Granular Markups and Inflation Surge: the role of managerial incentives*

Yuchen Chen† Juliana Salomao‡ Varun Sharma§ Yicheng Wang¶

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Abstract

We develop a novel methodology to estimate firm-specific markup premiums using highly granular product-level data that controls for common shocks, isolating the premium as a residual. We validate this measure by comparing it to existing accounting-based estimates and by showing that it exhibits expected correlations with firm size and market share. Unlike traditional approaches, our method can be applied to both public and private firms, enabling an analysis of how financial structure and managerial incentives influence pricing decisions. We find that financial structure matters: public firms systematically increase markups following an IPO. Moreover, during the 2021–2022 inflation surge, publicly listed firms expanded their margins by capitalizing on inflationary pressures—especially among firms with high retail ownership, large early-pandemic stock declines, and strong equity-based pay incentives.

Keywords: Markup, IPO, stock-based compensation, inflation

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†Chen: Gies College of Business, University of Illinois Urbana-Champaign (chen3912@illinois.edu).

‡Salomao: Carlson School of Management, University of Minnesota, NBER and CEPR (jsalomao@umn.edu).

§Sharma: Kelley School of Business, Indiana University (vs12@iu.edu).

¶Wang: Carlson School of Management, University of Minnesota (wang9543@umn.edu).

1. Introduction

The ability of firms to price above marginal cost—commonly captured by markups—has long been central to economic research and policy debates. A growing literature documents rising markups over the past four decades, often attributing this trend to increased market concentration and industry consolidation, particularly among large, dominant firms Autor et al. (2020); De Loecker et al. (2020). While much of this work focuses on aggregate trends, less is known about how markups vary across firms, product lines, and financial structures. This paper fills that gap by using highly granular product-level data to study how financial structure and managerial incentives shape firm-level pricing power.

The COVID-19 pandemic and its aftermath intensified concerns about rising markups and their role in fueling inflation. While price increases may initially have been driven by supply chain disruptions, labor shortages, and rising input costs, many firms—particularly those with market power—sustained elevated prices even after these pressures subsided. This pattern aligns with evidence of persistently high corporate profits post-pandemic, suggesting that some firms capitalized on inflationary conditions to expand margins rather than simply passing through higher costs Palazzo (2024). These dynamics contributed to broader inflationary pressures and raised important questions about the role of firm pricing behavior in the post-COVID inflation surge.

We address these questions by developing a novel measure of firm-product-level markup premiums using highly granular data from the Kilts NielsenIQ Retail Scanner (RMS). The dataset spans 2006 to 2022 and includes weekly pricing and quantity data from approximately 30,000 to 50,000 U.S. grocery, drug, and mass merchandise stores. By linking product-level prices to firm-level financials, we isolate firm-specific pricing premiums across time and product categories. We find that markup expansions were particularly pronounced among publicly listed firms, where financial incentives and shareholder pressures may have reinforced this behavior. These effects were most evident during the 2021–2022 inflation surge, especially for firms with high stock-based managerial compensation, substantial retail investor ownership, and steep stock price declines—highlighting the role of financial structure and managerial incentives in shaping pricing dynamics.

We construct our markup measure by decomposing product prices into cost-related components and firm-specific pricing premiums. Thanks to the exceptional granularity of the RMS data—where we observe weekly prices and quantities for highly specific products sold across thousands of retail locations—we can assume that firms operating within the same narrowly defined product category face common demand, supply, and cost shocks. This granularity allows us to isolate firm-specific pricing behavior using a simple, model-free re-

gression framework. Specifically, we regress product-level prices on time-varying fixed effects at the product-module level (e.g., American cheddar cheese), which absorb common shocks and average markups. The residual from this regression captures a firm-product-specific markup premium: the extent to which a firm systematically prices above or below the average markup charged by other firms selling comparable products.[1]

This methodology offers several advantages. Unlike approaches that rely on firm-level financial data—such as De Loecker et al. (2020) —our method does not require cost or revenue data, allowing us to compute markups for both public and private firms. Compared to structural industrial organization (IO) approaches, which are often limited to specific industries with detailed demand estimation, our framework is flexible and scalable: it can be applied at a highly granular product level across a broad range of sectors. This enables us to capture markup variation not only across firms, but also across products within the same firm, covering a wide array of consumer goods that represent a large share of household spending. Its simplicity, transparency, and broad applicability make it a powerful tool for analyzing the relationship between firm characteristics and pricing behavior at scale.

