.85	0.90	0.83
44	Retail Trade	0.73	0.75	0.83	0.72
48	Transportation and Warehousing	0.53	0.70	0.75	0.75
51	Information	0.43	0.47	0.44	0.48
54	Prof., Scient., Tech. Services	0.61	0.67	0.73	0.75
55	Management of Companies	0.65	0.69	0.79	0.74
61	Education Services	0.49	0.61	0.60	0.54
62	Health Care	0.49	0.54	0.61	0.66
71	Arts, Entertainment, Recreation	0.50	0.60	0.71	0.73
72	Accomodation and Food Services	0.65	0.48	0.56	0.48

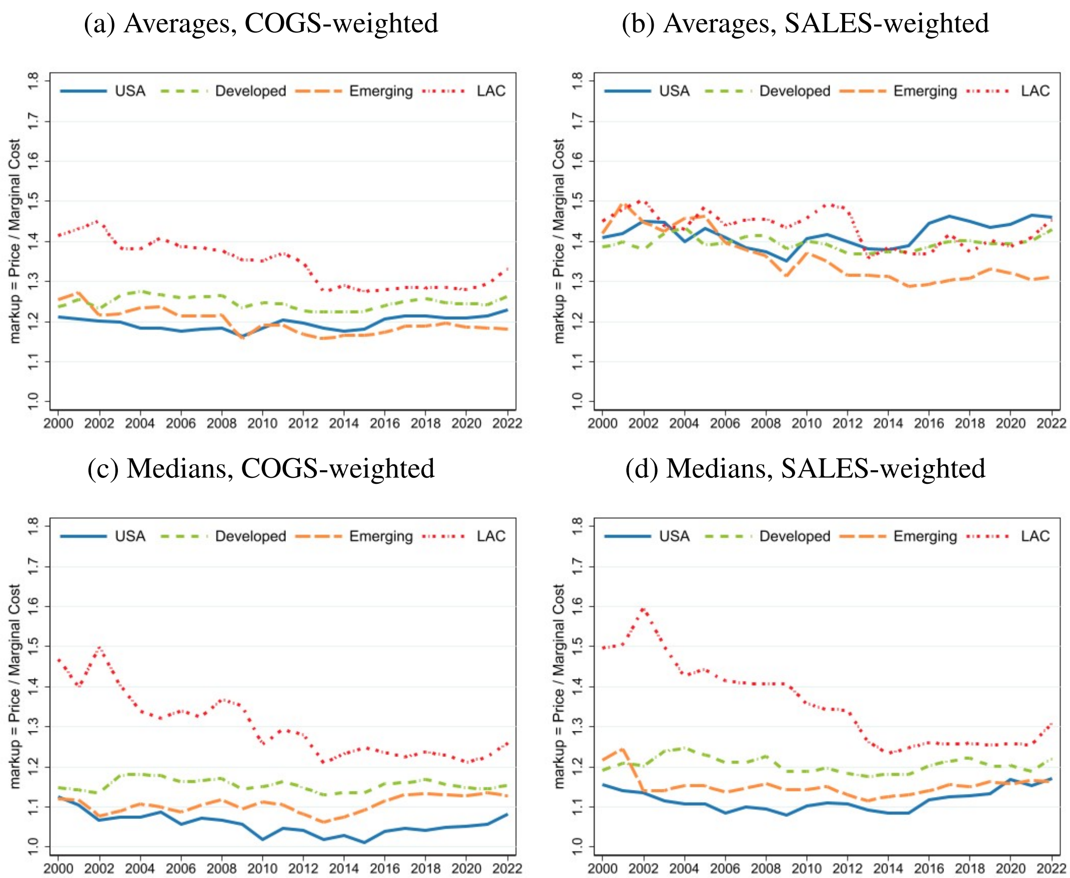
Notes: The table reports $\overline{\alpha}^{x} = \frac{1}{T}\sum_t \sum_i m_{it}\alpha_{it}^{x}$, that is, the weighted averages across firms with SALES-based weights m_{it}, and then simple averaging across years for each NAICS two-digit sector (rows) and country group (columns).

4 The Evolution of Markups over the Last Two Decades

Equipped with firm-level data to compute the expenditure share of the variable input, α_{it}^{x}, and the estimated output elasticities, β_{it}^{x}, I compute firm-level markups, μ_{it}, directly using equation (3). Figure 1 shows the evolution of markups by country groups in the last two decades: Panels (a) and (b) illustrate COGS-weighted and SALES-weighted **averages**, respectively, while panels (c) and (d) display analogously weighted **medians**.[4] All results are reported for the second-order trans-log production function case.

From a worldwide perspective, Figure 1 reveals that market power, measured as the wedge between a firm's price and its marginal cost, is relatively high in Latin America. Regardless of the weighting scheme (COGS vs. SALES) and central tendency measures (mean vs. median), LAC countries display the largest markups over most, if not all, of the years in the sample. When looking at medians, the ranking over country groups is fairly stable, with LAC displaying the largest markups, followed by developed countries, emerging economies, and then the United States.

