Markups, Production Technology, and the Cost of Capital in Financial Markets

Ginha Kim
James Traina*

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Abstract

We develop a new approach to measuring markups by combining cost share and implied cost of capital techniques. Recent markup measures suggest US market power has surged since 1980, but largely neglect heterogeneity in costs of capital. Applying our approach to US public firms from 1970 to 2023, we find average markups remain stable around 1. Markup dispersion increases significantly, with top-quartile firm markups rising and bottom-quartile falling. The top percentile in the markup distribution faces costs of equity capital around 7%, substantially below the 13% market average. Overall, we find a strong negative relationship between markups and the cost of equity capital—lower financing costs predict higher markups. These patterns support the superstar hypothesis of increasing differences between firms, suggesting a mechanism through cheaper funding. Our approach resolves identification problems in production function estimation and points to financial markets and technological change as key drivers of macroeconomic patterns in markups.

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*Kim: Chicago Booth, ginhaki1@chicagobooth.edu. Traina: NYU Stern AD, james.traina@nyu.edu. We thank Arshia Hashemi and Uyen Tran for their valuable help and feedback.

Production-based markup estimates following (Hall, 1988) largely overlook differences in financing costs when calculating the user cost of capital, despite finance research documenting substantial heterogeneity in risk premia and required returns (Fama and French, 1992; Cochrane, 2009). Motivated by this gap in the literature, we ask: How does incorporating firm-specific financing costs change our understanding of markup trends and firm heterogeneity? Firms pay different costs to finance their capital. A stable manufacturer might pay 5% while a growing tech venture might pay 25% because of different risk profiles. These values have also changed substantially from the 1980s to today (Duarte and Rosa, 2015). This variation matters because underestimating costs leads to overestimating markups, directly affecting our measurement of market power.

We address our research question by synthesizing insights from two literatures—one in productivity and macroeconomics, the other in accounting and finance—to measure user costs and markups in Compustat microdata. We work from the cost share approach to production function estimation, which equates elasticities to input cost shares under general conditions and avoids the severe non-identification problems common in other approaches (Gandhi et al., 2020; Bond et al., 2021). A key challenge is measuring the user cost of capital, particularly the risk premia embedded in the cost of equity capital. To overcome this challenge, we recover the implied cost of equity capital by applying the present value relation to market values and expected future profits from an earnings forecast model, specifically following Gebhardt et al. (2001) and Hou et al. (2012).[1] Our innovation is to combine these two highly flexible and empirically successful methodologies, allowing rich firm-year-level heterogeneity in costs of capital, production technologies, and markups for nearly all US public firms.

We find this synthesis alters the narrative of broadly rising market power. When accounting for firm-specific capital costs, average markups for US public firms remain close to 1 throughout our sample period (1970 to 2023), with mean and median markups stable between 1.00 and 1.05, indicating broadly competitive pricing. However, we document a significant increase in the dispersion of markups across firms consistent with the superstar hypothesis of Autor et al. (2020)—where economic changes create winner-take-all effects that favor the most productive firms. Supporting this view, we find a strong negative relationship between markups and the implied cost of equity capital, suggesting an advantage in financial funding might be a key mechanism that generates superstars (Liu et al., 2022). Our findings also suggest technological change, not declining competition, drives the increasing dispersion in markups, which implies potential welfare losses through misallocation (Baqaee and Farhi, 2020; Edmond et al., 2023).

We develop a unified model linking investment decisions, capital costs, and markups. Building on the dynamic cost minimization framework of Basu and Fernald (2001), we extend it to incorporate how investors value expected future profits and thus connect firm behavior to investor-required returns in financial markets. Consider the thought experiment of holding fixed a firm's choice of labor

[1] Pástor et al. (2008) and Frank and Shen (2016) are strong empirical precedents showing this method successfully predicts the positive risk-return relationship and negative investment-cost relationship, respectively. See Lee et al. (2021) for a review in the finance and accounting literatures.

and investment. Mechanically, a higher cost of equity capital implies a higher user cost of capital (Jorgenson, 1963), which implies a higher capital cost share, a higher estimated output elasticity of capital, a lower estimated output elasticity of labor, and a lower estimated markup. Firms might also respond to a higher user cost by decreasing their investment rates and capital stocks, so the bias depends on endogenous responses.

We then introduce our finance-based approach to estimating firm-specific user costs of capital, production technologies, and markups. Specifically, we apply the implied cost of equity capital method developed by Gebhardt et al. (2001) and extended by Hou et al. (2012) to estimate risk-adjusted discount rates for individual firms. We adjust for differences in leverage, depreciation, and taxes in the user cost formula. Our method only requires firms to have publicly traded equity and data on basic accounting items, enabling us to construct a panel of over 15,000 public firms from 1970 through 2023. These estimates display significant variation across firms and over time. We then combine these capital-cost estimates with the cost-share approach to production function estimation to recover firm-year-level production technologies and markups.

Our markup estimates reveal several key patterns. First, we find substantial variation in the implied cost of equity capital across both time and in the cross-section of firms. The inter-quartile difference of the implied cost of equity capital has varied from 2.5 to 6.3 percentage points overtime. Second, high implied costs of equity capital strongly predict low markups—a percentage point increase in the implied cost of capital is associated with 0.5% lower markups. Third, once we incorporate firm-specific capital costs, average markups remain stable around 1.0 from the 1980s onward, showing no significant aggregate increase. Fourth, we estimate a sizable rise in markup dispersion; average markups of the top quartile increased from 1.03 to 1.14 over 1980 to 2023, while the bottom quartile has declined from 0.9 to 0.8 over the same period. The markup at the 99th percentile shows an especially large rise from 1.1 in 1980 to 1.25 in 2023. On average, these firm that charge markups above these levels face a 6.5% cost of equity capital, which is considerably lower relative to the overall median of 9.1% and mean of 13%. Finally, we find that production-based markup estimates are highly sensitive to assumptions about capital costs. Using fixed values for implied cost of capital across industry or years, we find that ignoring firm-year level heterogeneity in user costs leads to depressed markup estimates.

Our first contribution is methodological: we develop a new approach to measuring markups that combines the cost shares method with firm-specific financing cost estimates from the finance and accounting literature. Our innovation fills a critical gap in the literature. Cost share estimators are quickly becoming a common workhorse model for markup estimation, as they avoid the severe nonidentification problems of Olley and Pakes (1996)-style estimators documented by Bond and Söderbom (2005), Gandhi et al. (2020), Klette and Griliches (1996), and Bond et al. (2021). Our finance-based approach tackles one of the most pressing problems in applying cost shares, namely measuring the user cost of capital. Our approach provides two other key advantages: it accounts for differences in capital costs across firms and time, and it applies to nearly all public firms with traded equity. By solving these measurement issues, we directly address concerns raised by Basu (2019) and

Syverson (2019) about potential biases in markup estimates.

Our second contribution is empirical: we document novel patterns in firm heterogeneity that challenge existing narratives about rising market power in the US economy. When accounting for firm-specific capital costs, we find average markups for US public firms remain close to 1 throughout 1970 TO 2023, with mean and median values stable between 1.00 and 1.05, indicating that markets have remained broadly competitive. Taken together with results on concentration and profits (Grullon et al., 2019; Barkai, 2020; Covarrubias et al., 2020), we therefore show the markups hypothesis has conflicting evidentiary support. We also emphasize that properly accounting for user costs matters greatly for markup estimates (Karabarbounis and Neiman, 2019).

While averages remain stable, we observe a significant increase in markup dispersion across firms, with top-quartile firms showing rising markups while bottom-quartile firms show declining markups. This pattern is consistent with the superstar hypothesis proposed by Autor et al. (2020) and Van Reenen (2018) and highlights microdata heterogeneity that was a key theme in Syverson (2011). Markup dispersion is also a key sign of misallocation, implying potentially large welfare losses (Baqaee and Farhi, 2020; Edmond et al., 2023). We further document a strong negative relationship between markups and the implied cost of equity capital, suggesting that financing advantages might be a key mechanism that generates these superstars (Liu et al., 2022). Because only systematic risks that investors cannot diversify away enter the user cost, markups may still compensate idiosyncratic risks borne by entrepreneurs (Boar et al., 2022; Di Tella et al., 2024). Our empirical evidence is also consistent with findings from David and Venkateswaran (2019) and Foster et al. (2022) highlighting the role of technological heterogeneity in the increasing dispersion in firm performance and capital allocation.

The remainder of the paper is organized as follows: Section 1 develops our model that derives the relationship between markups, production technology, and the cost of capital in financial markets. Section 2 details our empirical implementation on the Compustat sample. Section 3 presents our empirical results, and Section 4 concludes.

