Market power, ownership concentration and income inequality*

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Abstract

We quantify the distributional effects of market power by decomposing capital income into competitive returns and market-power rents and assigning these components to ultimate individual owners. Using matched firm-level and taxpayer-level administrative data for Chile from 2008 to 2016, we estimate firm-level markups and trace monopoly rents through ownership networks. Capital income is highly concentrated, but competitive returns are more skewed than market-power rents because very large firms exhibit lower markups. As a result, market-power rents account for a smaller share of income at the very top of the distribution. Inequality decompositions imply that reductions in market power lower inequality despite increases in competitive returns, as the associated rise in the labor share dominates. Our results provide new empirical evidence on how ownership structure mediates the link between market power and inequality.

Keywords. Markups, capital concentration, ownership links, income distribution, retained earnings, wedges.

JEL Classification: D31, D41, D63.

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1 Introduction

Over the last four decades, advanced and emerging economies have experienced profound changes in the distribution of income and wealth. Income and wealth inequality have risen substantially (Alvaredo et al., 2013; Piketty, 2014; Piketty et al., 2018), while labor's share of GDP has declined (Karabarbounis and Neiman, 2014; Autor et al., 2020; Barkai, 2020). Over the same period, firms' markups and profitability have increased (De Loecker et al., 2020), reflecting a broad rise in market power. Together, these trends have sparked intense debate over whether rising market power is an important driver of inequality (Furman and Orszag, 2015; Posner and Weyl, 2018).

The central mechanism linking market power to inequality is straightforward. When firms exert market power, they charge prices above marginal cost or pay factor prices below marginal productivity, generating wedges that reallocate income from consumers and workers to business owners. Because capital income is substantially more concentrated than labor income, increases in market power are expected to amplify inequality (Ennis and Kim, 2017; Gans et al., 2019). Recent theoretical work has formalized this channel. In a general equilibrium model, Boar and Midrigan (2025) show that the distributional effects of markups depend critically on the concentration of capital ownership. Yet, despite abundant evidence on the rise of markups and on the concentration of income and wealth, there is little empirical evidence that directly decomposes income into competitive returns and market-power rents and traces these components to their ultimate owners.

This paper fills that gap. We exploit a unique administrative dataset for Chile covering the universe of firms and taxpayers between 2008 and 2016. The data combine firm-level tax records with detailed ownership links, allowing us to identify the final natural-person owners of each firm. Using these data, we proceed in three steps. First, we estimate firm-level markups following De Loecker and Warzynski (2012), using information on sales, flexible input expenditures, and labor costs. We interpret these markups as reduced-form wedges that capture a broad set of factor-specific distortions associated with market power (De Ridder et al., 2026). Second, we decompose capital income into three components: competitive (fair) returns to capital, rents arising from decreasing returns to scale, and rents due to market power. Third, we attribute each income component—together with labor income—to ultimate individual owners. This procedure delivers, for each taxpayer in Chile, a complete decomposition of income into labor income, competitive capital income, and market-power rents.

Our main finding is that both competitive and market-power capital returns are highly concentrated, but competitive returns are more skewed. The top 1 percent of capital-income earners capture nearly 90 percent of total capital income in both cases; however, market-power rents account for a smaller share of income lower in the distribution. This pattern arises because very large firms tend to exhibit relatively lower markups. As a result, for individuals at the very top of the income distribution—who hold large stakes in these firms—market-power rents constitute a smaller fraction of total capital income. We show that this result is not driven by differential portfolio allocation across sectors. Moreover, the relative concentration of competitive and market-power returns is remarkably stable over time.

These findings have direct implications for the mechanism linking market power to income inequality. In particular, reductions in market power that lower market-power rents may be partially offset by increases in competitive capital returns. To quantify these effects, we conduct a partial-equilibrium decomposition of the Gini index following Lerman and Yitzhaki (1985). Under this decomposition, competitive and market-power capital returns contribute similarly to overall inequality (17.1 percent versus 16.5 percent). In contrast, the alternative decomposition proposed by Shorrocks (1982) assigns a substantially larger role to competitive returns (54.9 percent versus 32.3 percent), reflecting their greater skewness. The Lerman and Yitzhaki (1985) decomposition further implies that all forms of capital income are similarly distributed, so that their aggregate income shares are sufficient statistics for their relative contributions to inequality. This property is persistent over time: variation in the relative contributions of competitive and market-power returns is entirely driven by changes in their aggregate shares. Finally, we show that a 20 percent reduction in markups—offset by increases in competitive capital income and labor income—leads to a 5.7 percent decline in the Gini index, primarily driven by the increase in the labor share.

By combining firm-level markup estimates with household-level income and ownership data, this study makes several contributions. Empirically, we connect two literatures that have largely advanced in parallel: the literature documenting rising market power (De Loecker and Eeckhout, 2018) and the literature measuring top incomes and capital concentration (Fairfield and Jorratt, 2016; Piketty et al., 2018). Our decomposition shows how these phenomena intersect at the individual level by tracing monopoly rents from firms to their ultimate owners. Conceptually, our findings provide empirical support for theoretical predictions that the distributional effects of markups depend on ownership concentration (Boar and Midrigan, 2025). Methodologically, we introduce a novel approach to splitting capital income into competitive returns and monopoly rents within a Distributional National Accounts framework.

A central implication is that the incidence of market-power rents is mediated by corporate ownership structure—a core theme in corporate finance. Tracing profits through ownership networks is essential because concentrated control and indirect ownership can shift who ultimately receives (and internalizes) market-power rents. Our administrative data allow us to measure this incidence directly rather than inferring it from firm-level outcomes alone.

Chile offers a particularly relevant setting for this analysis. The country is characterized by high inequality, a relatively low labor share, and significant capital concentration (Fairfield and Jorratt, 2016). Moreover, Chile's low level of informality relative to other Latin American economies allows us to rely on administrative tax records covering nearly the entire corporate sector and taxpayer population. The period we study, 2008–2016, spans the global financial crisis, a sharp recovery, and a major domestic shock—the 2010 earthquake—providing variation in macroeconomic conditions against which to assess the stability of our results.

Our findings clarify the mechanism linking market power to income inequality. Across alternative inequality decompositions, competitive returns contribute as much as—or more than—market-power returns, implying that reductions in market power are partially offset by higher competitive returns. However, the accompanying increase in the labor share is substantially larger, resulting in a net decline in inequality. These results highlight the distributional importance of policies that reduce monopoly rents while strengthening competition in product and labor markets.

The remainder of the paper is organized in short sections that present the main results while details of the data and estimations are presented in the Appendix. Section 2 presents a simple framework for decomposing capital income into fair and market-power returns. Section 3 describes the data and study measures. Section 4 shows the effect of accrued returns on income distribution. Section 5 provides a discussion of firm-level markups. Section 6 provides a decomposition of inequality. Finally, Section 7 concludes.

2 Framework

2.1 Firms and markups

We follow De Loecker and Warzynski (2012) to connect firm behavior to income inequality by quantifying how market power shapes factor shares and the distribution of capital income. We distinguish (i) competitive returns to capital, (ii) rents due to market power, and (iii) payments associated with non-constant returns to scale. We recover firm-level markups and use them to decompose firms' gross payments to capital into these economically interpretable components.

In year t, there are N_t firms indexed by $f = 1, \dots, N_t$. Firm f produces $Y_{ft} = Y(A_{ft}, K_{ft}, V_{ft})$, where A_{ft} is productivity, K_{ft} is the stock of physical capital, and V_{ft} is a vector of flexible variable factors, including labor and inputs. Economic profits are

$$\Pi_{ft} = P_{ft} A_{ft} \left(K_{ft}^{\theta_{Kf}} V_{ft}^{\theta_{Vf}} \right)^{\gamma_f} - R_{ft} K_{ft} - P_{ft}^{V} V_{ft},$$

where R_{ft} is the user cost of capital and P_{ft}^{V} is the price of variable factors. The markup μ_{ft} is price over marginal cost.

Assuming V_{ft} adjusts freely within the period and firms take input prices as given, the first-order condition for V_{ft} implies

$$\mu_{ft} = \theta_{Vf} \gamma_f \frac{P_{ft} Y_{ft}}{P_{ft}^{V} V_{ft}}, \tag{1}$$

where $\theta_{Vf}\gamma_f$ is the output elasticity of the flexible input and $P_{ft}Y_{ft}/(P_{ft}^{V}V_{ft})$ is the inverse of its expenditure share. In estimation, we obtain output elasticities and returns-to-scale parameters at the sector level and hold them constant over time. In this stylized setting,

μ_{ft} is a product-market markup. Empirically, we interpret our estimates as reduced-form wedges that may capture a broader set of factor-specific distortions associated with market power (De Ridder et al., 2026; Eslava et al., 2023).[1]

We adopt a Cobb–Douglas production function,

$$Y_{ft} = A_{ft} \left(K_{ft}^{\theta_{Kf}} V_{ft}^{\theta_{Vf}} \right)^{\gamma_f}, \qquad \theta_{Kf} + \theta_{Vf} = 1,$$

so that γ_f governs returns to scale. Using the first-order conditions, economic profits can be written as

$$\Pi_{ft} = P_{ft} Y_{ft} \left(1 - \frac{\gamma_f}{\mu_{ft}} \right). \tag{2}$$

If the firm owns its capital stock, the total gross payment to capital equals the sum of physical capital payments and profits:

$$GPK_{ft} = P_{ft} Y_{ft} \left(\frac{\theta_{Kf} \gamma_f}{\mu_{ft}} + 1 - \frac{\gamma_f}{\mu_{ft}} \right). \tag{3}$$

This admits the decomposition

$$GPK_{ft} = P_{ft} Y_{ft} \frac{\theta_{Kf} \gamma_f}{\mu_{ft}} + P_{ft} Y_{ft} (1 - \gamma_f) + P_{ft} Y_{ft} \gamma_f \left(1 - \frac{1}{\mu_{ft}} \right). \tag{4}$$

The first term is the competitive return to physical capital. The second captures payments associated with non-constant returns to scale (positive under decreasing returns, $\gamma_f < 1$). The third term reflects rents from market power (positive when $\mu_{ft} > 1$).