Figure 1: Markups by Country Group



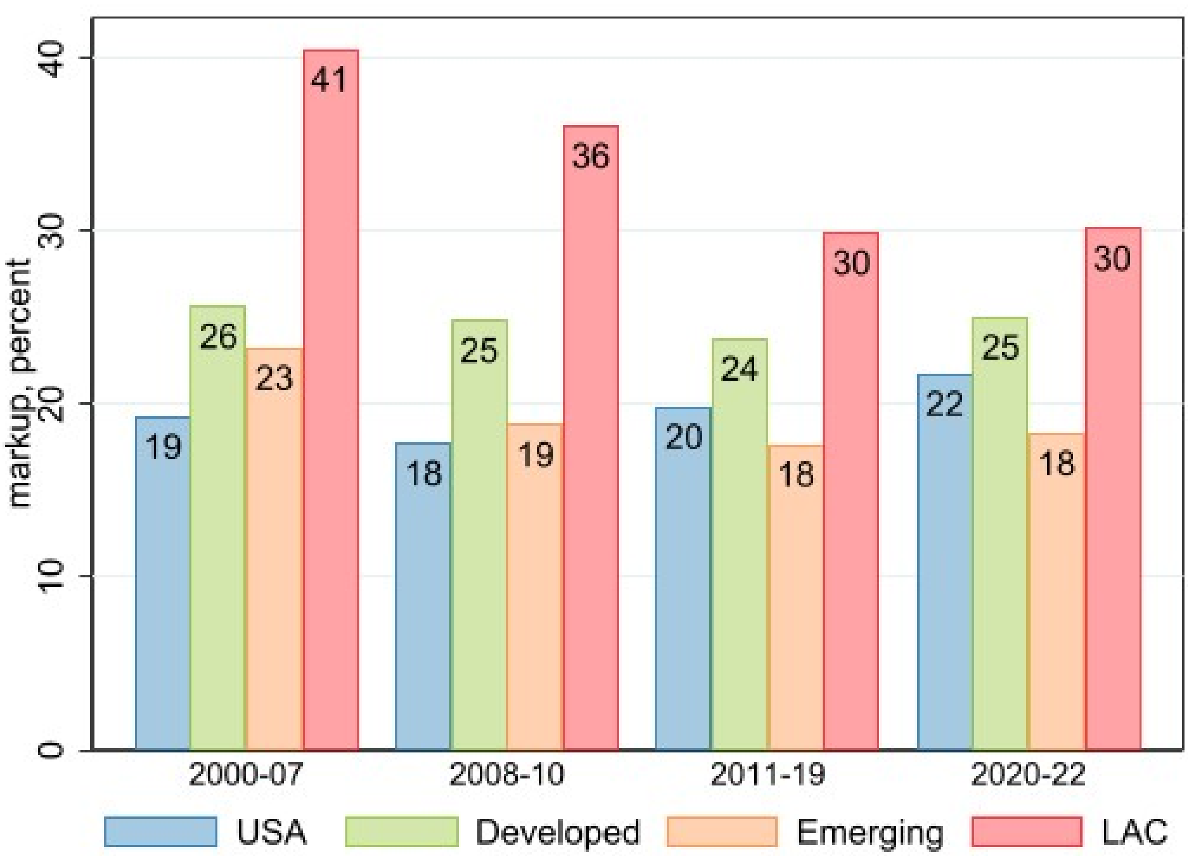
Notes: Authors' calculations based on data from Refinitiv. Firm-level markups are computed using equation (3) with the output elasticity estimated under a second-order trans-log production function.

[4]Using a classic monopolistically competitive framework of endogenously heterogeneous markups, Edmond et al. (2023) shows that the theoretically relevant weighting scheme for aggregating markups is the variable input cost, COGS, as opposed to the more frequently used SALES variable.

Using panel (a) as the benchmark, I compute a weighted average markup of 41% for LAC in the pre-Great Recession period 2000-07, compared to 23% in other emerging economies, 26% in developed countries, and 19% in the USA. However, markups in the region registered a downward trend from the very high levels reached in the mid-2000s and until the end of the commodity supercycle around 2013, to stabilize thereafter as illustrated in Figure 2. For instance, from 2011 to 2019, average markups in the region fell to 30%, lower than in the first decade of the 21st century but still significantly higher than in other emerging countries (18%), developed economies (24%), or the United States (20%). This same pattern is even more pronounced when analyzing weighted medians in panels (c) and (d) of Figure 1, which is reassuring as we confirm outlier values do not drive the main trends observed in the data.

On the other hand, comparing weighting schemes across panels (a) and (b), we observe that for all country groups, SALES-weighted markups are higher than the COGS-weighted ones: in other words, high-markup firms have, on average, higher SALES-based weights than COGS-based weights, a pattern also found by De Loecker et al. (2020) for the U.S. economy since the 1960s, and by De Loecker and Eeckhout (2018) worldwide since the 1980s. I will return to this issue in Section 6, discussing the firm-level relationship between markups and size.

Figure 2: Average Markups by Country Group and Subperiods



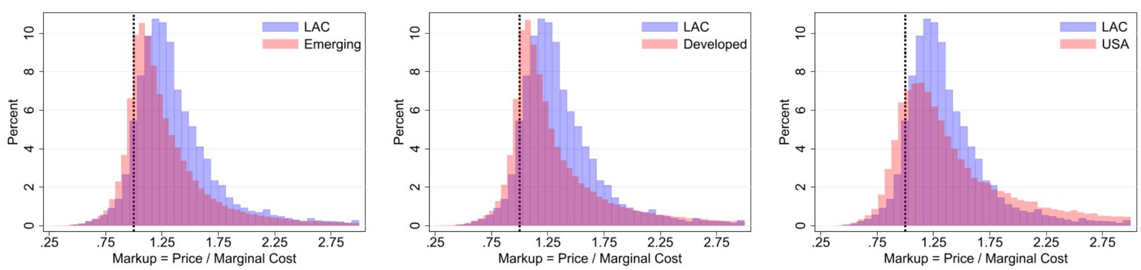
Notes: Authors' calculations based on data from Refinitiv. Each bar is obtained as the simple average across years of the COGS-weighted average markups reported in Panel (a) of Figure 1. Firm-level markups are computed using equation (3) with the output elasticity estimated under a second-order trans-log production function.