We validate our markup premium measure using several exercises. First, we compare our estimates to those from accounting-based approaches, such as De Loecker et al. (2020). Among publicly listed firms, we find a significant correlation of 20%, lending credibility to our method. Regression-based comparisons across methodologies further reinforce the robustness of our approach. Importantly, we do not expect a perfect correlation: accounting-based methods capture overall firm-level markups, while our measure captures markup premiums at a more granular, firm–module level. Moreover, because our approach does not rely on financial statement data, it can be applied to both public and private firms, enabling broader coverage across the firm distribution.

Our measure also exhibits intuitive empirical patterns. Firms with higher market share and larger size systematically charge higher markups: a one-unit increase in market share is associated with a 25.7% rise in markup premiums, even after controlling for other characteristics. While firm size contributes to markup variation, it does not fully explain it—smaller firms with strong product positioning can also sustain high markups. Markups are higher in more concentrated industries, though this effect weakens with market size, consistent with increased competition in larger markets. We also find that markup dispersion narrows in concentrated sectors, suggesting convergence in pricing strategies among dominant firms.

While we document a modest decline in average excess markups over the long run—driven by both falling individual premiums and a shift in consumer spending toward lower-markup

[1]Products in the RMS data are organized hierarchically into departments (e.g., Dairy), groups (e.g., Cheese vs. Spread), and modules (e.g., American Cheddar vs. Mozzarella).

firms—this trend reversed in the aftermath of the COVID-19 pandemic. Markups surged among publicly listed firms, suggesting that those with greater market power capitalized on inflationary conditions to expand margins rather than pass cost reductions onto consumers. This pattern, often referred to as "greedflation," highlights the role of firm-level pricing power in post-pandemic inflation dynamics. Recent evidence supports this view: research from the Federal Reserve Board documents elevated corporate profits despite declining production costs Palazzo (2024), while Leduc et al. (2024) shows that markup increases were concentrated in firms with substantial market power, even as aggregate markups remained stable.

A central focus of our study is the relationship between firms' financial structures and their pricing behavior. We analyze how publicly listed and private firms differ in their markup strategies by leveraging a stacked difference-in-differences (DiD) methodology. This approach allows us to estimate dynamic treatment effects in settings with staggered treatment timing while avoiding biases from standard two-way fixed effects models. We construct cohorts of firms that undergo IPOs or receive private equity (PE) deals and compare them to matched firms that remain private, using rich pre-treatment firm- and product-level controls—including market share, firm size, total and module-level sales, and pre-period markups. By combining this matching design with cohort-by-time and cohort-by-firm-module fixed effects, we account for time-varying common shocks and unobserved firm-specific heterogeneity.

Our results show that firms transitioning from private to public status increase their markup premiums by approximately 3.4% more than matched private counterparts. This effect is especially pronounced in concentrated industries and markets where public firms hold substantial share. During the 2021–2022 inflation surge, publicly listed firms increased markup premiums by an additional 1.8%, and posted faster price growth—about 0.7 to 0.9 percentage points higher than private firms—suggesting that financial structure affects both pricing and inflation pass-through.