In Section 5 we implement this decomposition by constructing firm-year income shares that we apply to an observed firm-level measure of gross payment to capital:

$$\phi_{ft}^c = \frac{P_{ft} Y_{ft} \theta_{Kf} \gamma_f / \mu_{ft}}{GPK_{ft}}, \quad \phi_{ft}^m = \frac{P_{ft} Y_{ft} \gamma_f \left(1 - 1/\mu_{ft}\right)}{GPK_{ft}}, \quad \phi_{ft}^s = \frac{P_{ft} Y_{ft} (1 - \gamma_f)}{GPK_{ft}}. \tag{5}$$

These objects quantify how much of capital income reflects competitive compensation, market-power rents, or the returns-to-scale component.

[1] Moreover, as emphasized by Raval (2023), production-based markups may also arise from non-neutral productivity heterogeneity, further motivating a reduced-form interpretation.

2.2 Individuals

In year t, each individual i receives primary (pre-tax) income from four sources.[2] The first is dependent labor income and pensions. The second is self-employment income. The third is financial income, including realized capital gains from financial instruments. The fourth is capital income arising from firm ownership. For this last component, we distinguish distributed income (dividends/withdrawn profits) from accrued income (distributed income + retained earnings).

We decompose accrued capital income into competitive returns, market-power rents, and the returns-to-scale component using the firm-level decomposition above. Because our data contain the universe of firm ownership links in Chile, we observe, for each individual, the fraction of shares held in each firm. Individual i's accrued capital income in year t is therefore

$$GPK_{it} = \sum_f \alpha_{ift} GPK_{ft}, \tag{6}$$

where $\alpha_{ift} \in [0, 1]$ denotes the (direct and indirect) ownership share of individual i in firm f during year t.

3 Data and study measures

We combine several administrative datasets from Chile's tax authority, the *Servicio de Impuestos Internos* (SII), covering all formal firms and individuals from 2008–2016. All records are linked through the unique taxpayer identifier (*Rol Único Tributario*, RUT), which allows us to trace income flows and firm ownership over time.[3] Appendix A provides institutional details, additional summary statistics, and the inequality measures and decompositions used below.

[2] Our analysis is conducted before taxes and government transfers; we abstract from fiscal redistribution.

[3] This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the SII. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

3.1 Income measurement

We measure individual income as the sum of dependent labor income, formal self-employment income, pensions, financial income, withdrawn profits, and attributed gross payments to capital from firm ownership. Financial income is observed only when taxable capital gains are realized, for example through dividends, deposits, or redemptions of investment and mutual funds. More generally, financial income is measured only at realization.

We treat withdrawn profits as largely reflecting contemporaneous distributed profits. When constructing accrued individual income and imputing gross payments to capital from firm ownership, we therefore exclude withdrawn profits to avoid double counting.

In measuring accrued individual income, we impute gross payment to capital, GPK_{ft}, to individuals in proportion to their total ownership stakes whenever GPK_{ft} is positive. We do not symmetrically allocate corporate losses to individuals. This asymmetric treatment follows standard practice in the inequality literature and in the construction of distributional national accounts. Conceptually, retained earnings expand households' current saving capacity and future consumption possibilities even when not distributed as dividends, whereas corporate losses are primarily absorbed through firms' balance sheets and asset valuations rather than realized as reductions in household disposable income. From an empirical perspective, allocating corporate losses would generate large and transitory negative incomes that are difficult to interpret and poorly aligned with observed consumption behavior or tax liabilities. Our approach therefore captures the distributional relevance of undistributed profits while preserving an income concept that remains economically meaningful and comparable across individuals and over time[4]

Section A.2 of the Appendix provides more details on individual-level variables construction.

3.2 Firm-Level Data

Our main firm-level variable is the observed gross payment to capital, defined as profits before taxes minus dividend income received from other firms. This definition attempts to

[4]This treatment follows Piketty et al. (2018) and the Distributional National Accounts (DINA) guidelines (Alvaredo et al. (2025)), which impute retained corporate profits to individuals when profits are positive but do not symmetrically allocate corporate losses to households.

prevent double counting when allocating retained and distributed earnings to final owners. In practice, the empirical measurement of GPK_{ft} departs from the theoretical construct in Equation 3, as observed profits before taxes incorporate fixed and general costs and additional income sources that are excluded from the simplified framework from which Equation 3 is derived. Section A.5 in the Appendix provides more details on firm-level variable construction and summary statistics.

3.3 Firm Ownership Data

To attribute GPK_{ft} to final local owners, we use firm ownership records from the SII. These data contain information on the direct ownership links for all Chilean firms from 2008 to 2016. Using this dataset more than 95% of firms' gross payment to capital can be assigned to a final owner, and roughly 60% of these profits accrue to resident taxpayers.[5] However, it is not possible to identify the ultimate beneficiaries of shares held by pension, mutual, or investment funds, and thus, they are excluded when attributing the gross payment to capital.

Section A.6 of the Appendix provides a general description of the firm ownership dataset. Avilés et al. (2025) provide details on the construction of the ownership dataset and the procedure to obtain total ownership links from these data.

4 Accrued GPK and Income Distribution

After matching tax records with firm ownership data, our final sample comprises 9.8 million individuals in 2016. Table 1 reports inequality measures by pre-tax income source. Columns (1)–(5) present alternative inequality metrics for each source. Panel A shows profits as recorded in tax data and therefore reflects realized (withdrawn) profits. Panel B, in contrast, attributes the gross payment to capital to individuals using ownership links.

Accounting for retained earnings substantially changes measured inequality. The aggregate share of capital rents increases from 8.8% to 28.8%, while the top 1 percent income share rises from 15.3% to 32.6%. Similarly, the Gini coefficient for total income increases

[5] World Bank (2015) report similar figures and assign around 97% of non-negative profits to ultimate owners.

from 0.63 to 0.71. These changes reflect the strong concentration of capital income among top-income households in Chile, as illustrated in Figure A.1 in the Appendix. Consistent with this pattern, Table 1 shows that capital income concentration increases markedly once gross payments to capital are attributed to individuals. Comparable findings have been documented for other countries (e.g., Piketty and Saez, 2003; see also Atkinson et al., 2011).

Although not directly comparable, our estimates are broadly in line with previous studies of Chile that incorporate retained earnings into inequality measures. For example, the World Inequality Database— which imputes retained profits using survey data and National Accounts—reports a top 1% income share of 28.9% in 2016 (De Rosa et al. (2020)). Fairfield and Jorratt (2016), combining tax records with SII ownership data, estimate a top 1% share of 23% in 2009, increasing to 32.5% once firm profits from National Accounts are imputed. Similarly, the World Bank (2015) reports a top 1% income share of 33% in 2013. Applying our methodology, we obtain a comparable estimate of 34.4% for that same year.[6]

Insert Table 1 here

5 Firm GPK and Owners' Market-power Income

We now decompose firm-level gross payments to capital into competitive returns, market-power rents, and the returns-to-scale component. We estimate sector-specific production functions at the 42-sector level and compute firm-year markups using Equation 1. We then apply Equation 5 to decompose the observed firm-year gross payment to capital.[7] Appendix B and C provide additional details on the estimation procedures and summary statistics for markups and aggregate rent shares.

We use this framework to study how market power contributes to income inequality through the joint distribution of firm-level GPK, ownership concentration, and markups. Because firm ownership is highly concentrated among top-income individuals, the analysis is most informative about outcomes in the upper tail.

[6]Studies lacking ownership-link data rely on indirect imputation methods and generally report lower levels of inequality. For instance, López (2016) estimate a top 1% share of 21.2% in 2013, while Flores et al. (2020) report a share of around 22% in 2016. Using survey data, Díaz et al. (2021) estimate a Gini coefficient of 0.65 for 2016.

[7]Because markups enter only the decomposition of firm-year GPK, aggregate labor and capital shares are directly measured in the data and do not rely on production function estimates.

Figure 1 reports binned averages of several firm and individual level outcomes by firm (log) GPK for 2016. The sample is restricted to firms with strictly positive GPK that can be attributed to ultimate owners. We use a 100 bins that span 14.5 to 22, covering annual GPK from approximately 2 million pesos (USD 3,000) to 3,500 million pesos (USD 5.4 million) in the top bin.[8] Publicly traded firms fall within this upper bin, contributing to substantial within-bin dispersion. The largest firm has GPK of 600 billion pesos (about USD 900 million), far above the bin mean.