5 The Distribution of Markups

In this section, I characterize the full distribution of markups to better grasp the heterogeneity in market power across firms and countries. Figure 3 shows the (unweighted) histogram of markups in LAC compared to three benchmarks: Emerging economies, Developed economies, and the United States. The histograms pool data from firms in all sectors and years in the sample 2000-2022. Overall, the results confirm that LAC displays high markups relative to other regions worldwide. For instance, focusing on the most common markup values from 1 to 2, the region displays significantly more mass of firms than the three benchmarks considered. In contrast, for values above 2, the LAC distribution is similar to other emerging or developed economies, except the United States. Indeed, the United States displays an especially fat right tail, which means it is significantly more likely to find U.S. firms with markups above 2 than in LAC or any other country group.

Figure 3: Markups Distribution by Country Groups

(a) LAC versus Emerging (b) LAC versus Developed (c) LAC versus USA



Notes: Probability distribution of markups by country group. The sum of the height of the bars equals 100, so that the y-axis represents the probability of observing that markup value in the sample. Pooling all years in the period 2000-2022. Firm-level markups are computed using equation (3) with the output elasticity estimated under a second-order trans-log production function. The vertical line at markup $\mu = 1$ denotes the perfect competition benchmark.

Table 4 summarizes the distributions illustrated in Figure 3. Specifically, I compute COGS-weighted statistics for each year and country group and then average the results across all years in the sample 2000-2022. As noted above, the LAC region registers the largest weighted average (1.34 or 34%) and weighted median (1.30) markup over the sample. It is noteworthy that the median markup of 30% in LAC doubles the median markup in developed economies (15%), almost triples the median in other emerging economies (11%), and is five times larger than in the United States (6%)!

Firms in Latin America and the Caribbean also display the lowest markup dispersion measured by the standard deviation, with a value of 0.35 versus 0.4 in other emerging and developed economies and 0.5 in the USA. In contrast, the interquartile range (IQR) is relatively high in LAC (0.34) relative to the benchmarks (0.32 in the United States, 0.28 in Developed, and 0.25 in Emerging), which, combined with the relatively low standard deviations in the region, suggests that most of the differences between LAC and the rest of the world are located at the tails of the distribution. On the one hand, the incidence of markups below one is much smaller in LAC than in other regions: for instance, firms at the 1st percentile of the markup distribution in the United States have average markups of 0.75 (-25%), while the analogous figure in LAC is 0.91 (-9%). On the other hand, LAC firms at high percentiles of the markup distribution do not "enjoy" the same degree of market power as analogous firms worldwide: for instance, firms in the 99th percentile have markups of 3.35 (235%) in the USA versus 2.73 (173%) in LAC.

Notably, for all percentiles between p1 and p75, the typical firm in LAC displays a higher markup than its peer in any other country group; excluding the United States from the analysis, the latter statement is also true for all percentiles between p1 and p95! Only around the 95th percentile do high-markup firms in the rest of the world start catching up and surpassing the values observed in LAC. Also noteworthy is the fact that U.S. firms record the largest markups in the world, starting at p90, which can be interpreted as a combination of lower competition in certain industries (Covarrubias et al. (2020)) and/or the rise of superstar firms in other sectors (Autor et al. (2017)).

In turn, Table 5 reproduces the results in Table 4 for each LAC country in the dataset. On average, the largest weighted average markups over the period are observed in Peru (1.40) and Brazil (1.39), although Brazil also displays by far the largest median markups (1.38), followed by Mexico (1.31) and Argentina (1.30). In contrast, Chile and Colombia show the lowest markup levels and markup dispersion in the region.

Table 4: Key Statistics of the Markups Distribution, by Country Groups

	mean	sd	p1	p5	p10	p25	p50	p75	p90	p95	p99
USA	1.20	0.50	0.75	0.83	0.88	0.93	1.06	1.25	1.68	2.05	3.35
Developed	1.25	0.41	0.80	0.90	0.96	1.04	1.15	1.32	1.62	1.88	2.95
Emerging	1.20	0.40	0.78	0.90	0.96	1.01	1.11	1.26	1.51	1.76	2.82
LAC	1.34	0.35	0.91	0.98	1.03	1.13	1.30	1.47	1.63	1.90	2.73

Notes: The table reports the simple average across years in the sample 2000-2022 of the COGS-weighted statistics computed for each year and country group.

Table 5: Key Statistics of the Markups Distribution, by LAC country

	mean	sd	p1	p5	p10	p25	p50	p75	p90	p95	p99
Argentina	1.35	0.43	0.83	0.93	1.01	1.14	1.30	1.42	1.62	2.11	2.98
Brazil	1.39	0.32	0.97	1.01	1.07	1.23	1.38	1.49	1.62	1.76	2.73
Chile	1.24	0.29	0.90	0.99	1.05	1.12	1.17	1.31	1.45	1.58	1.98
Colombia	1.26	0.24	1.01	1.07	1.07	1.15	1.24	1.27	1.50	1.60	2.01
Mexico	1.35	0.35	0.99	1.01	1.01	1.08	1.31	1.49	1.80	2.06	2.25
Peru	1.40	0.46	0.95	1.01	1.04	1.10	1.21	1.58	1.99	2.34	2.95

Notes: The table reports the simple average across years in the sample 2000-2022 of the COGS-weighted statistics computed for each year and country.

Table 6 summarizes the distribution of markups in Latin America for each two-digit (non-financial) economic sector. Education and Accommodation and Food Services stand out as the sectors with the highest average markups (1.91 and 1,82, respectively), followed by Manufacturing sectors related to Food and Textiles (1.60), Mining and Quarrying (1.58), and Health Care (1.54). In contrast, Wholesale and Retail Trade display the lowest average markups in the region (1.11 and 1.12, respectively). Accommodation and Food Services is also one of the industries with the largest heterogeneity within the sector, with a standard deviation of 0.66 and an interquartile range of 1.11 (2.50-1.39), followed not so closely by Manufacturing of Food and Textiles, Utilities, and Information, with a standard deviation of around 0.44. The Wholesale Trade sector registers not only the lowest average markup but also the lowest dispersion, pointing to a relatively more competitive sector.