1 A Unified Model of Investment and Markups

This section develops a framework that connects investment decisions, markups, and capital costs. Our starting point is the investment literature tracing back to Jorgenson (1963) and Hayashi (1982). We draw on insights from Cooper and Ejarque (2001), Abel and Eberly (2011), and Balvers et al. (2017) to highlight how markups or concavity in the profit function can affect investment incentives, even with frictionless capital processes. We begin by modeling how firms dynamically minimize costs as in Basu and Fernald (2001). We then introduce market power via markups and show how these markups relate to marginal cost, output elasticities, and revenue shares (Hall, 1988). Under constant returns to scale, labor and capital cost shares reveal their underlying production elasticities. Next, we derive the user cost of capital from the firm's envelope condition and investment equations, linking it to depreciation and risk. Finally, we connect these results to asset prices by comparing investment

returns, financial-market returns, and their risk premia in capital-market equilibrium.

1.1 A Dynamic Cost-Minimization Problem

We consider a panel of firms $i = 1, 2, \ldots$ operating in discrete time $t = 0, 1, 2, \ldots$. Each firm i produces output Y_{it} using capital K_{it} and labor L_{it} according to a production function:

$$Y_{it} = F(K_{it}, L_{it}, t) \tag{1.1}$$

where the time argument captures possible technological change and other time-varying factors. The production function exhibits constant returns to scale, consistent with evidence from industry-level (Basu and Fernald, 1997) and establishment-level (Syverson, 2004) data. Capital evolves through investment according to:

$$K_{it+1} = (1 - \delta_{it})K_{it} + I_{it} \tag{1.2}$$

where $\delta_{it} \in (0, 1)$ is the firm and time-specific depreciation rate and I_{it} is gross investment.

Each firm minimizes the present value of costs—labor plus investment—across an infinite horizon, discounting future outlays by a stochastic discount factor M_{t+1}. Such an approach follows the style of Cochrane (1991) and the subsequent production-based asset pricing literature. The firm's value function $V(K_{it}, t)$ represents the minimum expected discounted cost:

$$V(K_{it}, t) = \min_{L_{it}, I_{it}} \Big\{ W_{it}L_{it} + I_{it} + \mathbb{E}_t\big[M_{t+1}V(K_{it+1}, t+1)\big] \Big\} \tag{1.3}$$

subject to $Y_{it} = F(K_{it}, L_{it}, t)$ and the capital law of motion in (1.2). Here, W_{it} is the wage rate, and $\mathbb{E}_t[\cdot]$ denotes expectations conditional on information at time t. As additional capital reduces future production costs, we have $\partial V/\partial K_{it} < 0$.

1.2 First-Order Conditions

To find optimal input choices, we form the Lagrangian with multiplier λ_{it} on the production constraint:

$$\mathcal{L}_{it} = W_{it}L_{it} + I_{it} + \mathbb{E}_t\Big[M_{t+1}V(K_{it+1}, t+1)\Big] + \lambda_{it}\Big[Y_{it} - F(K_{it}, L_{it}, t)\Big] \tag{1.4}$$

The multiplier λ_{it} represents the marginal cost of production. The firm's optimization yields three conditions that characterize optimal behavior.

Differentiating the Lagrangian with respect to L_{it}:

$$\frac{\partial \mathcal{L}_{it}}{\partial L_{it}} = W_{it} - \lambda_{it}\frac{\partial F}{\partial L} = 0$$

Rearranging:

$$W_{it} = \lambda_{it}\frac{\partial F}{\partial L} \tag{2.1}$$

The firm hires labor until the wage equals the value of labor's marginal product.

Differentiating with respect to I_{it} and considering $\frac{\partial K_{it+1}}{\partial I_{it}} = 1$:

$$\frac{\partial \mathcal{L}_{it}}{\partial I_{it}} = 1 + \mathbb{E}_t\Big[M_{t+1}\frac{\partial V}{\partial K_{it+1}}\Big] = 0$$

This simplifies to:

$$1 = -\,\mathbb{E}_t\Big[M_{t+1}\frac{\partial V}{\partial K_{it+1}}\Big] \tag{2.2}$$

The firm invests until the expected discounted marginal benefit of additional capital equals its unit cost.

To derive how the value function changes with current capital, we apply the envelope theorem:

$$\frac{\partial V}{\partial K_{it}} = \frac{\partial \mathcal{L}_{it}}{\partial K_{it}} = -\,\lambda_{it}\frac{\partial F}{\partial K} + (1-\delta_{it})\,\mathbb{E}_t\Big[M_{t+1}\frac{\partial V}{\partial K_{it+1}}\Big] \tag{2.3}$$

We assume depreciation is known at time t, hence outside the expectation. This equation captures both the immediate production benefit of capital and its future value after depreciation.

Substituting the investment FOC (2.2):

$$\frac{\partial V}{\partial K_{it}} = -\,\lambda_{it}\frac{\partial F}{\partial K} - (1-\delta_{it}) \tag{2.4}$$

This connects the current shadow value of capital to its productive contribution and continuation value. Intuitively, the marginal value of capital depends negatively on the marginal product (since more capital lowers marginal cost) and positively on its continuation value after depreciation.

1.3 Markups

Cost minimization is broadly compatible with many market structures including various forms of imperfect competition. Firms minimize cost given whatever output price they face, even under monopoly power.

The markup is the ratio of output price to marginal cost:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}} \tag{3.1}$$

From the labor FOC (2.1), we have $\lambda_{it} = \frac{W_{it}}{\partial F/\partial L}$. Substituting:

$$\mu_{it} = \frac{P_{it}\,\frac{\partial F}{\partial L}}{W_{it}} \tag{3.2}$$

Multiplying both the numerator and denominator by L_{it}/Y_{it}:

$$\mu_{it} = \left(\frac{\partial \ln F}{\partial \ln L}\right)\left(\frac{P_{it}Y_{it}}{W_{it}L_{it}}\right) \tag{3.3}$$

The markup equals the ratio of labor's output elasticity to labor's revenue share. When $\mu_{it} = 1$, the firm behaves competitively. Values above 1 indicate market power, where firms price above marginal cost because they face downward-sloping (residual) demand curves. Markups can also fall below 1. Real-world factors (e.g., regulatory constraints, strategic underpricing, long-term contracts, empire building) might push firms to price below statically profit-maximizing levels.

This ratio approach to measuring markups follows Hall (1988), who first showed how researchers can infer markups from production data using cost-minimization conditions. Recent empirical work by De Loecker et al. (2020) has documented significant increases in market power applying this insight to microdata, though this finding remains debated (Traina, 2018; Syverson, 2019; Basu, 2019).

1.4 Cost Shares

Under constant returns to scale, a fundamental relationship emerges between factor cost shares and output elasticities. Euler's theorem gives:

$$F(K_{it}, L_{it}, t) = K_{it} \frac{\partial F}{\partial K} + L_{it} \frac{\partial F}{\partial L} \tag{4.1}$$

We define the total economic cost in period t as:

$$\mathcal{C}_{it} = W_{it} L_{it} + R_{it} K_{it} \tag{4.2}$$

where R_{it} is the user cost of capital. This formulation of the user cost concept builds on Jorgenson (1963), who showed how interest rates, depreciation, and (in later work) taxes determine capital's implicit rental price. The user cost of capital measures the total cost incurred by using an additional unit of capital. We introduce it explicitly to quantify capital costs consistently across periods.

From cost minimization:

$$W_{it} = \lambda_{it} \frac{\partial F}{\partial L}, \quad R_{it} = \lambda_{it} \frac{\partial F}{\partial K} \tag{4.3}$$

Multiplying Euler's theorem (4.1) by λ_{it} and substituting (4.3):

$$\lambda_{it} F(K_{it}, L_{it}, t) = \lambda_{it} K_{it} \frac{\partial F}{\partial K} + \lambda_{it} L_{it} \frac{\partial F}{\partial L} = R_{it} K_{it} + W_{it} L_{it} = \mathcal{C}_{it} \tag{4.4}$$

Since $F(K_{it}, L_{it}, t) = Y_{it}$, we have $\lambda_{it} Y_{it} = \mathcal{C}_{it}$.

Dividing each factor's cost by total cost gives:

$$\frac{W_{it} L_{it}}{\mathcal{C}_{it}} = \frac{\lambda_{it} L_{it}}{\lambda_{it} Y_{it}} \frac{\partial F}{\partial L} = \frac{L_{it}}{Y_{it}} \frac{\partial F}{\partial L} = \frac{\partial \ln F}{\partial \ln L} \tag{4.5}$$

$$\frac{R_{it} K_{it}}{\mathcal{C}_{it}} = \frac{\lambda_{it} K_{it}}{\lambda_{it} Y_{it}} \frac{\partial F}{\partial K} = \frac{K_{it}}{Y_{it}} \frac{\partial F}{\partial K} = \frac{\partial \ln F}{\partial \ln K} \tag{4.6}$$

This equivalence between factor shares and output elasticities holds regardless of market structure. Under constant returns to scale, each factor's share in total cost equals its output elasticity, regardless

of markup values.