Panel (a) plots the firm-level Herfindahl–Hirschman Index (HHI) of ownership concentration, computed using the shares of final owners. Panel (b) reports the log ownership-share-weighted average total income of these owners. Panel (c) reports the firm markup and Panel (d) the ownership-share-weighted average monopolistic share of final owners, with the monopolistic share defined as the ratio of an individual's market-power rents to total income

Panel (a) shows a strong negative relationship between ownership concentration and firm GPK, particularly in the upper tail. This contrasts with a large corporate finance literature documenting a positive association between firm size and ownership concentration among privately held firms.[9] Despite this negative correlation, declining ownership concentration does not offset the increase in firm profits. Panel (b) shows a positive relationship between the average income of owners and firm GPK. This implies that individuals with large stakes in large firms are concentrated at the very top of the income distribution, consistent with controlling shareholders and business groups in Latin America (La Porta et al. (1999); Khanna and Yafeh (2007)). Moreover, average values of log income and log GPK suggests that owners of the largest firms derive substantial income beyond any single firm, consistent with diversified ownership across very large firms.

Panel (c) indicates that markups are, on average, increasing in gross payments to capital, but this relationship breaks in the upper tail of the distribution. Evidence based on publicly listed firms—corresponding in our data to the largest firms—has found a negative unconditional relationship between markups and firm size across sectors De Loecker et al. (2020).

[8] Binscatter plots are used for descriptive comparisons of averages across values of log GPK; accordingly, we use a fixed number of bins (Cattaneo et al. (2024)).

[9] See Jensen and Meckling (1976) and Shleifer and Vishny (1986). Financial frictions may reinforce this pattern: external equity issuance dilutes control and entails disclosure costs, leading controlling owners to rely more on debt (Berger and Udell (1998); Almeida and Wolfenzon (2006)).

Relatedly, Heresi (2024) documents a similar pattern for Latin America, while emphasizing that the relationship turns positive at the extreme right tail. In our data, however, markups exhibit no systematic relationship with GPK among firms in the top bin. Taken together, these patterns provide limited support for a "superstar firm" explanation (Autor et al., 2020) of the link between market power and inequality in Chile.

This has direct implications for rent exposure at the very top of the distribution. Because top-income individuals derive a substantial share of their income from large firms, the absence of elevated markups in this segment implies that their exposure to market-power rents is comparatively lower. Panel (d) formalizes this point, showing that the market-power share of total income declines for individuals with large stakes at large firms. Importantly, this pattern does not appear to reflect differential portfolio allocation across sectors. As shown in Figure A.4 of the Appendix, individuals at the top of the distribution are not disproportionately invested in sectors with systematically lower markups relative to other owners. Finally, these patterns are stable over time over our sample period, 2008–2016.

6 The Impact of Market Power on Income Inequality

How does market power shape the income distribution? Figure 2a reports the contribution of each income source for percentiles 80–100 in 2016. While the share of capital income increases with total income, dependent labor income remains the dominant source across almost the entire distribution. The main exception is the top 1 percent, for whom capital income accounts for nearly 80 percent of total income, reflecting the high concentration of firm ownership.

Figure 2a also shows that market-power income exceeds competitive income across the distribution except within the top 1 percent. Panel (b) zooms in on this group and shows that the reversal is driven by individuals at the very top. These individuals hold large stakes in very large firms, consistent with the patterns in Section 5. The results imply that market-power income is not more unequally distributed than competitive income; if anything, it is relatively less important at the very top. More generally, all forms of capital income appear similarly distributed along the upper tail, except at the extreme top, where the market-power share is lower.

In a counterfactual where all firms reduce markups proportionally, inequality changes through two channels: (i) a shift from capital to labor income, and (ii) a shift from market-power to competitive capital income. Our results suggest that the first channel dominates, while the second partially offsets it.

Insert Figure 2 here

6.1 Gini decomposition

To quantify how each income source contributes to overall inequality—and to discipline the comparative statics above—we decompose the Gini coefficient by factor components following Lerman and Yitzhaki (1985). This decomposition provides an intuitive mapping from source-specific concentration and income shares to aggregate inequality (Section A.4). In particular, the Gini coefficient (G) can be written as

$$G = \sum_{h=1}^{H} S_h \, G_h \, Q_h, \tag{7}$$

where S_h is the share of source h in total income, G_h is the source-specific Gini, and Q_h is the Gini correlation of source h with total income. The contribution of source h to overall inequality is

$$\frac{S_h G_h Q_h}{G}.$$

The term $\partial G/\partial S_h = G_h Q_h - G$ captures whether source h is more or less unequally distributed than total income. Scaling by S_h yields the marginal effect

$$\frac{\partial G}{\partial e_h} = S_h(G_h Q_h - G),$$

which is the percentage change in G when all individuals' income from source h increases by 1% (ceteris paribus).[10]

Table 2 reports the decomposition for 2016. Dependent labor income contributes the most to inequality (56.7%). Although it is more equally distributed than total income ($G_h Q_h = 0.6104 < 0.7108$), its large share in total income (66.1%) drives its contribution. Its marginal contribution is negative: a uniform 1% increase in wages reduces the Gini by

[10] We report results using the Shorrocks decomposition (Shorrocks, 1982) in Appendix A.8.

0.093%. Capital income is more unequally distributed ($G_h Q_h \approx 1$) but represents a smaller share of total income (28.8%), so it accounts for 38.8% of inequality; a uniform 1% increase in capital income increases the Gini by 0.082%.

Under this decomposition, competitive and market-power income contribute similarly to overall inequality. Competitive capital income explains 17.1% of the Gini, compared with 16.1% for market-power income (and 5.7% for the returns-to-scale component). By contrast, the Shorrocks decomposition assigns a larger role to competitive returns, consistent with the lower market-power share among top-income individuals. Because the aggregate income shares of competitive and market-power income are also close (12.6% vs. 12.0%), their marginal effects are nearly identical: a uniform 1% increase in either component raises the Gini by just over 0.04%.

Insert Table 2 here

Consistent with the graphical evidence, Table 2 shows that all forms of capital income are similarly distributed, with $G_h Q_h$ close to one, so aggregate income shares are sufficient statistics for relative contributions to inequality. Figure 3 tracks the relative contribution of competitive versus market-power income over time and decomposes it into (i) relative shares and (ii) relative $G_h Q_h$ terms.[11] The relative distributive component remains close to one throughout 2008–2016; changes in relative contributions are driven almost entirely by changes in aggregate shares.

Insert Figure 3 here

6.2 A partial-equilibrium counterfactual

What would be the effect of reducing markups on overall inequality? In the framework presented in Section 2.1, a reduction in markups reduces market-power income and mechanically increases labor income and competitive returns to inputs. To a first-order approximation, the effect of a change in income shares on the Gini is given by:

[11] According to Equation 5, the firm-level share of income from returns to scale depends only on the parameter γ. Because we do not estimate time-varying production functions, this component is stable over time and is therefore omitted from the figure.

$$dG \approx \frac{\partial G}{\partial S_m} dS_m + \frac{\partial G}{\partial S_c} dS_c + \frac{\partial G}{\partial S_l} dS_l$$

where S_m, S_c and S_l denote the aggregate shares of market-power, competitive, and labor (dependent and self-employed) income, respectively. The partial derivatives correspond to $G_h Q_h - G$ for income source h, and d denotes a percentage change.

Assuming a value-added production function at the firm level with $\theta^k + \theta^l = 1$, a reduction in market-power income $dSm < 0$ is offset by increases in competitive and labor income of magnitudes $\theta^k \times dS_m$ and $\theta^l \times dSh^m$, respectively. We construct aggregate parameters $\bar{\theta}^k$, $\bar{\theta}^l$, $\bar{\gamma}$ and and aggregate markup $\bar{\mu}$ so that implied aggregate shares match those observed in the data (Table 2).[12] Using this approach we obtain $\bar{\gamma} = 0.958$, $\bar{\theta}^k = 0.149$ $\bar{\mu} = 1.136$ and $\bar{\theta}^l = 0.85$. These parameters allow us to approximate the response of aggregate income shares to uniform changes in markups across firms. Combining these responses with the partial derivatives obtained from Table 2 we find that a uniform 20% reduction in markups leads to a 5.67% decline in the Gini coefficient, from 0.7108 to 0.6705.

7 Conclusion

This paper studies how market power affects income inequality by decomposing capital income into competitive returns and market-power rents and tracing these components to ultimate individual owners. Using administrative tax records for the universe of firms and taxpayers in Chile between 2008 and 2016, together with detailed ownership links, we estimate firm-level markups and allocate accrued gross payments to capital to final natural-person owners. This allows us to construct, for each taxpayer, a decomposition of total income into labor income, competitive capital income, and income attributable to market

[12] For example, the aggregate competitive income share can be written as:

$$S_c = \frac{\sum_f CompRents_f}{\sum_f GPK_f} = \sum_f w_f \phi^c_f = \sum_f \frac{w_f \theta^k_f w_f \gamma_f}{w_f \mu_f} \frac{PY_f}{GPK_f}$$

where $w_f = \dfrac{GPK_f}{GPK}$ and ϕ^c_f is the firm-level competitive share. If cross-term covariances are small, $\bar{\phi}^c \approx \dfrac{\bar{\theta}^k \bar{\gamma}}{\bar{\mu}} \times \dfrac{\bar{PY}}{G\bar{P}K}$. Importantly, these parameters need not coincide with weighted averages of firm-level estimates, as they are chosen to match aggregate shares across all income components, not just capital income.

power.