Table 6: LAC: Markups Distribution by Economic Sector

NAICS	Sector Description	mean	sd	p25	p50	p75
11	Agriculture, Forestry, Fishing	1.32	0.18	1.25	1.30	1.39
21	Mining, Quarrying	1.58	0.33	1.42	1.62	1.68
22	Utilities	1.24	0.44	1.02	1.12	1.34
23	Construction	1.21	0.30	1.05	1.14	1.30
31	Manuf1, Food, Textile, Apparel	1.60	0.44	1.28	1.44	1.86
32	Manuf2, Wood, Paper, Chemicals	1.43	0.21	1.33	1.47	1.50
33	Manuf3, Metals, Machinery	1.31	0.13	1.25	1.30	1.35
42	Wholesale Trade	1.11	0.06	1.07	1.12	1.13
44	Retail Trade	1.12	0.16	1.00	1.07	1.21
48	Transportation and Warehousing	1.29	0.34	1.15	1.21	1.36
51	Information	1.43	0.43	1.24	1.41	1.48
54	Prof., Scient., Tech. Services	1.30	0.19	1.24	1.26	1.36
55	Management of Companies	1.19	0.39	1.02	1.13	1.21
61	Education Services	1.91	0.31	1.75	1.91	2.11
62	Health Care	1.54	0.22	1.42	1.51	1.60
71	Arts, Entertainment, Recreation	1.27	0.13	1.24	1.27	1.30
72	Accomodation and Food Services	1.82	0.66	1.39	1.62	2.50

Notes: The table reports the simple average across years in the sample 2000-2022 of the COGS-weighted statistics computed for each year and sector, pooling all firms in Latin American Countries (LAC).

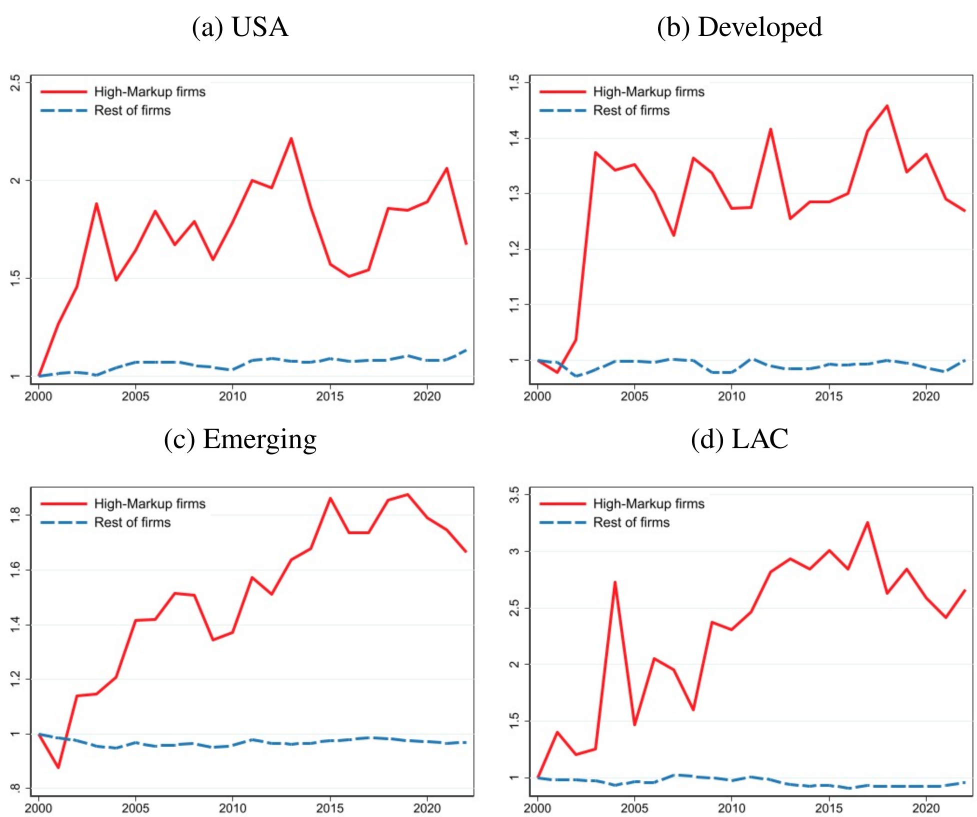
Turning to the time evolution of the distribution of markups, several studies have found a disconnect between the evolution of markups for the average firm versus firms at the top of the markup distribution. To see this, for each country group, I ranked the firms by their average markup over the full sample and then separated them into two groups: firms in the top decile of the markup distribution and the rest. To study the progression of markups in each group, I run a simple regression of markups on the left-hand side against year dummies, also controlling for sector-country fixed effects. Figure 4 plots, for each country group, the coefficients on the year dummies for the regression ran on the high-markup firms (solid-red lines) and the rest (blue-dashed lines). Note the dummy for the year 2000 is excluded from the regression, so all coefficients are interpreted relative to the base omitted year, which is normalized to 2000=1.

The results show that aggregate markup dynamics are overwhelmingly driven by high-markup firms. For instance, U.S. firms in the top decile of the markup distribution register a markup rise of about 70% between 2000 and 2022, in stark contrast to the rest of the firms, which only increase their markups by about 10% in the same period (Panel (a)).