1.5 User Cost of Capital

We now derive the user cost of capital from our dynamic framework. Starting with the envelope condition (2.3):

$$\frac{\partial V}{\partial K_{it}} = -\lambda_{it}\frac{\partial F}{\partial K} + (1-\delta_{it})\,\mathbb{E}_t\Big[M_{t+1}\frac{\partial V}{\partial K_{it+1}}\Big]$$

Substituting the investment FOC (2.2):

$$\frac{\partial V}{\partial K_{it}} = -\lambda_{it}\frac{\partial F}{\partial K} - (1-\delta_{it}) \tag{5.1}$$

Rearranging and using $R_{it} = \lambda_{it}\,\frac{\partial F}{\partial K}$ from (4.3):

$$R_{it} = -\frac{\partial V}{\partial K_{it}} - (1-\delta_{it}) \tag{5.2}$$

This formulation shows how the user cost directly relates to the firm's shadow value of capital (capturing the savings on future costs due to additional capital), adjusted for depreciation.

From the envelope condition at time $t+1$:

$$\frac{\partial V}{\partial K_{it+1}} = -\lambda_{it+1}\frac{\partial F}{\partial K} - (1-\delta_{it+1})$$

Substituting into the investment FOC and using $R_{it+1} = \lambda_{it+1}\frac{\partial F}{\partial K}$:

$$1 = \mathbb{E}_t\Big[M_{t+1}\big(R_{it+1} + (1-\delta_{it+1})\big)\Big] \tag{5.3}$$

Defining the investment return as $R^I_{it+1} \equiv R_{it+1} + (1-\delta_{it+1})$:

$$\mathbb{E}_t\big[M_{t+1}\,R^I_{it+1}\big] = 1 \tag{5.4}$$

This equation is a standard asset-pricing Euler equation stating that the discounted expected return on investing in capital must equal its marginal cost today. Investors will invest until their expected discounted marginal benefit equals their marginal cost, i.e., until there are no arbitrage opportunities in equilibrium.

1.6 Market Values and Expected Returns

Market outcomes and firm decisions align through pricing relationships that connect capital markets to firm optimization. The investment return derived in (5.4):

$$R^I_{it+1} = R_{it+1} + (1-\delta_{it+1}) \tag{6.1}$$

combines the productive service value R_{it+1} and the undepreciated capital value $(1 - \delta_{it+1})$. The investment FOC implies:

$$\mathbb{E}_t\big[M_{t+1}\, R^I_{it+1}\big] = 1 \tag{6.2}$$

Similarly, the firm's equity return R^E_{it+1} must satisfy:

$$\mathbb{E}_t\big[M_{t+1}\, R^E_{it+1}\big] = 1 \tag{6.3}$$

Both equations share the same form, reflecting how capital market equilibrium eliminates persistent differences between investment and equity returns. Put plainly, if equity had systematically higher returns than physical investment (or vice versa), investors would shift resources accordingly until returns equalize. Firms themselves can equivalently invest internally or externally, eliminating persistent differences.

For any return, we can separate its expected value into risk-free and risk components:

$$\mathbb{E}_t[R^E_{it+1}] = R^F_t + \theta_{it} \tag{6.4}$$

where θ_{it} is the risk premium determined by the covariance of returns with the stochastic discount factor. Assets positively correlated with the stochastic discount factor offer insurance and thus command lower returns; negatively correlated assets, bearing systematic risk, require higher expected returns.

Both investment and equity returns derive from the same underlying assets and cash flows, thus their expected values converge in equilibrium. This convergence results from no-arbitrage conditions ensuring that returns on assets yielding identical future payoffs must align, consistent with standard asset-pricing theory.

Defining the required return $\rho_{it} = \mathbb{E}_t[R^I_{it+1}] - 1$, we get:

$$R_{it} = \rho_{it} + \delta_{it} \tag{6.5}$$

This formula holds across market structures because capital acquisition occurs in competitive markets separate from product markets. Economic rents from market power accrue to truly scarce factors—patents, brand assets, or entry barriers—rather than to competitively supplied capital inputs.

This theoretical framework directly guides our empirical approach. The markup equation (3.3) connects to observable firm behavior—for example, a technology firm with high fixed costs but low marginal production costs (like software companies) would show a high ratio of revenues to labor costs, indicating substantial markup power. The user cost formula (5.2) provides the foundation for our measurement using financial statement data, where we will estimate depreciation rates and risk premia from observable company accounts and market prices. Finally, the link between capital market returns and investment returns established in equations (6.2) and (6.3) explains why we can use market-based measures of expected returns in our production-based markup estimates.

2 A Finance Approach to Markup Estimation

Having established our framework linking investment decisions, capital costs, and markups, we now implement this approach using financial statement data. We analyze over five decades of standardized accounting information for US public companies, constructing a panel that allows us to track markup patterns across firms, industries, and time. De Loecker et al. (2020) document the rise of market power using similar production-based techniques, but our approach differs by incorporating financial market information to estimate capital costs.

Our empirical method follows a sequential process: we first develop a cross-sectional statistical model to forecast firm-level earnings, then use these projections to estimate the cost of equity, and finally calculate markups based on the resulting user cost, implied production technology, and observed sales and expenditures. Our approach allows us to measure markups without requiring detailed product-level information, instead using readily available financial statements.

2.1 Terminology and Notation

When analyzing capital costs, different fields often use the same term—"cost of capital"—to mean different things. To avoid confusion, we use specific terms for each component:

- **User Cost of Capital** (R_{it}): The total economic cost of using capital, which includes financing, depreciation, and tax effects
- **Weighted Average Cost of Capital** (WACC or R_{it}^A): The cost of financing through both debt and equity
- **Cost of Equity Capital** (R_{it}^E): The required return to equity investors (also called the implied cost of capital or ICC in some literature)
- **Cost of Debt Capital** (R_{it}^D): The interest rate paid on borrowed funds

These components relate through two simple equations:

$$\text{User Cost} = \text{WACC} + \text{Depreciation Rate} + \text{Tax Adjustment} \tag{1}$$

$$\text{WACC} = (\text{Equity Share} \times \text{Cost of Equity}) + (\text{Debt Share} \times \text{Cost of Debt}) \tag{2}$$

Our theoretical model showed a simplified version where user cost equals expected return plus depreciation. Our empirical implementation extends this to include financing structure and taxes.

2.2 Data

We obtain accounting data for US public firms from Compustat North America from 1970 to 2023. This dataset provides standardized financial statement information for companies trading on major US exchanges. Following standard practice in finance and accounting, we focus on industrial and service firms, excluding financial institutions (SIC 6000-6999) and utilities (SIC 4000-4999) because

of their distinct regulatory environments and accounting practices that make direct comparisons with other sectors problematic.

We apply several filters to ensure data quality and consistency. First, we require firms to have non-missing values for earnings, sales, operating expenses, and invested capital. Second, we remove observations with zero or negative sales, as these typically represent non-operational periods or data errors rather than normal business activities. Third, we exclude cases with negative invested capital or operating expenses, which show accounting irregularities. Finally, we require positive common equity (CEQ), as negative equity represents financial distress that complicates standard financial analysis.

These filters help ensure our sample comprises firms engaged in typical business operations with reliable financial reporting. We include firms of all sizes and sectors. Overall, Compustat offers a broad view of US corporate activity.

The resulting panel dataset is unbalanced, as firms enter and exit the sample due to new listings, delistings, mergers, acquisitions, and bankruptcies. The number of firms increases substantially during the 1980s and 1990s, reflecting the broader expansion of public equity markets during this period. Our sample peaks in the late 1990s with over 6,000 firms per year, before declining in recent years as merger activity and decreased public listings reduced the number of independent public firms. For example, while we observe nearly 7,000 firms in 1997, this number falls below 3,500 by 2023. This pattern is consistent with documented trends in US equity markets.

We define our key variables:

Invested Capital (ICAPT) represents the total resources allocated to business operations. This measure captures all non-financial assets employed by the firm, including property, plant and equipment, inventories, and recorded intangible capital such as goodwill, patents, and trademarks. Unlike theoretical models that separate tangible and intangible capital, we follow accounting conventions in using this comprehensive measure of productive assets.

Operating Expenses (XOPR) measure the firm's variable costs of conducting business. As noted by Traina (2018), treatment of this variable significantly affects markup estimates. This category may include research and development (R&D) expenses. We maintain Compustat's classification rather than reclassifying R&D as a capital expenditure to ensure consistent treatment across firms.