Our central empirical finding is that both competitive and market-power capital returns are extremely concentrated, but competitive returns are more skewed. The top 1 percent captures nearly 90 percent of both forms of capital income, yet market-power rents account for a smaller share of income at the very top. This pattern is consistent with the fact that the largest firms—those most relevant for top incomes through ownership—exhibit relatively lower markups, so that market-power rents represent a smaller fraction of their owners' total capital income. Importantly, the result does not appear to be driven by sectoral portfolio allocation and is stable over time in our sample.

These distributional patterns matter for how policies that reduce market power translate into inequality outcomes. Inequality decompositions imply that competitive and market-power returns contribute similarly to overall inequality under the Lerman and Yitzhaki (1985) decomposition, while the Shorrocks (1982) decomposition assigns a larger role to competitive returns, reflecting their greater skewness. In a partial-equilibrium counterfactual, a uniform reduction in markups lowers inequality despite an offsetting increase in competitive returns, because the associated rise in the labor share is quantitatively larger and dominates the net effect on the Gini.

Our results highlight a broader point: the link between market power and inequality depends not only on the aggregate level of rents but also on who owns the firms that generate them. Tracing rents through ownership networks is therefore essential for assessing incidence and for quantifying the distributional consequences of competition policy.

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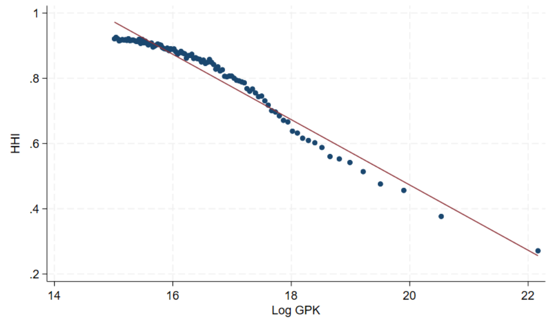
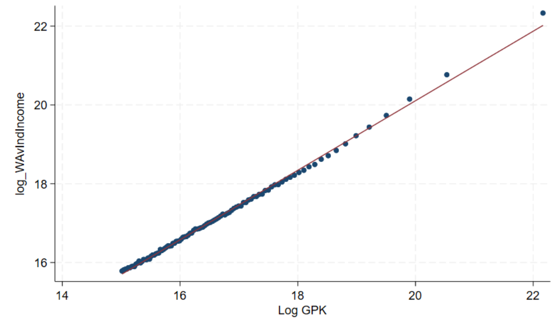
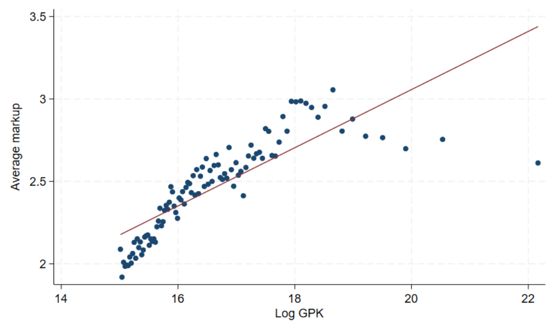
Figure 1: Gross Payment to Capital, Firm Ownership and Markups



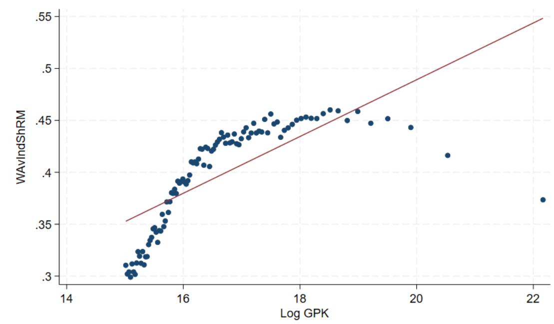
(a) Ownership concentration (HHI)



(b) Owner Total Income



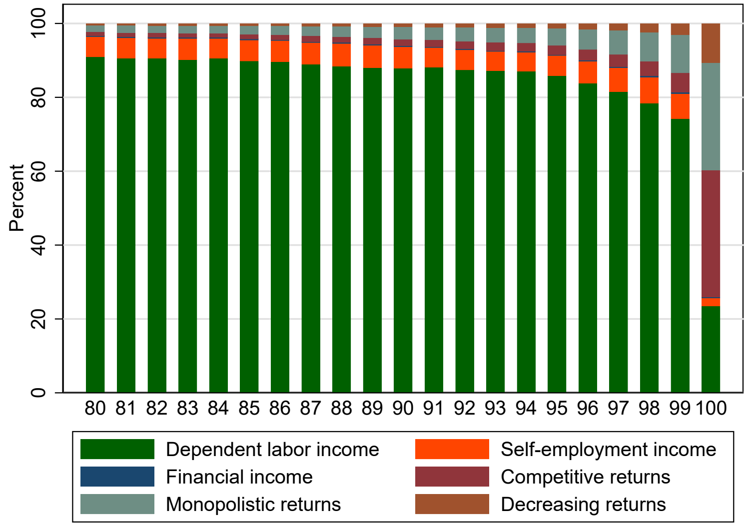
(c) Average Markup



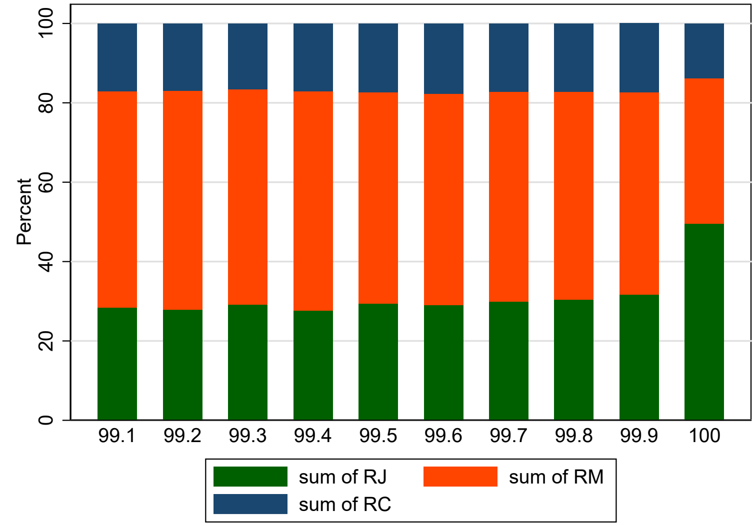
(d) Owner Monopolistic Share

Note: This figure reports bin-scatter plots of firm-level (log) GPK for 2016 in the horizontal axis. The sample is restricted to firms with strictly positive GPK that can be attributed to ultimate owners. Bins span 14.5 to 22, covering annual GPK from approximately 2 million pesos (USD 3,000) to 3,500 million pesos (USD 5.4 million) in the top bin. Panel 1a plots the firm-level Herfindahl–Hirschman Index (HHI) of ownership concentration, computed using the shares of final owners. Panel 1b reports the ownership-share-weighted average income of these owners. Panel 1c reports the firm markup and Panel 1d the ownership-share-weighted average monopolistic share of final owners, with the monopolistic share defined as the fraction of income from monopolistic rents over total income of the individual.