Analogously, the results for the rest of the developed economies reveal an increase of almost 30% in the average markup of the top decile firms, as opposed to zero growth for the remaining nine deciles of the distribution (Panel (b)). Non-LAC emerging economies display a similar increase of 70%, as in the United States, for the top decile, but in this case, with even a slight decline in the average markup of the remaining nine deciles (Panel (c)).

Finally, it is noteworthy that the rise in the markup of the already high markup firms is especially pronounced in LAC, with an overall increase above 150% in 2022 relative to the base year 2000, with no growth whatsoever in the average markup of the remaining nine deciles of the distribution (Panel (d)).

Figure 4: Markup Dynamics Driven by High-Markup Firms, Index 2000=1



Notes: Authors' calculations based on data from Refinitiv. The figures show year-fixed effects from regressions of markups, also controlling for sector-country fixed effects. Firms in each country group are ranked into deciles according to their average markup over the full sample period. The solid red lines show the results for the top decile of the markup distribution, while the dashed blue lines depict the results for the rest of the firms. The omitted base year in the regression is normalized to 2000=1, so all coefficients are interpreted as relative to 2000.

6 Do Larger Firms Charge Higher Markups?

To illustrate the unconditional correlation between firm size and markups, I compute an Olley and Pakes (1996) (OP) style decomposition of aggregate markups, μ_t, into the unweighted aggregate markup, $\overline{\mu}_t$, and the covariance between firm weights (ω_{it}) and firm markups (μ_{it}), as follows:

$$\mu_t = \underbrace{\sum_i \omega_{it}\mu_{it}}_{\text{Weighted Markup}} = \underbrace{\overline{\mu}_t}_{\text{Unweighted Markup}} + \underbrace{\sum_i (\omega_{it} - \overline{\omega}_t)(\mu_{it} - \overline{\mu}_t)}_{\text{reallocation (covariance)}},$$

where bar variables denote the unweighted average across all firms in all sectors in a given year.

The time evolution of the unweighted markup captures shifts in the markup distribution. The covariance term measures the importance of firm reallocation. If the unweighted average increases over time, some firms are moving up in the markup distribution. An increasing covariance term points to high markup firms gaining market share. In the cross-section, a positive covariance term indicates larger firms have higher markups, as most classic theories of heterogeneous markups predict. For instance, under Cournot competition, the firm's size measured as the SALES-based market share is a sufficient statistic to recover a firm's markup (see Atkeson and Burstein (2008) and Edmond et al. (2015)). Similarly, under monopolistic competition with Kimball (1995) demand, more productive firms grow larger, face less competition, and therefore can charge higher markups (see Edmond et al. (2023)).

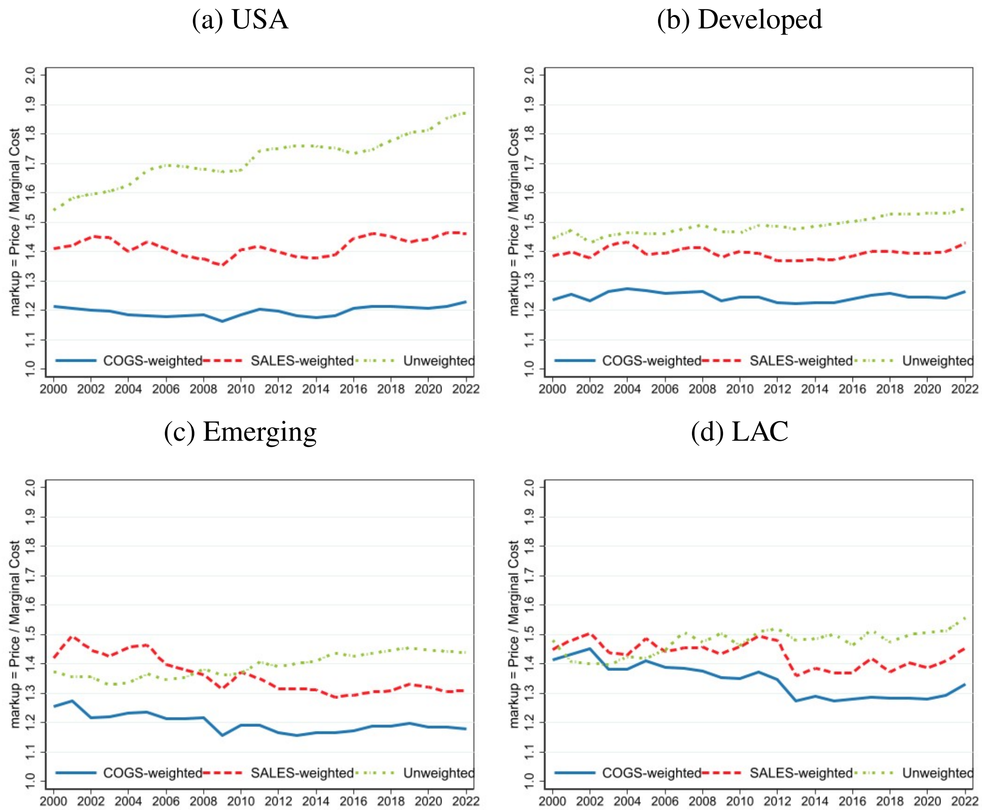
Figure 5 illustrates the OP decomposition results for each country group. Unweighted averages are usually higher than weighted average markups, implying a negative covariance term: larger firms have lower markups! As emphasized by De Loecker and Eeckhout (2017), the latter empirical result is obtained when comparing all firms **across** all sectors, while the theoretical prediction is **within** a given industry. Using Compustat data **across** all sectors in the U.S. economy in the period 1960-2014, De Loecker and Eeckhout (2017) find that larger (sales-based) firms charge **lower** markups than smaller firms. However, when looking at **within** narrowly defined industries, they recover the theoretical prediction of a positive correlation between firm size and market power. In contrast, using Orbis data for 20 (mostly European) countries from 2000-2015, Díez et al. (2021) find a negative correlation between size and markups, even within narrowly defined industries. They also find the relationship is highly nonlinear as the negative correlation may become positive at the top of the size distribution.