To unpack these dynamics, we examine heterogeneity in markup adjustments across dimensions that proxy for investor pressure (e.g., retail ownership share, pandemic stock price loss), managerial incentives (e.g., stock-based compensation, Delta, inside ownership), and financial flexibility (e.g., liquidity and leverage). These characteristics are measured prior to the inflation surge and matched across firms to isolate the role of public ownership. We find that markup increases were most pronounced among public firms with high investor pressure and equity-based managerial incentives, even after controlling for firm size, sales, and product positioning.

To assess whether these effects extend to other sources of equity capital, we also exam-

ine PE- and VC-backed firms using PitchBook deal data. We show that PE/VC-backed firms also experience markup increases of 2.8–3.5% following investment. However, unlike publicly listed firms, they did not significantly expand markups during the inflation surge—highlighting the distinctive role of public markets, where real-time stock valuation, investor scrutiny, and performance-based pay generate stronger pressures to respond to inflationary shocks. Taken together, our methodology and results highlight how ownership structure, beyond simple capital access, shapes firms' pricing responses to macroeconomic conditions.

Literature Review

Our paper speaks to three strands of the literature.

This paper contributes to a broad literature that examines the relationship between market power and finance. Relevant studies include research on the predictability of expected returns based on market competition (Corhay et al. (2020a); Corhay et al. (2022); Dou et al. (2021); Dou et al. (2022)), the link between market competition and credit risk (Corhay (2017); Chen et al. (2023)), the relationship between market power and firm investment (Gutiérrez and Philippon (2017)), as well as the connection between markups, Tobin's Q and firm valuation (Gutiérrez and Philippon (2019);Corhay et al. (2020b); Crouzet and Eberly (2023)). All of these studies emphasize the role of firm markups in shaping corporate policies and asset prices. In contrast, our paper contributes to this literature by highlighting the reverse channel—how firms' financial structure and governance shape pricing responses to macroeconomic shocks. Gorodnichenko and Weber (2016) show that sticky prices are costly. Using data from the 2008 financial crisis, Gilchrist et al. (2017) find that liquidity constrained firms raise prices more. In the context of COVID, we provide new evidence that publicly listed firms—especially those facing strong capital market pressure and equity-based managerial incentives—expanded markups and prices more aggressively during the 2021–2022 inflation surge. This complements earlier findings by Fracassi et al. (2022), who document long-run strategic changes in pricing and product lines under private equity ownership.

This paper also builds on a broad macro-finance literature that examines markups in relation to recent aggregate trends—such as declining interest rates, falling labor shares, weak investment, and the growing divergence between Tobin's Q and investment. This literature begins with the pioneering work of Farhi and Gourio (2018) and continues with studies by Covarrubias et al. (2020), Crouzet et al. (2022), etc. These studies identify rising intangibles and increasing market power—possibly due to heightened barriers to entry—as well as shifts in risk premia as key drivers of these macroeconomic developments in the U.S. economy. Our paper contributes to this literature by documenting a new trend: a declining trend of markup premium, despite the upward trends in market concentration and aggregate markups

over time. In addition, recent research has examined firm pricing strategies in the context of monetary policy and high-inflation periods after COVID, including work by Gutiérrez et al. (2021), Bilbiie and Känzig (2023), Alvarez et al. (2024) and Chen and Wang (2025). In particular, our findings align with the inflationary behavior described in Palazzo (2024) and Leduc et al. (2024) showing heightened corporate profits and pricing power during the pandemic recovery. Our results suggest that the institutional features of public markets—such as real-time valuation, investor demands, and stock-linked compensation—can amplify firms' responsiveness to inflationary environments.

This paper also builds on a broad literature that examines the dynamics of the product markets such as determinants of product pricing (DellaVigna and Gentzkow (2019); Sharma (2021); Kim (2021); Klemperer (1987)); Chevalier and Scharfstein (1996)), product segmentation (Neiman and Vavra (2018); Clara et al. (2019)), households' product affordability (Kaplan and Schulhofer-Wohl (2017); Jaravel (2019)), and product partisanship (Hsieh et al. (2024)). We add to this literature by computing granular product-level markups and analyzing their time trends and cross-sectional heterogeneity.