Figure 2: Income Composition in the Upper Tail



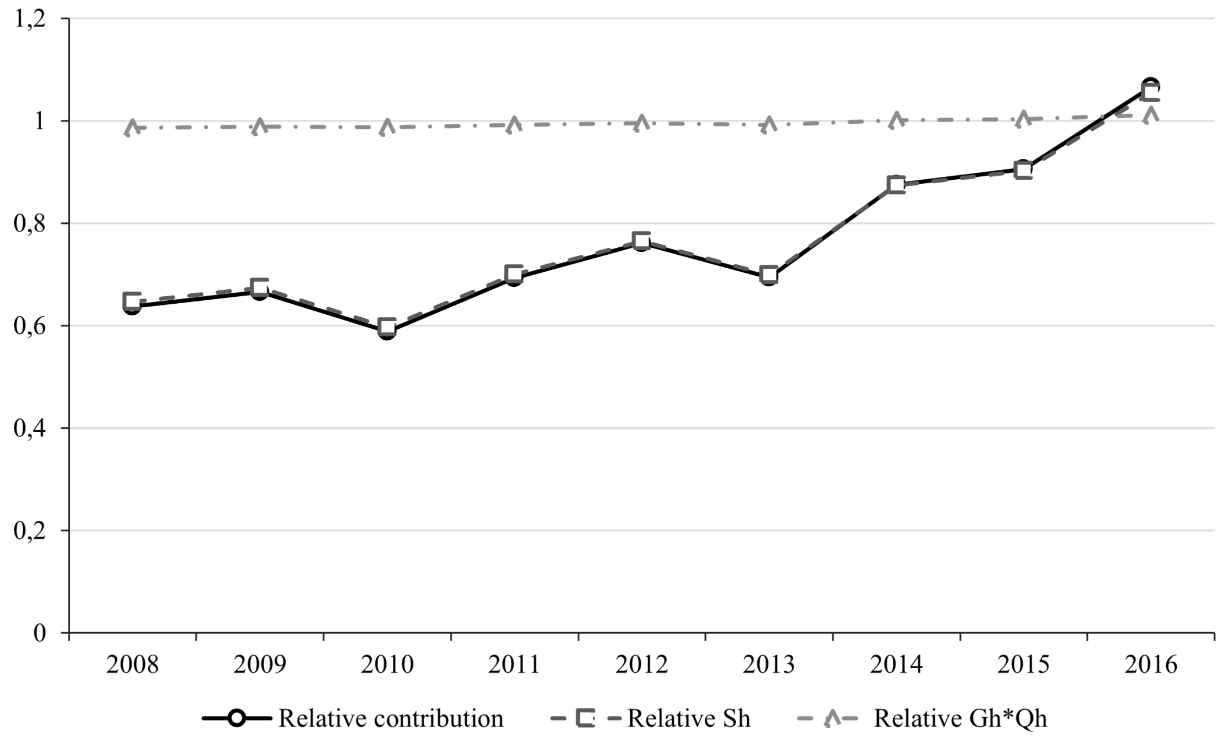
(a) Income sources for the top 20%



(b) Capital income sources for the top 1%

Note: This figure reports the composition of income across top centiles of the distribution in 2016. Panel 2a displays the shares of all income sources for centiles within the top 20 percent. Panel 2b focuses on the top 1 percent and decomposes capital income into competitive income, monopolistic income, and income from returns to scale.

Figure 3: Relative Contributions of Competitive and Monopolistic Income



Note: This figure reports the relative contribution of competitive and monopolistic over time following the Gini index decomposition of Lerman and Yitzhaki (1985). Relative contribution is defined as the ratio of the terms $\frac{S_c G_c Q_c}{S_m G_m Q_m}$ from Equation 8. Accordingly, Relative Sh corresponds to the ratio of aggregate shares S_h and Relative $G_h Q_h$ to the ratio of those terms, which capture the distributive content of each income source independent of its aggregate share.

Table 1: Inequality in Chile by Source

	Inequality measures			Top shares		
	Share	Gini	Theil	10%	5%	1%
		(1)	(2)	(3)	(4)	(5)
Panel A. Perceived income						
Total perceived income	1.000	0.629	0.880	48.71	34.91	15.13
Self-employment income	0.063	0.782	1.422	96.81	86.11	48.33
Dependent labor income	0.846	0.597	0.721	48.48	34.34	14.54
Financial income	0.003	0.966	3.936	100.00	99.96	96.01
Withdrawn profits	0.088	0.731	1.842	100.00	99.25	67.47
Panel B. Accrued income						
Total accrued income	1.000	0.710	1.964	59.97	49.08	32.61
Self-employment income	0.049	0.782	1.422	96.81	86.11	48.33
Dependent labor income	0.661	0.597	0.721	48.48	34.34	14.54
Financial income	0.003	0.966	3.936	100.00	99.96	96.01
Gross payment to capital	0.288	0.925	4.136	100.00	99.71	90.76

Notes. This table reports inequality measures by income source in 2016. Panel A uses profits reported in Form F22 and therefore corresponds to perceived income. Panel B assigns net profits—both distributed and retained—to final owners using ownership links and therefore corresponds to accrued income. *Share* denotes the share of each income source in total perceived or accrued income. Column (1) reports the Gini coefficient computed over strictly positive observations. Column (2) reports the Theil index for the full sample. Columns (3) through (5) report the share of each income source accruing to individuals in the top 10, 5, and 1 percent of that source's distribution, respectively.

Table 2: Gini Decomposition by Source

Source of income (h)	S_h	G_h	Q_h	Contribution	Marginal
Self-employment income	0.0491	0.9551	0.6228	0.0411	−0.0080
Dependent labor income	0.6608	0.6455	0.9457	0.5674	−0.0933
Financial income	0.0026	0.9963	0.8328	0.0030	0.0004
Gross payment to capital components:					
Competitive	0.1260	0.9981	0.9675	0.1712	0.0452
Market power	0.1195	0.9945	0.9606	0.1606	0.0411
Decreasing returns	0.0420	0.9951	0.9632	0.0566	0.0146
Total income		0.7108			

Notes: This table reports the Lerman and Yitzhaki (1985) decomposition of the Gini coefficient (G) for 2016, estimated using `descogini` (López-Feldman, 2006). S_h is the share of source h in total income, G_h its Gini coefficient, and Q_h its Gini correlation with total income. Contribution, defined as $\frac{S_h G_h Q_h}{G}$, measures the share of aggregate inequality attributable to source h. Marginal, defined as Contribution minus S_h, captures the percentage change of a 1% equiproportionate increase in source h on the overall Gini.

Appendix

A Data Appendix

A.1 The Chilean Income Tax System

Our main data sources come from Chile's tax authority, the *Servicio de Impuestos Internos* (SII). Chile's income tax system (*Impuesto a la Renta*) consists primarily of three taxes: a flat corporate tax (*Primera Categoría*, PC), a progressive labor income tax (*Segunda Categoría*, SC), and a progressive comprehensive personal income tax (*Global Complementario*, GC).[13] Taxes are assessed annually. The marginal tax rates and brackets for SC and GC coincide, and the GC serves as the final settlement tax: each individual aggregates all taxable income into a comprehensive base and applies the GC schedule. Until 2016, business taxes paid on distributed profits were fully creditable against the GC.[14] Retained profits do not enter the GC base, and credits for corporate taxes can be claimed only upon distribution.

Individuals and firms file annual income declarations using Form 22 (*Formulario 22*).[15] Filing is mandatory for all entities and individuals with non-exempt taxable income. We use the universe of Form 22 records from 2008–2016, which includes all corporations and all individuals aged 18 and above who file. Additional administrative sources allow us to identify individuals who do not submit Form 22 and to attribute retained profits to ultimate owners.

All residents and formal firms have a unique taxpayer identifier (*Rol Único Tributario*, RUT), which enables linkage across datasets and across years. Using these records, we construct accrued and distributed income at the individual level. Our analysis does not include informal income or imputed rents from owner-occupied housing.[16]

[13] A separate *Impuesto Único* applies to certain foreign entities.

[14] Beginning in 2017, creditability became full or partial depending on firm characteristics.

[15] Forms and instructions are available at `www.sii.cl`.

[16] OECD (2024) estimate that informality in Chile is approximately 20%, while the Central Bank of Chile's Household Finance Survey reports that about 60% of households were homeowners in 2017.

A.2 Income Sources and Individual-level Variables Construction

To measure income, we combine several tax forms from the SII that contain information on all individuals who report formal income to the SII. Table A.1 lists the tax forms and codes we use to measure each income source. We start with the F22 form, which includes information on approximately 1.9 million individual taxpayers in 2016. This form requires taxpayers to report various types of income, such as wages and pensions, self-employment income, financial income (including interest income, gains from the sale of mutual fund shares, capital gains, etc.), and dividends and distributed profits.[17]

Dependent workers with no income other than salaries and pensions and with a single employer are not required to file the F22 tax form because their employers or pension providers have already withheld all the necessary taxes. The F22 form is only filled out by individuals who receive income from multiple sources. In any given year, approximately 70% of taxpayers are exempt from filing this form. We use information from the DJ1887 form (*Declaración Jurada 1887*) filled out by employers to obtain labor income information for individuals who do not fill out the F22 form. We use the RUT to match individuals across datasets. It is worth noting that all reported income is pre-tax income. We report summary statistics of individuals' income sources in Section 4.

Table A.1: Individual-level income variables construction from tax records form

Variable name	**Form and code**
Self-employment income	F22, code 110 or DJ 1890
Dependent labor income	F22, code 161 or DJ 1887
Pensions	F22, code 161 or DJ 1812
Financial income	F22, code 155
Withdrawn profits	F22 codes 104 + 105 + 108 + 955 + 957 + 959

Notes: This table lists the tax forms and codes used to construct individual-level income categories. Our main data source is Form F22. For individuals not required to file Form F22, income is obtained from Forms DJ 1887, DJ 1879, or DJ 1812, ensuring full coverage without double counting. Pension information from Form DJ 1812 is available from 2013 onward.

A.3 Individual-level Summary Statistics

After matching tax forms and ownership data, our sample comprises nearly 9.8 million individuals in 2016. Table A.2 presents descriptive statistics of individual income and its sources

[17] Pensions and wages are reported together on the tax form F22. In the following discussion, we refer to dependent labor income as the sum of salaries and pensions.

for this year. Individuals report an average total accrued annual income of 11.32 million pesos or about 17.5 thousand dollars, above the 13.6 thousand dollars of GDP per capita reported by the World Bank indicators.[18] Dependent labor income emerges as the most significant income source, accounting for about two thirds of total income at the mean. While gross payment to capital are comparatively lower on average, their distribution exhibits high concentration, wide variation, and significant skewness. Less than **10**% of individual taxpayers own shares of businesses with positive profits. Figure A.1 illustrates the share of each income source for percentiles 80th to 100th in 2016. The participation of net profits increases gradually with percentiles, rising from around 3% in the 80th percentile to approximately 18% in the 99th percentile. However, a significant jump is observed for the top 1% of earners, with net profits constituting nearly 80% of their total accrued income. Accordingly, dependent labor income is the most relevant source of income for every percentile of the income distribution, except for the 100th percentile.