To uncover the systematic relationship between firm size and markups, controlling for sector-specific trends and firm characteristics, I follow Díez et al. (2021) and run the following econometric specification for each country group:

$$\log(\mu_{it}) = \alpha + \beta_1 SIZE_{it} + \beta_2 \left(SIZE_{it}\right)^2 + \gamma_1 \log(TFP_{it}) + \gamma_2 \log(SGA_{it}) + \varphi_{st} + \varphi_i + \varepsilon_{it}$$

where $SIZE_{it}$ is measured as the (SALES-based) market share of firm i in sector s in year t, TFP_{it} denotes total factor productivity, SGA_{it} is a measure of (fixed) overhead cost (selling, general, and administrative expenses), while φ_{st} and φ_i represent (two-digit) sector-year and firm fixed effects, respectively. I include time-varying firm characteristics, such as total factor productivity, to control for firms' ability, and overhead costs (SGA expenses) to control for the possibility that firms charge higher markups not due to market power but rather to cover high fixed/overhead costs.

Figure 5: Weighted and Unweighted Average Markups



Notes: Authors' calculations based on data from Refinitiv. For each country group, the solid blue (dashed red) line shows the COGS (SALES) weighted average markup level, while the dashed-dotted green line reports the unweighted average markup.

Table 7 presents the results by country group. The "Cross Section" regression (excluding firm fixed effects) confirms the results obtained in Figure 5: there is a negative correlation between markups and size. On average, larger firms charge lower markups. However, as emphasized by Díez et al. (2021), the markup-size relationship is remarkably nonlinear, as the coefficients associated with the quadratic term are largely positive and significant.

To illustrate this nonlinear relationship, I compute the marginal effects of size on markups ($\frac{\partial \log(\mu_{it})}{\partial SIZE_{it}} = \hat{\beta}_1 + 2\hat{\beta}_2 SIZE_{it}$) at different percentiles of the size distribution. For instance, from column (1) in Table 7, the margin evaluated at the median (p50) size worldwide is -0.396, meaning a one percentage point increase in the firm's market share is associated with a -0.396% lower markup. In contrast, evaluated at the 99th percentile (p99), the margin of size on markups becomes positive: at the very top of the size distribution, a one percentage point increase in market share is associated with a 0.425% higher markups. This nonlinear pattern is qualitatively robust across country groups, although some relevant quantitative differences exist. For instance, in the United States, the correlation is negative even at the very top of the size distribution (column (2)), while in LAC the correlation becomes positive at the 95th percentile (column (5)).

While the cross-sectional regressions in columns (1) to (5) consider differences between firms, columns (6) to (10) identify the markup-size correlation based on within-firm changes over time. The results become more nuanced in the latter case, as the significant nonlinear relationship only survives in the United States and other developed economies.

Table 7: Dependent Variable: (log) Markup

$\log(\mu_{it})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Cross Section					Within Firm		
	World	USA	DEV	EME	LAC	World	USA	DEV	EME	LAC
$SIZE_{it}$	-0.397***	-1.777***	-0.482***	-0.509***	-0.490***	-0.037	-1.026*	-0.251***	0.042	-0.135
	(0.046)	(0.468)	(0.079)	(0.063)	(0.134)	(0.048)	(0.529)	(0.082)	(0.069)	(0.136)
$(SIZE_{it})^2$	0.429***	2.413***	0.465***	0.554***	0.372***	0.066	1.420	0.193**	0.030	0.145
	(0.051)	(0.707)	(0.088)	(0.071)	(0.128)	(0.047)	(0.864)	(0.077)	(0.068)	(0.129)
$\log(SGA_{it})$	0.028***	0.002	0.036***	0.028***	0.029***	0.032***	0.012*	0.043***	0.031***	0.045***
	(0.001)	(0.004)	(0.002)	(0.001)	(0.007)	(0.002)	(0.006)	(0.003)	(0.002)	(0.012)
$\log(TFP_{it})$	0.133***	0.263***	0.498***	0.336***	0.588***	0.233***	0.153***	0.283***	0.230***	0.272***
	(0.013)	(0.054)	(0.028)	(0.030)	(0.122)	(0.014)	(0.051)	(0.029)	(0.022)	(0.083)
Margins $SIZE$										
at p50	-0.396***	-1.775***	-0.481***	-0.507***	-0.460***	-0.037	-1.024*	-0.250***	0.042	-0.123
at p75	-0.387***	-1.761***	-0.472***	-0.494***	-0.358***	-0.036	-1.016*	-0.247***	0.043	-0.083
at p90	-0.329***	-1.695***	-0.416***	-0.405***	-0.102***	-0.027	-0.977*	-0.223***	0.048	0.017
at p95	-0.191***	-1.574***	-0.273***	-0.208***	0.173*	-0.006	-0.905**	-0.163***	0.058	0.124
at p99	0.425***	-1.106***	0.367***	0.598***	0.253*	0.089*	-0.630**	0.103	0.102	0.156
Firm FE	no	no	no	no	no	yes	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	417,144	42,186	197,154	167,611	10,178	415,160	41,892	196,527	166,556	10,170
N. firms	36968	4021	15676	16524	747	34984	3727	15049	15469	739
N. countries	70	1	27	36	6	70	1	27	36	6
R-sqr Adj.	0.078	0.082	0.111	0.097	0.175	0.780	0.790	0.795	0.752	0.757
Dep. var. mean	0.290	0.395	0.293	0.258	0.322	0.289	0.394	0.293	0.257	0.322

7 Market Power and Firm Investment

Do high markup firms invest more? In theories of "good" market concentration, higher market power reflects a technological change process in which a few leading firms gain market share through efficiency gains and high investment rates (see "winner takes most" argument by Autor et al. (2017) and "the rise of superstars firms" theory in Autor et al. (2020)). In contrast, in theories of "bad" concentration, high market power reflects barriers to entry, monopolistic rents, low pass-through from cost reductions into prices, and low incentives to invest and innovate by market leaders (see Gutiérrez and Philippon (2017) and Covarrubias et al. (2020)).