Accruals (AC) capture the difference between reported income and actual cash flows. Before 1988, we use the balance sheet method, calculating accruals as changes in non-cash current assets minus current liabilities (excluding short-term debt and taxes payable) minus depreciation and amortization. From 1988 on, we use the cash flow statement method, calculating accruals as net income minus cash flow from operations.

Earnings (E) come from reported net income, which we include whether positive or negative. Dividends (DV) record annual shareholder distributions. Total Assets (AT) measure overall firm size. Depreciation (DP) captures annual capital costs expensed, while Interest Expense (XINT) records

debt financing costs.

Table 1 presents summary statistics for the key variables used in our analysis. We use nominal values as reported, without inflation adjustments, as our analysis focuses primarily on cross-sectional comparisons within years rather than absolute value comparisons across time.

Table 1: Summary statistics of Compustat input variables

	N	Mean	SD	p10	p25	Median	p75	p90
E_t	169,598	103.33	529.92	-15.20	-0.71	2.79	28.80	182.42
A_t	169,598	2,787.43	13,618.14	10.17	32.49	149.47	903.57	4,288.90
D_t	169,598	43.23	225.07	0.00	0.00	0.00	4.50	53.22
DD_t	169,598	0.47	0.50	0.00	0.00	0.00	1.00	1.00
$NegE_t$	169,598	0.29	0.46	0.00	0.00	0.00	1.00	1.00
AC_t	169,598	-121.76	561.06	-211.55	-38.70	-3.87	0.18	6.14
Sales	169,598	2,580.66	14,197.44	8.78	32.84	157.01	870.30	3,920.00
Total variable cost	169,598	2,207.26	12,432.90	9.44	31.27	138.90	742.36	3,321.47
Capital stock	169,598	1,897.84	10,798.90	6.34	21.42	103.32	628.48	2,827.68
Common equity	169,598	1,171.54	7,018.50	4.15	14.36	67.84	381.69	1,634.40
Debt	169,598	726.31	4,688.35	0.43	2.76	20.34	195.62	1,059.42
Interest expense	169,598	42.81	266.60	0.09	0.41	2.24	15.59	74.68
Income taxes	169,598	66.89	553.80	-0.60	0.00	1.70	15.23	86.68
Depreciation	169,598	130.48	808.01	0.32	1.11	5.56	36.34	179.85

Notes: This table presents summary statistics for our sample of non-financial, non-utility US public firms from 1970 to 2023. The statistics include time-series averages of cross-sectional means, medians, standard deviations, and various percentiles. All level variables are winsorized each year at the 1st and 99th percentiles to mitigate the influence of extreme observations.

In constructing our sample, we make minimal adjustments to the underlying data, preferring to let the empirical patterns emerge naturally. This approach avoids imposing researchers' priors about what constitutes "normal" operations. The long time series also allows us to examine how corporate behavior and financial structures evolve through multiple business cycles, technological changes, and regulatory shifts.

Variables used in the earnings forecast regressions, denoted with the subscript t, are winsorized at the 1st and 99th percentiles by year. We do so separately each year to account for changing distributions over time. This approach helps address measurement issues, like data errors or unusual transactions like major acquisitions or restructurings, without discarding possibly informative observations.

Our baseline sample also excludes firm-years for which we lack valid implied cost of capital and markup estimates. Invalid estimates include those missing input data, have negative implied cost of capital estimates, or are outside the top and bottom 1 percentiles.

While our dataset provides a large view of US corporate activity over several decades, some limitations

merit acknowledgment. First, accounting practices have evolved over our sample period, potentially affecting the consistency of certain variables. For example, the treatment of goodwill, R&D expenses, and leases has changed significantly over time. Second, our reliance on as-reported financial data means we incorporate each firm's accounting choices without change, which may introduce some measurement variation across firms. Third, Compustat primarily covers public companies, so our findings may not generalize to private firms. This limitation is shared by De Loecker et al. (2020), who also focuses on publicly-traded companies. Finally, we note that the reporting of items like depreciation, interest, and accruals can vary across industries and over time, though we expect any resulting measurement errors to be random rather than systematic.

2.3 Earnings Forecast Estimation

We estimate firm-level earnings forecasts using a cross-sectional model that captures systematic patterns in future profitability. These forecasts serve as inputs for our implied cost of capital calculations, which in turn contribute to user cost and markup estimates. Hou et al. (2012) show cross-sectional earnings models outperform analyst forecasts for estimating implied cost of capital. Following this approach, we construct earnings predictions using accounting variables rather than analyst forecasts. It provides broader coverage and avoids potential analyst biases.

For each year between 1970 and 2023, we estimate the following pooled cross-sectional regression using the previous ten years of data:

$$E_{it+\tau} = \alpha_0 + \alpha_1 A_{it} + \alpha_2 D_{it} + \alpha_3 DD_{it} + \alpha_4 E_{it} + \alpha_5 NegE_{it} + \alpha_6 AC_{it} + \varepsilon_{it+\tau}$$

where $E_{it+\tau}$ denotes the earnings of firm i in year $t+\tau$ ($\tau = 1$ to 3), A_{it} is total assets, D_{it} is dividend payment, DD_{it} is a dummy variable that equals 1 for dividend payers and 0 otherwise, $NegE_{it}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, and AC_{it} is accruals.

Each variable in our model serves a specific purpose. Total assets account for firm size effects, dividends signal financial stability, and current earnings capture persistence in performance. The negative earnings indicator addresses the different behavior of loss-making firms, while accruals help bridge the gap between accounting profits and cash flows.

We use a ten-year rolling window for estimation because it balances two competing needs: gathering enough observations for reliable coefficient estimates while adapting to changing economic conditions.

Before 1988, we calculate accruals using the balance sheet method, as the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense. After 1988, we calculate accruals using the cash flow statement method, as the difference between earnings and cash flows from operations.

We obtain our earnings forecasts by multiplying the independent variables in year t with the coefficients from the cross-sectional regressions. For each firm-year observation, we forecast earnings up

to five years ahead. To make sure our forecasts are out-of-sample, we use independent variables from the previous ten years of data only up to year t to forecast earnings for years $t+1$ through $t+5$.

This cross-sectional approach provides several advantages over firm-specific time-series models. It requires fewer observations per firm, making it applicable to companies with limited history. The rolling estimation window adapts to changing economic conditions by incorporating new information as it becomes available.

The models show strong predictive power, with average R-squared values exceeding 0.80 for one-year-ahead forecasts and remaining above 0.70 even for three-year projections. The coefficients demonstrate that earnings display significant persistence—past earnings substantially predict future earnings. The estimates also reveal that larger firms and dividend-paying companies generally deliver more predictable future performance.

For horizons beyond our three-year model estimates, we extend forecasts using linear interpolation. This method gradually transitions firm-specific projections toward industry-median profitability levels, reflecting the economic tendency for competitive forces to erode abnormally high or low returns over time.

Table 2: Coefficient Estimates of the Earnings Forecast Model

		Intercept	A_t	D_t	DD_t	E_t	$NegE_t$	AC_t	Adj.R^2
E_{t+1}	Coefficient	-0.4200	0.0021	0.2342	1.5126	0.7680	1.1876	-0.0833	0.80
	t-statistic	-0.25	17.37	28.68	2.80	201.84	2.54	-35.67	
E_{t+2}	Coefficient	0.4502	0.0039	0.3494	1.6396	0.6747	1.6755	-0.1097	0.72
	t-statistic	0.83	23.42	32.36	2.97	134.36	2.48	-37.29	
E_{t+3}	Coefficient	1.8722	0.0055	0.4177	1.8660	0.6393	2.2612	-0.1076	0.67
	t-statistic	1.73	27.15	32.41	3.02	107.58	2.67	-32.58	

Notes: This table presents the average coefficients from our annual cross-sectional earnings regressions. We estimate the model each year from 1970 to 2023 using the previous ten years of data. The dependent variable is future earnings for horizons of one to three years.

2.4 Implied Cost of Capital Estimation

We calculate each firm's implied cost of capital (ICC) using a residual income model that connects current market values to expected future cash flows (Gebhardt et al., 2001). This approach extends beyond our earnings forecasts to estimate the discount rate that investors apply to a firm's long-term income stream. The ICC represents the internal rate of return that equates the firm's current market price to the present value of its expected future cash flows.

Following Gebhardt et al. (2001), we solve for the discount rate R in the equation:

$$M_t = B_t + \sum_{\kappa=1}^{11} \frac{E_t\left[(ROE_{t+\kappa} - R) \times B_{t+\kappa-1}\right]}{(1+R)^{\kappa}} + \frac{E_t\left[(ROE_{t+12} - R) \times B_{t+11}\right]}{R\,(1+R)^{11}}$$

where M_t is the market equity in year t, R is the implied cost of capital, B_t is the book equity, $E_t[\cdot]$ denotes market expectations based on information available at year t. $(ROE_{t+\kappa} - R) \times B_{t+\kappa-1}$ is the residual income in year $t+k$, defined as the difference between the return on book equity and the ICC multiplied by the book equity in the previous year.