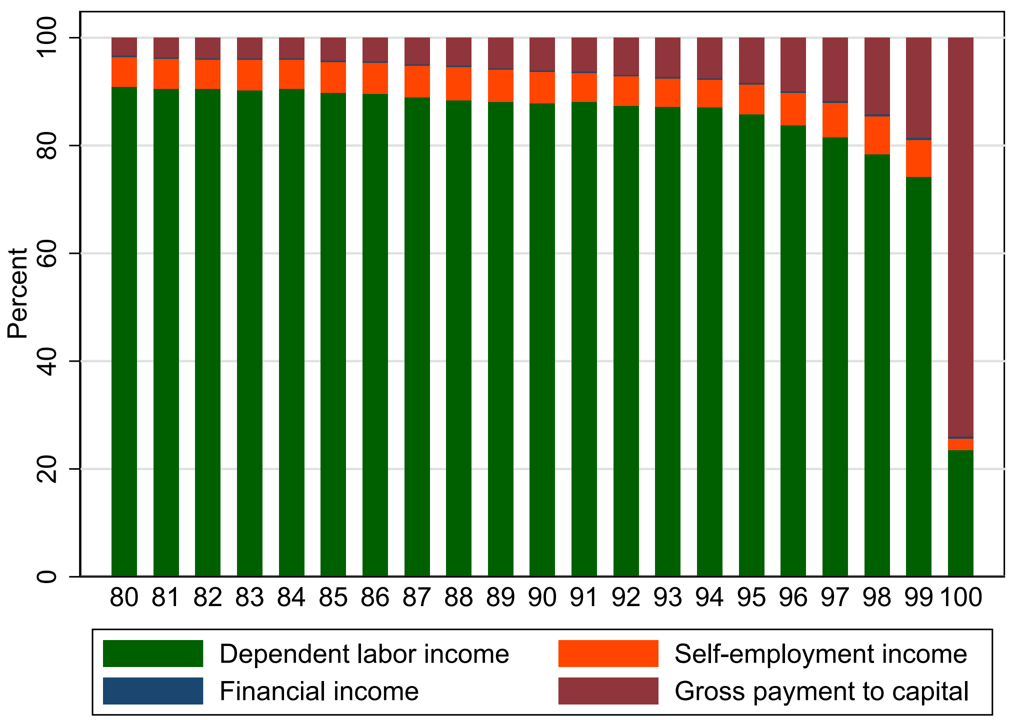
Table A.2: Income sources summary statistics

	Variables description (annual, in million pesos)								
	Mean	S.D.	P10	P25	P50	P75	P90	P99	Obs.
Total accrued income	11.32	425.14	0.42	1.59	4.36	9.60	19.68	81.48	9,776,621
Dependent labor income	7.48	16.67	0.00	1.05	3.68	8.60	17.07	60.02	9,776,621
Self-employment income	0.56	7.70	0.00	0.00	0.00	0.00	0.51	11.59	9,776,621
Financial income	0.03	2.58	0.00	0.00	0.00	0.00	0.00	0.20	9,776,621
Gross payment to capital	3.26	423.81	0.00	0.00	0.00	0.00	0.00	26.71	9,776,621
Withdrawn profits	0.78	148.08	0.00	0.00	0.00	0.00	0.00	20.49	9,776,621

Notes: 2016

[18]See https://data.worldbank.org/. The difference may be partly explained by informality.

Figure A.1: Income sources at the top 20%



Notes: This figure shows the share of each income source for the top centiles of the distribution. We show the different sources of income obtained directly from the F22 tax records for the year 2016, except for net profits which were attributed to their final owners.

A.4 Inequality Measures and Decompositions

We quantify income inequality using indices that admit factor decompositions. Our goal is to assess the contribution of income generated through market power to overall inequality, and we therefore focus on decompositions that separate the role of each income source. We present results using two complementary approaches.

We begin with the decomposition of the Gini index developed by Lerman and Yitzhaki (1985). Let h index income sources and let s_h denote the share of source h in total income. The Gini coefficient can be written as

$$G = \sum_{h=1}^{H} s_h \, G_h \, Q_h, \tag{8}$$

where G_h is the Gini coefficient of income source h and Q_h is the Gini correlation, defined as the correlation between income source h and the rank of total income.[19] This decomposition provides an intuitive interpretation of each source's contribution to overall inequality. Moreover, Lerman and Yitzhaki (1985) show that the marginal effect of a uniform proportional change in source h—from y_h to $e\,y_h$ with e close to one—on total inequality is

$$\frac{dG/de}{G} = \frac{s_h \, G_h \, Q_h}{G} - s_h, \tag{9}$$

which measures how increasing source h affects the Gini index through both its concentration and its correlation with total income.

This decomposition allows income sources to take negative values, provided that the mean of the source is nonzero and that G_h and Q_h are well defined. In such cases, however, the interpretation of G_h as a measure of inequality is less direct. This is not a concern in our setting, as we do not attribute negative gross payments to capital (i.e., firm losses) and bound markups at 1 in the left tail of their distribution.

As a second approach, we use the decomposition proposed by Shorrocks (1982), which applies to a broad class of inequality measures, including the Gini coefficient and generalized entropy indices such as I_2 and the Theil index. Under this decomposition, the contribution of income source h to inequality is given by

$$m_h = \frac{\operatorname{cov}(y_h, \, y)}{\sigma^2(y)},$$

where y_h denotes income from source h and y total income. An advantage of this approach

[19] The Gini correlation ranges from -1 to 1 and measures the extent to which income from source h is concentrated among individuals at different points of the total income distribution.

is that it remains well defined when some income components take negative values.

A.5 Firm-level Variables Construction and Summary Statistics

We define a firm as any legal entity (natural or artificial persons) subject to the corporate income tax. Form 22 of the SII (F22) provides annual information on sales and other revenues, the book value of assets, intermediate input purchases, the wage bill, financial and administrative expenses, tax depreciation, dividends received from other firms, and profits. Table A.3 describes how each variable is calculated from the corresponding line codes.[20]

Table A.3: Variables construction from the F22 form

Variable name	**F22 code**
Panel A. Firm-level variables	
Sales	628
Wage bill	631
Stock of capital	647
Input purchases	630
Overhead costs	968 + 941 + 852 + 897 + 967 + 966 + 632 + 633 + 853 + 969 + 635
Profits (before taxes)	636
Gross payment to capital	636 − 642
Other income	851 + 629 + 651

Notes: This table reports the tax codes from the F22 form used to construct firm-level variables. Sales include both domestic sales and exports. The stock of capital corresponds to the book value of physical assets. Profits are measured before taxes. Other income captures income not classified as revenue, including dividends from firm ownership and sales of capital goods. The gross payment to capital is computed as profits minus dividends received from other firms in order to avoid double counting within ownership chains.

Our goal is to attribute GPK_{ft} to final local owners. Thus, we exclude from the data state-owned enterprises, non-profits, and firms fully owned by nonresidents. In 2016, 752.321 firms had at least one resident final owner, with combined sales of 295 trillion pesos—roughly 160% of GDP and 88% of gross output in the National Accounts.[21]

Our profit decomposition requires information on sales and labor plus intermediate inputs. These items are available for a subset of firms, which we refer to as the *decomposable* group. Firms missing at least one of these components form the *imputed* group. Table A.4 of

[20]The F22 form changes periodically. The codes used here correspond to the 2009–2017 versions of the form.

[21]By the end of 2016 the exchange rate was about 667 pesos per USD.

the Appendix summarizes both groups. In 2016, the decomposable group consists of 539,016 firms, accounting for nearly 97% of total sales. Sales constitute 79% of total revenues, and dividends from other firms about 1.5%.

Panel B of Table A.4 shows that imputed firms derive 32% of their revenue from sales and 25% from capital gains and dividends from the ownership of other firms. Many appear to function as passive holding or investment vehicles ("shell" firms). Because they do not report sales, employment, or input purchases, we cannot estimate markups or decompose profits. Given the limited scope for exercising market power in these entities, our baseline assumption assigns a markup of one, treating their gross payment to capital as competitive.[22]

[22]More generally, we also impose a unit lower bound on markups. This restriction eliminates negative monopolistic rents, which may invalidate the decomposition of some inequality measures and lack a clear economic interpretation. The effect on our main results is not significant, since negative markups are strongly correlated with negative profits and our framework attributes only positive gross payments to capital.