To study the relationship between firm markups and firm investment, I run the following empirical model:

$$\log\left(\frac{I_{it}}{K_{i,t-1}}\right) = \alpha + \beta_1 \log(\mu_{i,t-1}) + \beta_2 \left(\log(\mu_{i,t-1})\right)^2 + \gamma_1 \log(Q_{i,t-1}) + \gamma_2 \log(LEV_{i,t-1}) + \gamma_3 \log(CASH_{i,t-1}) + \varphi_{st} + \varphi_i + \varepsilon_{it}$$

where the left-hand side variable is the (log) investment rate measured as capital expenditures ($I =$ CAPEX) over lagged capital stock ($K =$ Property, Plants, and Equipment). Firm-level markups (μ_{it}) enter the equation with a linear and a quadratic term to test for the potentially nonlinear correlation between investment and market power. The right-hand side controls include firms'

Tobin's Q (Q_{it}, proxied as the ratio of the firms' market capitalization over the book value of total assets), leverage (LEV_{it}, total debt outstanding over total assets), and cash rate ($CASH_{it}$, cash and equivalents over total assets). All regressors are logged and lagged by one year. To reduce endogeneity concerns, the regression also includes sector-time fixed effects (φ_{st}) and, depending on the specification, firm fixed effects (φ_i).

In sum, the β coefficients measure the (potentially nonlinear) correlation between markups and investment at the firm level, controlling for standard theories of firm investment, including the Q-theory ($\gamma_1 > 0$), debt overhang ($\gamma_2 < 0$), and financial (liquidity) constraints ($\gamma_3 > 0$).

The results presented in Table 8 indicate there is a positive and significant correlation between firms' markups and investment rates, that is, $\hat{\beta}_1 > 0$ for all country groups considered. Interestingly, the results also confirm the hypothesis of a nonlinear relationship, as the coefficient on the quadratic markup term is significantly negative $\hat{\beta}_2 < 0$ in all specifications. These results are consistent with those obtained by Díez et al. (2018), who, focusing on advanced economies, also find evidence of a non-monotonic relation, with higher markups being correlated initially with increasing and then with decreasing investment.

In a nutshell, the results in Table 8 reveal that the relationship between markups and investment depends heavily on the level of the markup. To see this, the table reports marginal effects of markups on investment $\left(\frac{\partial \log(I_{it}/K_{i,t-1})}{\partial \log(\mu_{i,t-1})} = \hat{\beta}_1 + 2\hat{\beta}_2 \log(\mu_{i,t-1})\right)$ at different percentiles of the markup distribution. For instance, from the worldwide regression in column (1), for a typical firm with median markup (p50), the marginal effect is 0.86, meaning that a 1% increase in markups implies a 0.86% increase in the investment rate. Importantly, given that $\hat{\beta}_2 < 0$, these margins are monotonically decreasing when moving up in the markup distribution, rendering a negative effect at the very top of the markup distribution (p99). For firms at the 99th percentile of the markup distribution, a 1% increase in markups implies a -0.44% reduction in investment.

This nonlinear correlation between market power (proxied through markups) and investment is qualitatively similar across country groups and econometric specifications ("Cross Section" versus "Within Firm"), being especially strong in non-LAC emerging economies (columns (4) and (9)) and not so much in Latin American countries (columns (5) and (10)), for which the correlation at the top of the markup distribution is negative but statistically insignificant in the "Cross Section" while positive and insignificant in the "Within Firm" regression.

Finally, it is worth mentioning that the regressions are consistent with the classic Tobin's Q theory, which predicts a positive and significant relationship between firm-level market valuation and investment decisions. Similarly, the results suggest that liquidity-unconstrained firms (proxied as high-cash firms) invest significantly more than low-cash companies. Regarding leverage, the results reveal a significant difference between the "Cross Section" versus the "Within Firm" specification. On the one hand, there are significant debt overhang effects for the "Within Firm" regressions across country groups ($\hat{\gamma}_2 < 0$ in columns (5) to (10)). On the other hand, when comparing firms in the "Cross Section," the effect of high leverage on investment switches to positive and significant (except for the USA in column (2)), probably due to the selected sample of listed companies with a low probability of default and hence low overhang effects (see Heresi and Powell (2022)).