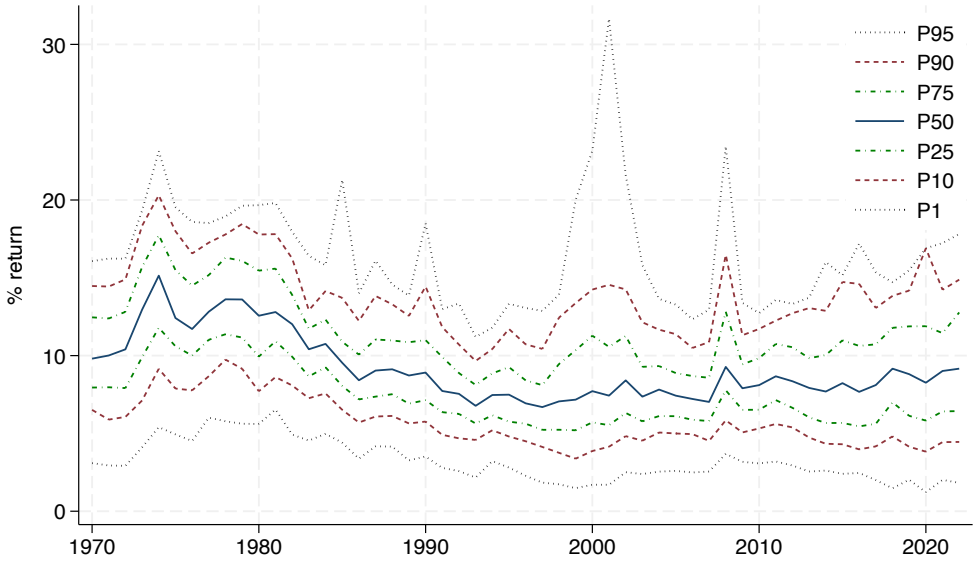
Expected ROE in years $t+1$ to $t+3$ are estimated using earnings forecasts from the cross-sectional model and book equity values computed based on clean surplus accounting $B_{t+k} = B_{t+k-1} + E_{t+k} - D_{t+k}$. E_{t+k} and D_{t+k} denote earnings and dividends in year $t+k$, respectively. Dividends are calculated using the current dividend payout ratio for firms with positive earnings. For firms with negative earnings, we use current dividends divided by $0.06\times$ total assets as an estimate of the payout ratio.

For longer horizons, the expected ROE is assumed to mean-revert to the historical industry median value by year $t+11$. This mean reversion reflects the economic reality that competition tends to eliminate abnormal returns over time. After $t+11$, the residual income becomes a perpetuity. We compute the industry target ROE as a moving median using at least the past five years' and at most the past ten years' ROE from all firms in the same industry.

High-performing firms attract competitors, while underperforming firms either improve or exit the market. Mean reversion is achieved through simple linear interpolation between period $t+3$ ROE and the industry median ROE. Following Gebhardt et al. (2001), we exclude loss firms when calculating the industry median ROE since persistent losses are not representative of long-term industry profitability.

Figure 1 shows the evolution of estimated ICCs at different percentiles over time. ICC estimates are weighted by common equity value (CEQ).

Figure 1: Trends in Estimated ICCs (Equity Value Weighted)



2.5 Markup Estimation

We now turn to the estimation of firm-level markups, which measure the gap between the price firms charge and the marginal cost they incur. Our approach builds on Hall (1988), who first showed how to identify markups from production data, but we extend this method by incorporating financial market information to measure capital costs. When firms use labor and capital inputs with constant returns to scale technology, each input's cost share equals its output elasticity. The markup arises by comparing a firm's observed revenues to its total economic cost.

We treat labor costs as operating expenses (WL) and capital costs as the user cost of capital (R). The R combines the depreciation rate, the effective tax rate, and the weighted average cost of capital (WACC), which itself incorporates the firm's implied cost of equity (ICC) and cost of debt. This approach captures all relevant costs of capital—opportunity costs, physical depreciation, and tax effects. Under CRS, capital's share in total costs is the ratio of capital expenses to overall production expenses, and labor's share follows from operating expenses. Because these shares must sum to one, we infer that labor's output elasticity equals its share, and capital's elasticity equals its own share.

A firm's total economic cost equals::

$$\mathcal{C}_{it} = WL_{it} + \big(\mathrm{R}_{it} \times \mathrm{K}_{it}\big),$$

where K_{it} is invested capital, and R_{it} is the per-dollar cost of capital. If labor claims a fraction $\theta_{\ell,it}$ of total costs, then capital receives the remaining fraction, $\theta_{k,it} = 1 - \theta_{\ell,it}$. We interpret these fractions as the respective elasticities in the production function under CRS.

A firm's markup μ_{it} is the ratio of its price to its marginal cost. Because price times output equals

total revenue, we can write:

$$\mu_{it} = \frac{\text{price} \times \text{output}}{\text{marginal cost} \times \text{output}} = \frac{\text{revenue}}{\text{variable cost of producing one unit of output} \times \text{output}}.$$

We approximate marginal cost by applying the cost shares to the firm's operating expenses and user cost of capital. Our approach follows the production-based techniques as in De Loecker et al. (2020), but addresses measurement challenges emphasized by Foster et al. (2022) when inferring markups from firm-level data. Our main formula (ignoring intermediate inputs) becomes:

$$\mu_{it} = \frac{\text{Sales}_{it}}{WL_{it}} \times \left(1 - \frac{\text{R}_{it}\,\text{K}_{it}}{WL_{it} + \text{R}_{it}\,\text{K}_{it}}\right) = \frac{\text{Sales}_{it}}{WL_{it} + \text{R}_{it}\,\text{K}_{it}}. \tag{3}$$

In practice, deviations from perfect competition in the input market or CRS can affect these relationships. If a firm exhibits increasing returns to scale or secures labor at below-market rates, the measured markup may deviate from the actual gap between price and marginal cost. Nevertheless, empirical work Basu and Fernald (1997) suggests CRS is a reasonable approximation for many industries, and Syverson (2004) offers microdata support.

Table 1 lists the Compustat variables used to derive these markup estimates. Once we have firm-level markups, we examine how they vary over time and across sectors. We also study whether markups differ for firms with dissimilar user costs of capital or different degrees of product-market concentration. Although the markup itself is unobservable, these production-based cost shares offer a systematic way to estimate how much prices exceed marginal costs. By incorporating our firm-specific ICC measures, we allow for the possibility that capital is more expensive for some firms than for others, introducing cross-sectional variation in markups within the same industry.

Table 3 describes all output variables estimated for the purpose of our analyses.

Table 3: Summary statistics of estimated variables

	N	Mean	SD	p1	p10	p25	Median	p75	p90	p99
Tax rate	169,598	0.03	0.08	-0.12	-0.01	0.00	0.02	0.06	0.10	0.22
Depreciation rate	169,598	0.08	0.23	0.00	0.02	0.04	0.06	0.09	0.13	0.41
Cost of debt	169,598	1.03	108.29	0.00	0.03	0.06	0.10	0.17	0.44	11.47
Implied cost of capital	169,598	0.13	0.14	0.00	0.04	0.06	0.09	0.14	0.23	0.76
WACC	169,598	0.13	0.21	0.01	0.05	0.07	0.09	0.14	0.21	0.67
User cost of capital	169,598	0.24	0.37	0.03	0.10	0.15	0.20	0.27	0.37	0.97
Markup	169,598	0.93	0.20	0.10	0.71	0.92	0.99	1.02	1.06	1.20
Output elasticity of capital	169,598	0.16	0.13	0.01	0.05	0.08	0.12	0.18	0.31	0.70
Variable cost share	169,598	0.84	0.13	0.30	0.69	0.82	0.88	0.92	0.95	0.99
Variable revenue share	169,598	1.09	1.39	0.35	0.74	0.83	0.90	0.96	1.12	6.90

Notes: This table presents summary statistics for all variables estimated using input variables described in Table 1.

This approach offers several advantages over traditional markup estimation methods. First, it uses readily available accounting data rather than requiring detailed product-level information. Second, it accommodates differences in capital intensity across firms and industries. Third, it accounts for variation in the cost of capital, recognizing that riskier firms face higher financing costs. Finally, it provides a theoretically grounded framework that connects firm-level decisions about investment and pricing to their financial market outcomes.