Table A.4: Firms' descriptive statistics

Panel A.	Decomposable firms (million pesos)						
	Obs.	Mean	S.D.	P10	P50	P90	Total*
Sales	539,016	535.39	18649.83	1.90	24.62	349.32	288.58
Other income	339,486	224.10	17406.15	-0.00	0.00	9.40	76.08
Profits	538,992	59.17	3766.40	-1.96	2.15	41.16	31.89
Wage bill	320,487	102.72	2121.03	0.16	6.79	115.26	32.92
Input purchases	490,972	404.66	19259.65	0.83	12.24	193.80	198.68
Overhead costs	480,945	210.37	14226.77	0.05	3.39	79.73	101.18
Gross payment to capital	539,016	48.98	3317.67	-2.12	2.11	39.20	26.40

Panel B.	Imputed firms (million pesos)						
	Obs.	Mean	S.D.	P10	P50	P90	Total*
Sales	60,688	116.45	2687.99	0.37	8.58	95.72	7.07
Other income	60,084	248.63	3850.94	0.00	0.32	96.24	14.94
Profits	125,089	98.32	2795.54	-6.23	0.05	39.93	12.30
Wage bill	8,313	29.08	545.18	0.12	3.13	35.31	0.24
Input purchases	8,032	45.90	988.08	0.07	1.29	29.74	0.37
Overhead costs	103,388	88.45	2467.60	0.05	2.39	51.23	9.14
Gross payment to capital	213,215	31.83	1946.70	-2.49	0.53	12.33	6.79

Notes: This table presents firms' characteristics for 2016 based on the F22 form from the SII. We exclude the following industries: Public Administration, Public Health, Public Education, Communities, Extraterritorial Institutions, Non-profit Organizations, and Pension, Mutual, and Investment Funds. Decomposable firms are those reporting sales, employment, and input purchases. Imputed firms report profits but lack information on sales, employment, and/or input purchases. All variables are measured in millions of pesos, except in the column "Total," where they are expressed in billions of pesos.

A.6 Details on the Firm Ownership Dataset

The individual taxpayers' F22 form only provides information on distributed profits. However, we aim to include all profits, whether distributed or not, in our analysis. Previous studies, such as Fairfield and Jorratt (2016) and World Bank (2015), have shown that a significant portion of profits in Chile is reinvested.[23] The ownership of these retained profits is primarily concentrated among the wealthiest individuals, which can substantially impact measures of income inequality.

To incorporate undistributed profits into our analysis, we use firm ownership data provided by the SII. This data is derived from various sources, including the Taxpayers Registry (RIAC), which contains information on equity participation in private firms, and tax forms that provide details on dividend payments and share transactions for publicly traded firms. Using these sources, the SII estimates the direct ownership relationships for each Chile firm at the year's end from 2008 to 2016.

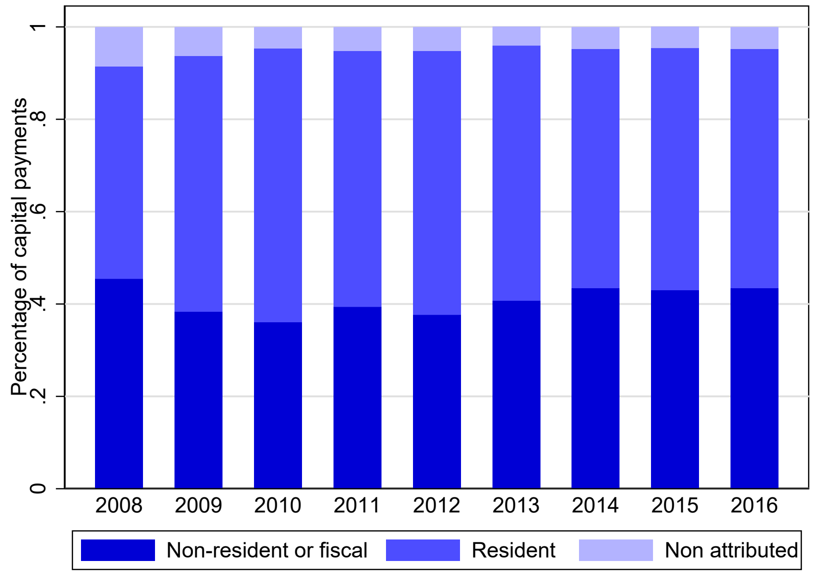
It is important to note that direct owners in the SII database can be individual taxpayers (resident or non-resident individuals) or other firms. Some of the largest firms are owned and controlled through complex ownership structures involving multiple layers of firm-to-firm ownership. However, we focus on attributing the retained profits to their final owners. Therefore, we need to identify the individuals at the top of the firm ownership networks and determine their total share in each firm. This requires considering the individual's direct participation in the firm and ownership share through other firms. The construction of direct ownership links and the methodology used to compute total ownership paths are detailed in **?**.

The ownership data we have is almost exhaustive. Figure A.2 illustrates that, on average, we can attribute over 95% of the firms' gross payment to capital in the sample to a final owner between 2008 and 2016. Approximately 60% of these profits correspond to resident taxpayers and thus are considered in the analysis.[24]

[23] **?** for the case of Norway.

[24] Using a similar ownership dataset, the World Bank (2015) obtained similar results in a study assessing the impact of the 2014 Chilean tax reform. For 2013, they assigned around 97% of non-negative firms' profits to their final owners (see footnote 18 in the report).

Figure A.2: Coverage of the Firm Ownership Data



Notes: This figure shows the fraction of gross payment to capital attributed to a final owner between 2008 and 2016.

B Production Function Estimation

We follow De Loecker et al. (2020) and estimate production-function elasticities at a narrow industry level using two standard approaches: Olley and Pakes (1996) (OP) and Ackerberg et al. (2015) (ACF). Both methods yield similar results; therefore, we report estimates based on the ACF procedure, which serves as our benchmark specification.[25] Given the relatively short time horizon of our data and the small number of firms in some industries, we pool all years from 2008–2016 and estimate a static production function at the 42-industry aggregation used by the Central Bank of Chile.

Our estimation sample includes all firms for which we observe sales, input purchases, labor expenses, and general costs from the annual F22 tax form filed with the SII over 2008–2016. We construct physical measures of output and intermediate inputs by deflating sales and input purchases using industry-level deflators from the 111-sector input–output tables of National Accounts. Labor expenses are deflated using the national wage index published by the Instituto Nacional de Estadísticas (INE). As discussed by De Loecker et al. (2020), the absence of firm-level input and output price deflators implies that the composite error term ϵ_{it} may embed price variation, which could bias parameter estimates. To mitigate this concern, we include firms' market shares as an additional control in the estimation.

For each industry, we estimate the following Cobb–Douglas production function in logs:

[25] OP-based estimates are available upon request.

$$y_{ft} = \theta \upsilon_{ft} + \alpha k_{ft} + \omega_{it} + \epsilon_{ft} \tag{10}$$

where y_{ft} denotes firm f's physical output in year t; υ_{ft} is the firm's cost of goods sold (input purchases plus labor expenses), assumed to be chosen after observing the productivity shock ω_{ft}; and k_{ft} is the firm's capital stock, determined prior to observing ω_{ft} and therefore treated as a state variable. The term ϵ_{ft} is an i.i.d. error.

Under the standard monotonicity condition—firm demand for the control variable being strictly increasing in productivity—ω_{ft} can be expressed as a function of (k_{ft}, d_{ft}), where d_{ft} is a proxy for the firm's variable input choice. Hence, Equation (10) can be re-written as

$$y_{ft} = \theta \upsilon_{ft} + \phi_t(d_{ft}, k_{ft}) + \epsilon_{ft} \tag{11}$$

where ϕ_t is an unknown function.

We estimate (11) using the standard two-step procedure with the following moment conditions:

$$E\left(\zeta_{ft}\left(\theta, \alpha\right)\begin{bmatrix} \upsilon_{ft-1} \\ k_{ft} \end{bmatrix}\right) = 0 \tag{12}$$

where $\zeta_{ft} = \eta_{ft} + \epsilon_{ft}$, with η_{ft} the error term in the exogenous Markov process for productivity ω_{ft}. As proxy variables d_{ft}, we use investment in the OP specification, and investment together with labor in the ACF specification.

Table A.5 presents the estimated output elasticity of variable inputs (V) and capital (K) at the 12 industry-level, weighted by variable input expenses for aggregation. The average output elasticity of inputs plus labor ranges from 0.71 to 0.99, while the average elasticity for capital is 0.11. Furthermore, at the 12 industry-level, all sectors exhibit decreasing returns to scale ($\gamma_s < 1$ for all s).

C Markups and the Aggregate Monopolistic Share

Once we obtain the parameters of the production function for each industry, annual firm-level markups are then computed according to Equation (1). Table A.6 reports descriptive statistics for firm-level markups for the final sample of firms, that is, for those that have a positive gross payment to capital. In 2016, the average markup is 2.05, larger than the estimates in **?** and Garcia-Marin and Voigtländer (2019) for Chilean manufacturing. This difference reflects the broader coverage of our data-particularly the inclusion of small firms for which sales or input mismeasurement can inflate the sales-to-inputs ratio-and the fact

Table A.5: Aggregate elasticities by industry

	Elasticities		
Industry	θ^V	θ^K	γ
Agriculture	0.92	0.08	0.89
Mining	0.95	0.05	0.89
Manufacturing	0.99	0.01	0.99
Utilities	0.94	0.06	0.91
Construction	0.76	0.24	0.85
Whosale and retail trade	0.91	0.09	0.94
Transport	0.93	0.07	0.97
Financial services	0.89	0.11	0.94
Real estate	0.92	0.08	0.97
Services	0.71	0.29	0.82
Other	0.98	0.02	0.87

Notes: This table shows average elasticities at the 12 industry-level weighted by variable inputs expenses. Elasticities obtained at the 42 industry-level.

that we only consider firms that have positive retained earnings. The time series is stable, and there is sizable within-year heterogeneity: in 2016, the median percentile markup is 1.08 while the 90th percentile reaches 3.88. Figure A.7 shows similarly large dispersion across sectors.