Table 8: Dependent Variable: (log) Investment Rate

$\log\left(\frac{I_{it}}{K_{i,t-1}}\right)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Cross Section					Within Firm				
	World	USA	DEV	EME	LAC	World	USA	DEV	EME	LAC
$\log(\mu_{i,t-1})$	1.01***	0.57***	0.88***	1.52***	1.54***	1.38***	0.73***	1.34***	1.75***	1.42***
	(0.04)	(0.08)	(0.06)	(0.06)	(0.23)	(0.09)	(0.13)	(0.14)	(0.09)	(0.25)
$(\log(\mu_{i,t-1}))^2$	-0.44***	-0.23***	-0.37***	-0.72***	-0.57***	-0.49***	-0.25***	-0.46***	-0.66***	-0.36***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.15)	(0.06)	(0.07)	(0.09)	(0.05)	(0.14)
$\log(Q_{i,t-1})$	0.38***	0.27***	0.41***	0.36***	0.31***	0.41***	0.38***	0.42***	0.41***	0.40***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)	(0.04)
$\log(LEV_{i,t-1})$	0.04***	-0.01*	0.04***	0.07***	0.05**	-0.03***	-0.02**	-0.04***	-0.02*	-0.06**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)
$\log(CASH_{i,t-1})$	0.04***	0.02***	0.04***	0.06***	0.08***	0.06***	0.05***	0.06***	0.05***	0.03**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Margins $\log(\mu_{i,t-1})$										
at p50	0.862***	0.459***	0.767***	1.283***	1.237***	1.216***	0.614***	1.197***	1.533***	1.227***
at p75	0.679***	0.330***	0.614***	1.009***	1.047***	1.014***	0.475***	1.009***	1.282***	1.107***
at p90	0.394***	0.152***	0.368***	0.613***	0.777***	0.700***	0.282***	0.705***	0.920***	0.936***
at p95	0.161***	0.0230	0.179***	0.227***	0.470***	0.444***	0.142*	0.472***	0.571***	0.744***
at p99	-0.442***	-0.288**	-0.325***	-0.788***	-0.209	-0.220**	-0.190	-0.146	-0.362***	0.312
Firm FE	no	no	no	no	no	yes	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	203,815	23,900	116,135	58,274	5,464	201,549	23,657	115,381	57,058	5,411
N. firms	22640	2214	11053	8789	584	20374	1971	10299	7573	531
N. countries	70	1	27	36	6	70	1	27	36	6
R-sqr Adj.	0.16	0.24	0.18	0.16	0.24	0.51	0.59	0.52	0.46	0.57
Dep. var. mean	-2.627	-2.424	-2.697	-2.570	-2.614	-2.631	-2.423	-2.702	-2.576	-2.622

8 Conclusions

This paper uses balance sheet data of about half a million listed companies across 70 developed and emerging economies, including the six largest Latin American countries, to provide an up-to-date picture of the time evolution and cross-sectional distribution of market power—defined as price-cost markups— over the last two decades.

The results reveal that firms' market power in LAC is relatively high compared to worldwide benchmarks, although the estimated markups have slightly declined from the levels observed during the commodity boom period between the early 2000s and 2012. The time evolution of the markup distribution displays a stark disconnect between firms at the top of the distribution, which register a large increase between 2000 and 2022, versus the typical firm, which registers not many changes in its markups over time.

In contrast to the prediction of most theories of endogenously variable markups, the results in this paper show a negative correlation between firm size and market power: larger firms charge lower markups, except at the very top of the size distribution. The econometric evidence also points to a positive and significant correlation between markups and investment, although this relationship is highly nonlinear, becoming negative for firms at the right tail of the markup distribution.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Akcigit, U. and Ates, S. T. (2021). Ten facts on declining business dynamism and lessons from endogenous growth theory. *American Economic Journal: Macroeconomics*, 13(1):257–298.

Akcigit, U. and Ates, S. T. (2023). What happened to us business dynamism? *Journal of Political Economy*, 131(8):2059–2124.

Atkeson, A. and Burstein, A. (2008). Pricing-to-market, trade costs, and international relative prices. *American Economic Review*, 98(5):1998–2031.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Reenen, J. V. (2017). Concentrating on the fall of the labor share. *American Economic Review*, 107(5):180–185.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709.

Barkai, S. (2020). Declining labor and capital shares. *The Journal of Finance*, 75(5):2421–2463.

Berry, S., Levinsohn, J., and Pakes, A. (1995). *Econometrica*, 63(4):841–890.

Covarrubias, M., Gutiérrez, G., and Philippon, T. (2020). From good to bad concentration? us industries over the past 30 years. *NBER Macroeconomics Annual*, 34(1):1–46.

De Loecker, J. and Eeckhout, J. (2017). The rise of market power and the macroeconomic implications. Working Paper 23687, National Bureau of Economic Research.

De Loecker, J. and Eeckhout, J. (2018). Global market power. Technical report, National Bureau of Economic Research.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2):561–644.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2016). Declining business dynamism: What we know and the way forward. *American Economic Review*, 106(5):203–207.

Díez, F. J., Fan, J., and Villegas-Sánchez, C. (2021). Global declining competition? *Journal of International Economics*, 132:103492.

Díez, M. F., Leigh, M. D., and Tambunlertchai, S. (2018). *Global market power and its macroeconomic implications*. International Monetary Fund.

Edmond, C., Midrigan, V., and Xu, D. Y. (2015). Competition, markups, and the gains from international trade. *American Economic Review*, 105(10):3183–3221.

Edmond, C., Midrigan, V., and Xu, D. Y. (2023). How costly are markups? *Journal of Political Economy*, 131(7):1619–1675.

Eslava, M., García-Marín, A., and Messina, J. (2023). Inequality and market power in latin america and the caribbean.

Eslava, M., Meléndez, M., and Urdaneta, N. (2021). Market concentration, market fragmentation, and inequality in latin america. Technical report, Working Paper. United Nations Development Programme.

Gutiérrez, G. and Philippon, T. (2017). Declining competition and investment in the us. Technical report, National Bureau of Economic Research.

Hall, R. E. (1988). The relation between price and marginal cost in us industry. *Journal of political Economy*, 96(5):921–947.

Heresi, R. and Powell, A. (2022). Corporate debt and investment in the post-covid world. *IDB Working Paper 1316*.

Kimball, M. S. (1995). The quantitative analytics of the basic neomonetarist model.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341.

Loecker, J. D. and Warzynski, F. (2012). Markups and firm-level export status. *American economic review*, 102(6):2437–2471.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment. *Econometrica*, 64(6):1263–1297.