3 Documenting Distributional Patterns

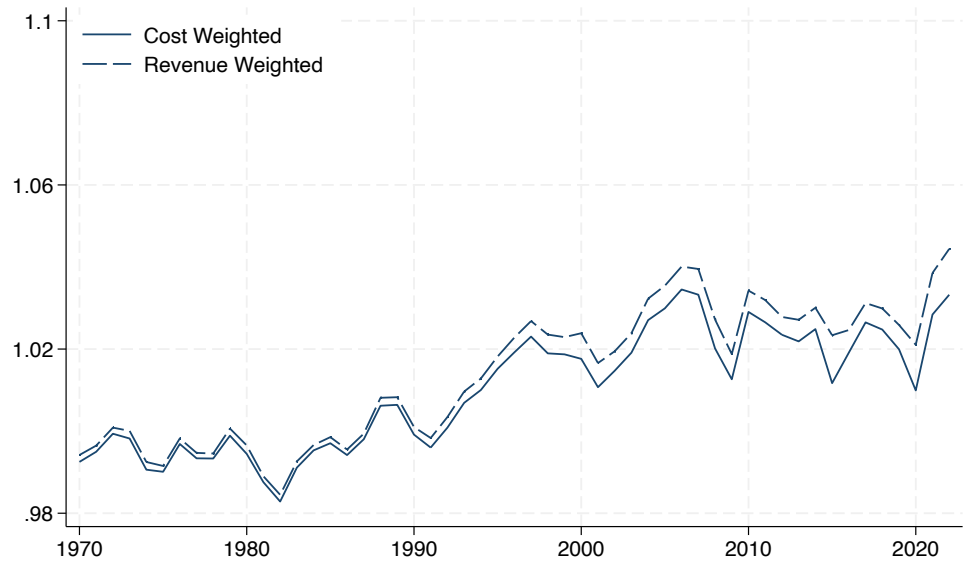
In this section, we examine the distributional patterns of estimated firm-level markups from 1970 to 2022, focusing on their evolution over time, sectoral differences, and increasing dispersion. We document how markup trends diverge across industries, explore changes in the distribution's shape, and consider how firm-specific financing conditions help explain markup variation.

Figure 2 shows average markups over time. Average markups are computed as $\mu_t = \sum_i w_{it}\mu_{it}$, where w_{it} denotes firm-specific weights. Panel (a) of Figure 2 presents average firm markups from 1970 to 2022, computed using both cost-weighted and revenue-weighted approaches. The cost-weighted series assigns weights based on firm i's share of total variable costs in a given year, while the revenue-weighted series uses firm i's sales. The two series track closely over time, suggesting that the observed trends in markups are not driven by weighting choices but reflect underlying economic shifts.

Average markups remained relatively stable until the early 1980s, followed by a period of steady increase through the 1990s and early 2000s. This rise coincides with broader shifts in market structure, technological change, and firm heterogeneity. The fluctuations post-2008 suggest cyclical variation, likely reflecting economic shocks such as the financial crisis and subsequent recovery.

Panel (b) of Figure 2 presents cost-weighted average markups by sector, highlighting distinct patterns across manufacturing, services, and wholesale and retail trade. Markups in manufacturing largely track the overall trend, rising modestly from the 1980s onward with cyclical fluctuations. In contrast, the wholesale and retail trade sector maintains consistently lower markups, with a flatter trajectory and minimal volatility, suggesting sustained competitive pressures that limit firms' ability to price above marginal cost. The services sector, which includes many technology-intensive firms, exhibits both higher average markups and greater variability over time. Notably, services markups diverge sharply from other sectors beginning in the 1990s, with periods of increases, consistent with the rise of high-margin firms in software, finance, and digital platforms. Markup increases are not economy-wide but rather concentrated in industries where firm-level heterogeneity in technology and financing might play a larger role.

Figure 2: Markups Estimates



(a): Cost-Weighted vs. Revenue-Weighted Markups

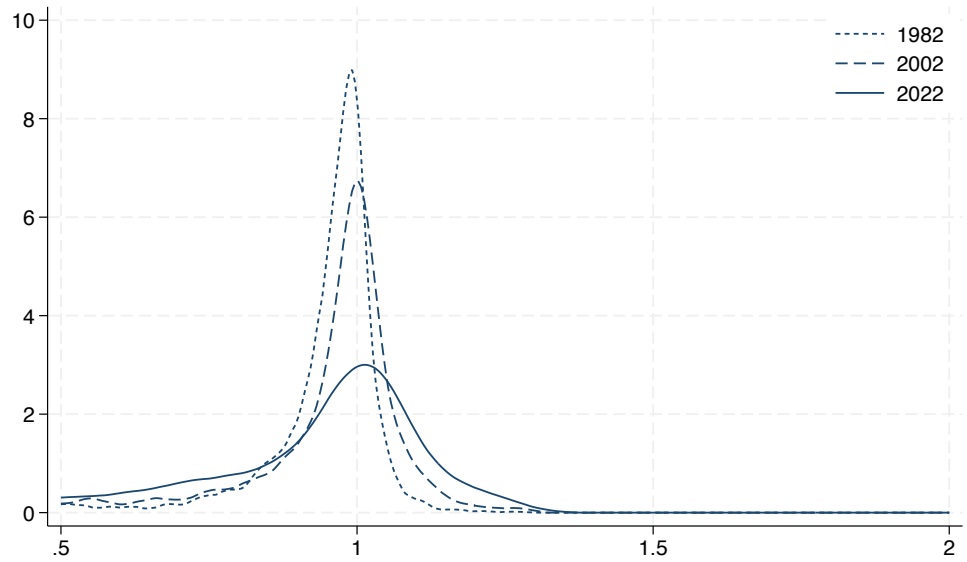


(b): Cost-Weighted Markups by Sector

To examine changes in the distribution of markups over time, Figure 3 presents kernel density estimates of unweighted markups for the years 1982, 2002, and 2022. The distribution has widened considerably with a more pronounced right tail in 2022. Although many firms continue to operate with markups near 1, a growing subset of firms set significantly higher markups. This increasing dispersion suggests that markup growth is concentrated among a select group of firms rather than being a uniform economy-wide trend, reinforcing the role of firm heterogeneity in shaping aggregate

markup dynamics.

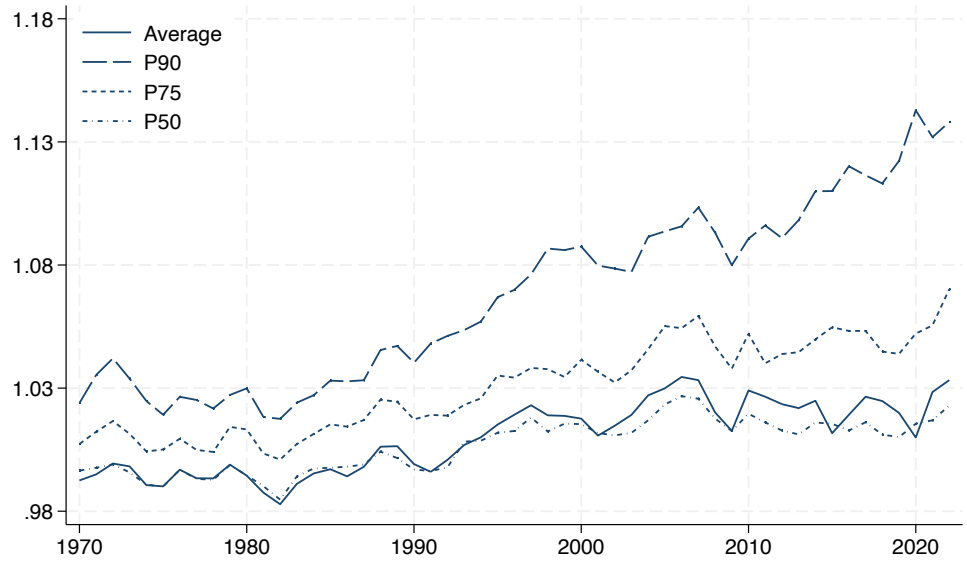
Figure 3: Kernel Density of Markups (unweighted)