Finally, using our markup estimates and the framework developed in Section 2, we decompose firm-level net profits, PK_{ft}, into three components: competitive returns ($RC_{ft} = \phi^c_{ft} PK_{ft}$), monopolistic rents ($RM_{ft} = \phi^m_{ft} PK_{ft}$), and rents arising from decreasing returns to scale ($RS_{ft} = \phi^s_{ft} PK_{ft}$). Figure A.3 reports the resulting decomposition of aggregate net profits by year.

On average over the 2008–2016 period, aggregate gross payments to capital are composed of 22% competitive returns, 61% monopolistic rents, and 17% rents from decreasing returns. The contribution of decreasing returns is relatively stable over time, whereas the competitive and monopolistic components display moderate year-to-year variation, though neither exhibits a clear trend. The share of competitive returns ranges between 16% and 25%, while the monopolistic component varies between 58% and 70%.

Table A.6: Firm-level markup distribution

	Summary statistics					
Year	Mean	S.D.	P10	P50	P90	Obs.
2008	1.98	3.01	1.00	1.06	2.97	438,848
2009	1.95	2.98	1.00	1.05	2.90	425,471
2010	1.92	2.88	1.00	1.06	2.81	477,072
2011	1.93	2.91	1.00	1.06	2.83	490,080
2012	1.96	2.96	1.00	1.06	2.90	514,052
2013	1.97	2.98	1.00	1.06	2.98	536,250
2014	2.00	3.03	1.00	1.06	3.04	545,971
2015	2.06	3.17	1.00	1.07	3.18	573,398
2016	2.05	3.09	1.00	1.08	3.22	582,265

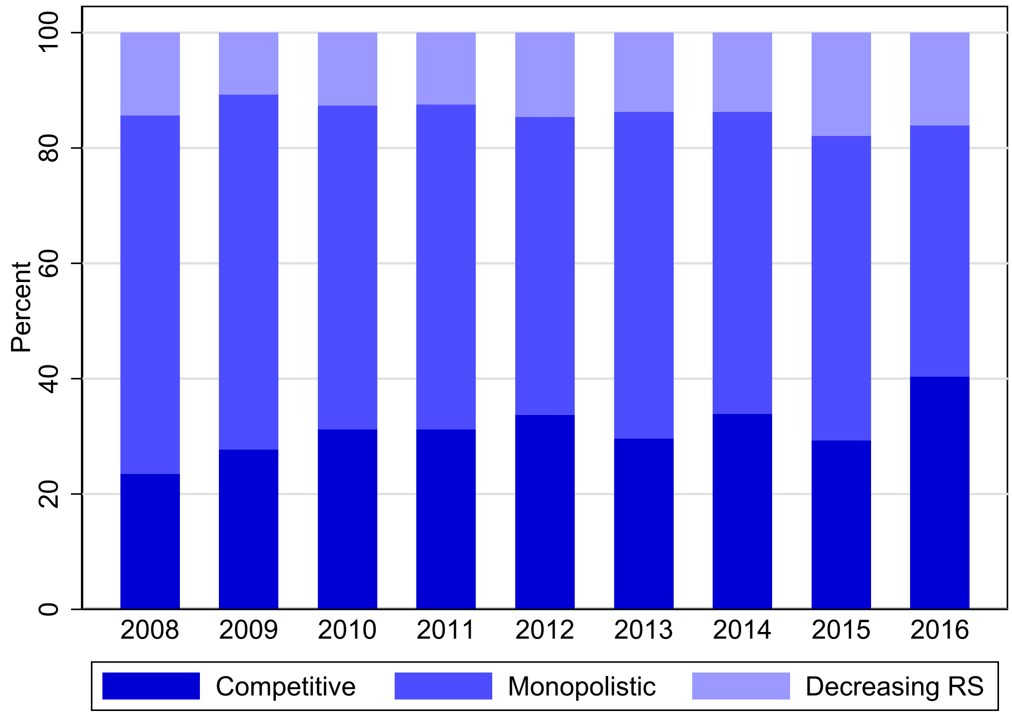
Notes: This table shows summary statistics for the distribution of markups at the firm level for the decomposable group of firms. Markups winsorized at the 1% level on the right tail. The minimum markup value is one.

Table A.7: Firm-level markup distribution by industry, 2016

	Summary statistics					
Industry	Mean	S.D.	P10	P50	P90	Obs.
Agriculture	1.52	2.18	1.00	1.00	1.89	62,536
Mining	2.47	3.34	1.00	1.33	4.62	2,012
Manufacturing	2.26	3.30	1.00	1.12	3.97	2,259
Utilities	2.03	2.66	1.00	1.25	3.22	48,985
Construction	1.94	2.98	1.00	1.00	3.00	1,443
Whosale and retail trade	2.51	3.62	1.00	1.26	4.59	43,605
Transport	1.69	2.30	1.00	1.11	2.25	224,933
Financial services	1.75	2.70	1.00	1.00	2.50	75,939
Real estate	2.94	4.37	1.00	1.21	6.38	72,190
Services	3.32	4.89	1.00	1.00	8.92	11,570
Other	3.09	4.39	1.00	1.30	7.16	36,793

Notes: This table shows summary statistics for the distribution of markups at the firm level. Markups winsorized at the 1% level on the right tail. The minimum value of markup is one.

Figure A.3: Decomposition of Aggregate Gross Payment to Capital



D Additional Tables

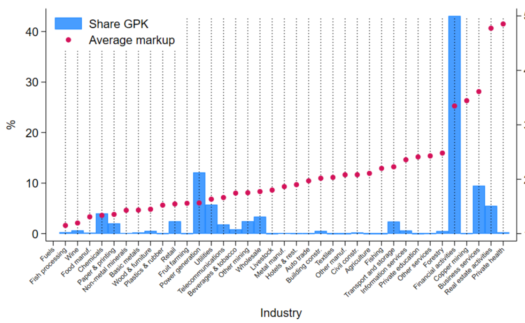
Table A.8: Shorrocks Decomposition by Source

	Contribution to inequality ($m_h \times 100$)	
Income source	(1)	(2)
Self-employment income	0.29	0.12
Dependent labor income	1.28	0.25
Financial income	0.05	0.04
Withdrawn profits	98.38	—
Gross payment to capital:		
Total	—	99.59
Competitive	—	54.90
Market power	—	32.25
Decreasing returns	—	12.44

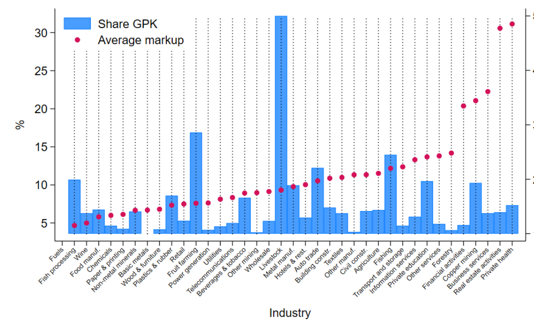
Notes. This table reports the Shorrocks (1982) decomposition (Section A.4) for 2016. Each entry $m_h \times 100$ denotes the percentage contribution of income source h to total inequality. Column (1) treats withdrawn profits as a single income source. Column (2) instead decomposes gross payments to capital into competitive, market-power, and decreasing-returns components. Contributions sum to 100 within each column.

E Additional Figures

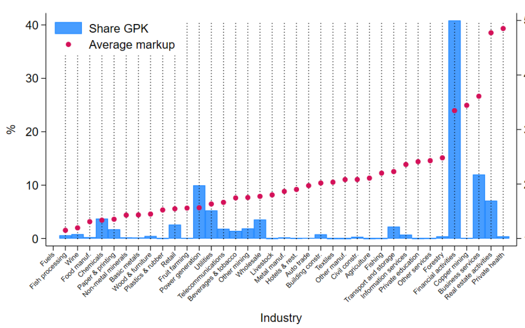
Figure A.4: Gross Payment to Capital, Sectors and Markups



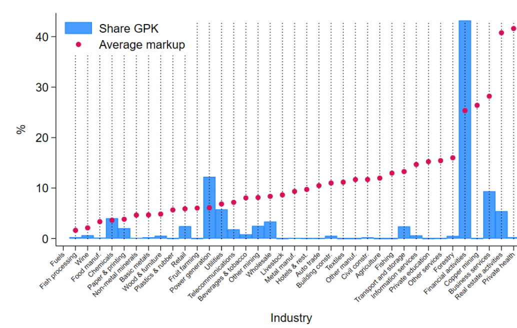
(a) Sectoral Share of GPK



(b) Share of GPK owned by the top 0.1%



(c) Allocation in the top 0.1%



(d) Allocation outside the top 0.1%

Note: This figure reports sectoral GPK, markups and investment across industries of individuals for 2016. Average markups are weighted by firm GPK. Panel A.4a plots the contribution of each sector to aggregate GPK attributed to final owners. Panel A.4b reports the share of each industrys GPK attributed to individuals in the top 0.1% of the income distribution. Panel A.4c reports the contribution of each sector to total GPK attributed to individuals in the top 0.1% of the income distribution. Panel A.4d reports the contribution of each sector to total GPK attributed to individuals outside the top 0.1% of the income distribution.