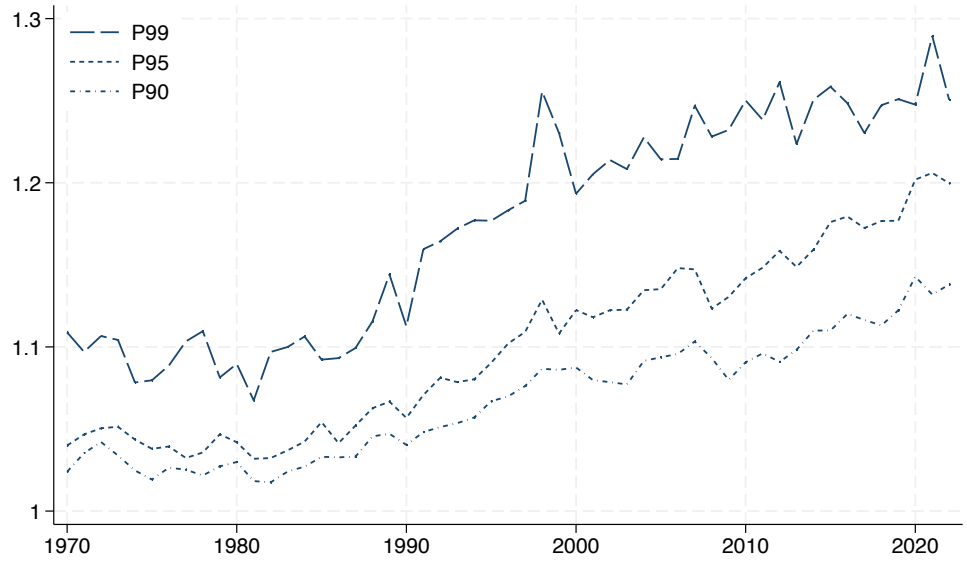
To further investigate the distributional changes in markups over time, we analyze different moments of the markup distribution while accounting for cost-weighting. Specifically, we compute percentile estimates for each year by ranking firm-level markups weighted by their share of total variable costs. This approach ensures that the percentiles are directly comparable to the weighted average markups reported earlier (De Loecker et al., 2020).

Figure 4 presents the trends in cost-weighted markups across different percentiles. Panel (a) tracks the 50th, 75th, and 90th percentiles, while Panel (b) focuses on the 90th, 95th, and 99th percentiles. The increase in average markups is primarily driven by firms in the upper percentiles, particularly the top 10%. While the median markup (50th percentile) has remained relatively stable since 1970, the 90th percentile and above exhibit a sustained rise, with the 99th percentile showing the most pronounced increase.

Figure 4: Markup Distributions (cost-weighted)



(a): 90th, 75th, 50th percentiles



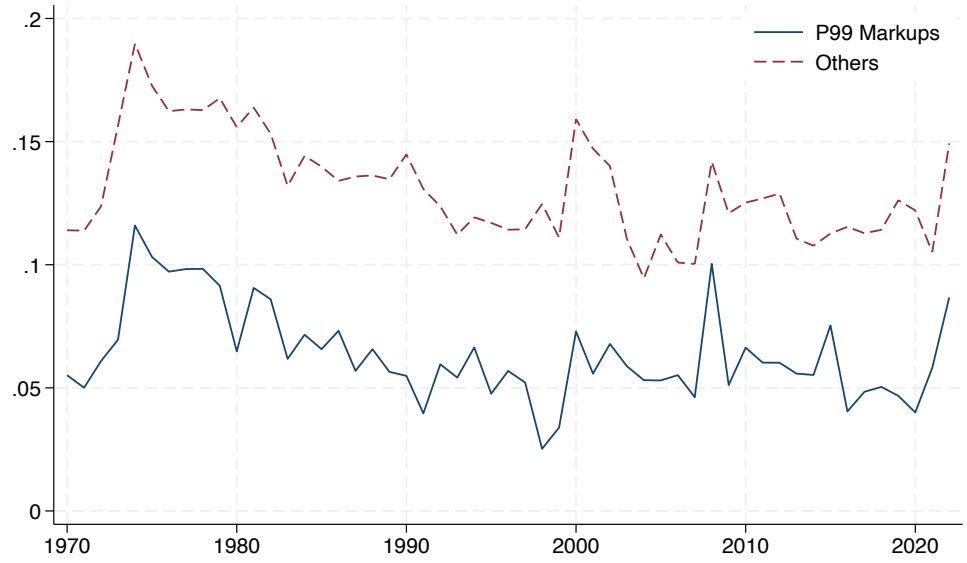
(b): 99th, 95th, 90th percentiles

This pattern reinforces the key finding that markup growth is not broad-based but rather concentrated among a subset of firms with the highest price-cost margins. The increasing dispersion in markups—evident from the widening gap between the median and upper percentiles—suggests that market power, technological advantages, or capital cost differentials may be enabling a select group of firms to command significantly higher markups over time.

To further examine the relationship between markups and the implied cost of capital (ICC), Figure 5

compares the average ICC for firms in the top 1% of the markup distribution (P99 Markups) to that of all other firms. The figure highlights a strong negative relationship between ICC and markups: firms with the highest markups consistently exhibit lower financing costs compared to the broader firm population. While ICCs for the top 1% of markup firms have remained below 7% for most of the sample period, the ICC for all other firms has been substantially higher, often exceeding 10-15%.

Figure 5: Average ICC for the Top 1% vs. All Others



This pattern supports the hypothesis that firms with better financing conditions—likely due to lower risk premia or stronger access to capital markets—are able to sustain higher markups. The divergence between the two groups has remained relatively stable over time, with a slight narrowing in recent years. These findings align with the regression results in Table 4, which show a statistically significant negative association between markups and ICC. In particular, Column (4) of Table 4 demonstrates that firm-year variations in ICC explain nearly 70% of the variation in markups (adjusted R^2=0.69).

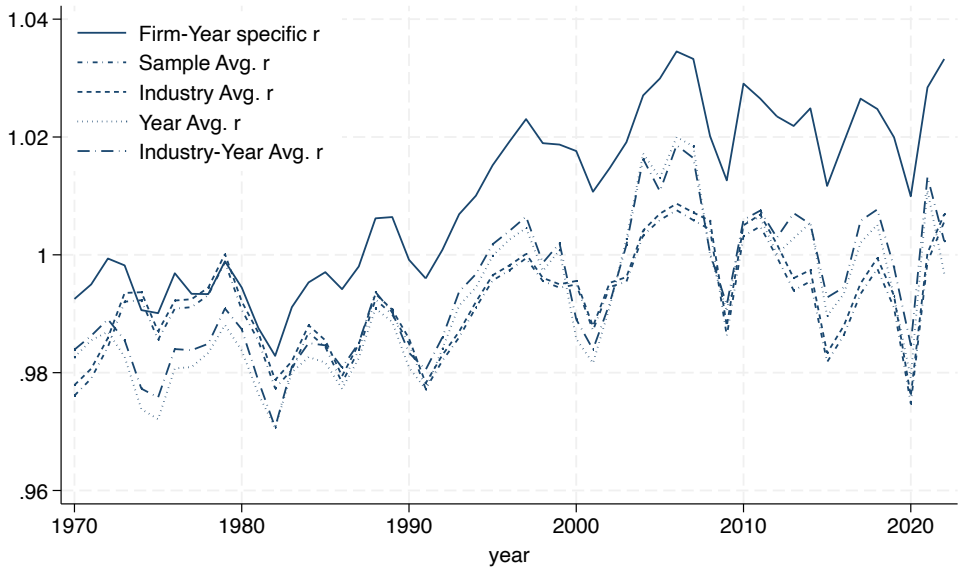
Table 4: Regressions of Markup on ICC

	(1)	(2)	(3)	(4)
Dependent Variable: Ln(Markup)				
Implied cost of capital	-0.917***	-0.961***	-0.946***	-0.486***
	(0.017)	(0.017)	(0.017)	(0.012)
Year FE	N	Y	Y	Y
Industry FE	N	N	Y	N
Firm FE	N	N	N	Y
Clusters (Firm)	18,927	18,927	18,927	16,444
Adjusted R-Squared	0.099	0.126	0.188	0.700
Observations	169,598	169,598	169,598	167,115

Notes: This table presents coefficient estimates of OLS regressions estimating the association between implied cost of capital (ICC) and markups. The sample is from 1970 to 2023. Standard errors clustered at the firm-level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

We further explore the role of firm-specific capital costs in shaping aggregate markup trends by analyzing how markups vary under different ICC assumptions. Figure 6 compares our *baseline cost-weighted markup estimates*, which incorporate firm-year ICCs, to alternative scenarios where ICCs are held constant at various aggregate levels. The solid line represents our main estimates, while the dashed lines show markups calculated using fixed ICC values—either at the sample-wide average, industry-specific average, or year-specific average.

Figure 6: Markups Estimates Ignoring ICC Heterogeneity



Ignoring firm-level ICC heterogeneity systematically distorts markup estimates. When a constant ICC is used, markup estimates are consistently lower, failing to capture the extent of markup dispersion seen in the baseline estimates. This suggests that much of the observed variation in markups is attributable to differences in firms' financing costs, reinforcing the central role of capital markets in explaining rising markup dispersion.

The regression results in Table 4 further confirm this relationship. Across all model specifications, the implied cost of capital exhibits a strong and statistically significant negative relationship with markups. Notably, in the most restrictive specification with firm and year fixed effects (Column 4), ICC explains nearly **70%** of the variation in markups (adjusted $R^2 = 0.700$), indicating that capital cost heterogeneity is a major determinant of markup differences across firms.

To assess the persistence of firm-specific capital costs and pricing behavior, we regress ICCs and markups on their lagged values. Table 5 presents the persistence estimates for ICC, while Table 6 reports the corresponding results for markups. Across all specifications, we find strong serial correlation in both variables, suggesting that firms' financing conditions and pricing power exhibit substantial persistence over time.

Table 5: Persistence - Cost of Capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: ICC								
ICC_{t-1}	0.493***	0.483***	0.480***	0.160***	0.379***	0.370***	0.369***	0.154***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.012)	(0.013)	(0.013)	(0.014)
ICC_{t-2}					0.151***	0.147***	0.146***	0.026**
					(0.010)	(0.010)	(0.011)	(0.011)
ICC_{t-3}					0.107***	0.105***	0.104***	0.016
					(0.010)	(0.010)	(0.010)	(0.010)
ICC_{t-4}					0.062***	0.065***	0.064***	-0.008
					(0.009)	(0.009)	(0.009)	(0.009)
ICC_{t-5}					0.046***	0.050***	0.050***	-0.018**
					(0.008)	(0.008)	(0.008)	(0.009)
Year FE	N	Y	Y	Y	N	Y	Y	Y
Industry FE	N	N	Y	N	N	N	Y	N
Firm FE	N	N	N	Y	N	N	N	Y
Clusters (Firm)	16,062	16,062	16,062	13,478	8,244	8,244	8,244	7,112
Adjusted R-Squared	0.199	0.212	0.214	0.365	0.274	0.283	0.284	0.394
Observations	141,400	141,400	141,400	138,816	78,255	78,255	78,255	77,123

Notes: This table reports coefficient estimates from OLS regressions estimating the association between implied cost of capital and its lagged values. The sample is from 1970 to 2023. Standard errors clustered at the firm-level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Persistence - Markups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Ln(Markup)								
$\ln(\text{Markup}_{t-1})$	0.799***	0.797***	0.785***	0.455***	0.696***	0.695***	0.690***	0.437***
	(0.006)	(0.006)	(0.006)	(0.012)	(0.020)	(0.020)	(0.021)	(0.021)
$\ln(\text{Markup}_{t-2})$					0.024	0.028	0.025	-0.021
					(0.019)	(0.019)	(0.019)	(0.018)
$\ln(\text{Markup}_{t-3})$					0.102***	0.101***	0.101***	0.065***
					(0.019)	(0.019)	(0.019)	(0.019)
$\ln(\text{Markup}_{t-4})$					0.060***	0.059***	0.058***	0.041***
					(0.018)	(0.018)	(0.018)	(0.016)
$\ln(\text{Markup}_{t-5})$					0.019*	0.019*	0.018	-0.018
					(0.012)	(0.012)	(0.012)	(0.013)
Year FE	N	Y	Y	Y	N	Y	Y	Y
Industry FE	N	N	Y	N	N	N	Y	N
Firm FE	N	N	N	Y	N	N	N	Y
Clusters (Firm)	16,062	16,062	16,062	13,478	8,244	8,244	8,244	7,112
Adjusted R-Squared	0.674	0.676	0.678	0.746	0.615	0.619	0.620	0.676
Observations	141,400	141,400	141,400	138,816	78,255	78,255	78,255	77,123

Notes: This table reports coefficient estimates from OLS regressions estimating the association between markups and its lagged values. The sample is from 1970 to 2023. Standard errors clustered at the firm-level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

For ICCs, the one-year lag coefficient remains above 0.48 across all models, with significance levels confirming the robustness of the estimates. Even at longer lags, ICCs display notable persistence, with coefficients remaining positive and statistically significant up to five years in most specifications. This indicates that firms with higher capital costs tend to experience persistently elevated financing expenses, potentially constraining their long-term investment and growth.

Similarly, markups exhibit substantial persistence, with an autoregressive coefficient near 0.80 for the one-year lag in models without firm fixed effects. When controlling for firm-specific heterogeneity, the one-year lag coefficient remains significant but decreases to approximately 0.45, indicating that while firm-specific factors contribute to markup stability, there is also considerable variation across firms. Higher-order lags show a gradual decline in explanatory power, but remain statistically significant, reinforcing the idea that firms with high markups tend to maintain pricing power over extended periods. These results provide further evidence that differences in financing conditions and firm-specific characteristics play a key role in markup dynamics.

Table 7: Regressions of Markup on Intangibles

	Intangibles = 1-PPENT/ICAPT				Intangibles = XRD/XOPR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Markup)								
Intangible Assets Intensity	0.003***	0.002*	0.002***	0.002***				
	(0.000)	(0.001)	(0.000)	(0.000)				
R&D Intensity					-1.497***	-1.502***	-0.829***	-0.832***
					(0.077)	(0.096)	(0.190)	(0.190)
Ln(Assets)				0.045***				0.045***
				(0.002)				(0.002)
Year FE	N	Y	Y	Y	N	Y	Y	Y
Industry FE	N	Y	N	N	N	Y	N	N
Firm FE	N	N	Y	Y	N	N	Y	Y
Clusters (Firm)	18,918	18,918	16,436	16,436	18,927	18,927	16,444	16,444
Adjusted R-Squared	0.000	0.086	0.680	0.685	0.196	0.239	0.691	0.696
Observations	169,464	169,464	166,982	166,982	169,598	169,598	167,115	167,115

Notes: This table presents coefficient estimates of OLS regressions estimating the association between markups and intangible or R&D intensity. The sample is from 1970 to 2023. Standard errors clustered at the firm-level are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

The results indicate a positive and statistically significant association between intangible asset intensity and markups (Columns 1-4). This suggests that firms with a higher share of intangible capital tend to charge higher markups, reinforcing the idea that intangible-intensive firms, such as those in technology and finance, may benefit from greater pricing power. In contrast, R&D intensity exhibits a strong negative relationship with markups (Columns 5-8), with coefficients ranging from -0.83 to -1.50. This suggests that firms with higher R&D spending relative to operating expenses tend to have lower markups, possibly due to the high upfront costs of innovation or competitive pressures in R&D-intensive industries. Finally, controlling for firm size (Columns 4 and 8) shows that larger firms tend to have higher markups, as indicated by the positive and significant coefficient on ln(Assets). This aligns with the broader literature on firm size and market power. Overall, these findings highlight the heterogeneity in the relationship between intangible investments and markups and the distinction between capitalized intangible assets and ongoing R&D expenditures.

4 Concluding Remarks

We combine two previously separate methodologies—cost share markup estimation and implied cost of capital approaches as in Gebhardt et al. (2001) and Hou et al. (2012)—to measure markups using financial statement data. This combination fills an important gap, connecting production and finance approaches that previously existed separately despite their natural fit. Accounting for firm-specific financing costs shows average markups have remained stable at around 1.0 since 1980, not rising as

previous studies suggest. The real story is increasing markup dispersion: firms in the top quartile increased markups from 1.03 to 1.14, while bottom-quartile firms saw markups fall from 0.9 to 0.8. We find firms with low capital costs maintain markups higher than typical firms. This negative relationship between financing costs and markups provides a missing mechanism in the superstar firm literature—cheaper access to capital might itself generate pricing power.

Our approach solves persistent measurement problems in the production approach to markups. The Hall (1988) cost share method requires accurate estimation of all input costs, but previous implementations used uniform or simplified capital costs. By incorporating firm-specific financing costs derived from market data, we allow capital costs to vary across firms and time. This variation matters—using simplified capital costs systematically distorts markup estimates. Our method directly addresses concerns raised by Basu (2019) and Syverson (2019) about markup measurement problems, bridging industrial organization and finance by showing how financial market conditions can inform our understanding of market power trends.

Future research should examine how companies invest in assets that don't appear on balance sheets, such as research and development expenses. These intangible investments create value but aren't treated as capital in standard accounting. This matters for our markup measures because a tech company might look like it has high markups when it's actually earning returns on its unmeasured intangible assets. Using our approach, researchers could directly measure how intangibles affect both capital costs and markups. Eisfeldt and Papanikolaou (2013) show organization capital carries unique risks affecting expected returns. Similarly, Crouzet and Eberly (2023) show how intangibles can generate both markups and higher user costs. This research direction is especially important as the economy shifts toward intangible-intensive industries.

Our findings raise practical questions for future research on competition. Do tech firms fund growth differently than manufacturing firms? Are rising profits a sign of market power or just returns on unmeasured investments? Why do some firms get better financing terms than others? Answering these questions would help explain whether rising profit gaps come from declining competition or technological change. This matters for policy debates about industry concentration and inequality. By showing how both production methods and financing costs affect our inference about market power, our paper offers economists new tools to tackle these important questions.

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