The remainder of the paper is organized as follows. Section 2 describes the construction of our firm-product-level panel using detailed price and quantity data from the NielsenIQ Retail Scanner dataset, along with matched firm-level financial characteristics. Section 3 introduces our empirical framework for estimating markup premiums and discusses the identification strategy. Section 4 validates the markup measure and examines its variation across firm size, market share, and industry concentration. Section 5 presents our main results on the relationship between financial structure and pricing behavior, focusing on markup changes around IPO events and during the 2021–2022 inflation surge. Section 6 considers private equity–backed firms to assess whether the effects observed for publicly listed firms extend to other forms of capital market access. Section 7 concludes.

2. Data

We use Retail Scanner (RMS) data from Kilts NielsenIQ to measure product prices and quantities. This dataset spans from 2006 to 2022, with a two-year reporting lag, and includes weekly pricing and quantity information for products identified by Universal Product Codes (UPCs) from participating retail stores across the U.S. [2]

The dataset covers approximately 30,000 to 50,000 grocery, drug, mass merchandiser, and other retail stores, encompassing a wide range of product categories such as food, non-

[2]A UPC, a series of black lines and numbers encoded as a Global Trade Item Number (GTIN), forms a complete barcode that uniquely identifies each product. This code is scanned at the point of sale to correctly identify the item and retrieve its price.

food grocery items, health and beauty aids, and select general merchandise. Products are organized into 10 departments (e.g., Dairy vs. Deli), 125 groups (e.g., Cheese vs. Spread), and 1,075 modules (e.g., American Cheddar vs. Mozzarella), representing $298.9 billion in sales in 2022. We aggregate the UPC data across all retailers as the variation of interest is across firms. We calculate total quantity and price for each UPC in each quarter.

The NielsenIQ sample accounts for a significant portion of household spending. It reflects approximately 8.57% to 13.39% of total household expenditures. Since goods make up about 34% of total spending (with the rest going to shelter, healthcare, transportation, services, and utilities), the NielsenIQ sample covers roughly 25% to 40% of household spending on goods. Coverage also varies by income level: for households in the lowest income quintile, the products tracked by NielsenIQ represent 12.04% to 17.42% of total spending, whereas for those in the highest quintile, the share ranges from 6.69% to 11.15% Jaravel (2019).

Since RMS data does not include manufacturer or producer information, we supplement it with data from GS1 US to link UPCs to the companies supplying products to retailers. This matching process connects 5 million products to 50,000 manufacturers.

To match manufacturers to firms, we employ a combination of fuzzy matching, manual cleaning, and supervised machine learning, resulting in 25,294 identified firms. We use price and quantity data from NielsenIQ to calculate markups and inflation indexes at the firm-product level. For the 298 publicly listed firms in our sample, we further integrate balance sheet data from Compustat.

Table 1 presents the distribution of sales and firms across departments. Since a single firm can operate in multiple departments, sales are calculated at the firm–department level. The table highlights that, on average, publicly listed firms are larger in terms of sales compared to private firms.

Table 2 presents summary statistics for key variables in our analysis. Using NielsenIQ data, we combine price and quantity information to construct firm-level inflation indices and markup premiums at various levels of product aggregation. To ensure comparability across producers within a category, we compute prices and quantities per standardized unit of measure (e.g., liters or ounces), rather than per package sold. This approach mitigates biases from changes in package size with stable prices. We compute firm-module inflation using the four-quarter change in the Fisher price index. Markup premium calculations are described in the next section.

3. Methodology/Measurement

A price, p, can be expressed as the product of a markup μ and a cost c:

(1) $$p = \mu c$$

The markup can be further decomposed into an average component and a firm-specific premium. This is represented as:

(2) $$p_i = \bar{\mu} \times \mu_i \times c$$

Here, ($\bar{\mu}$) represents the average markup across all firms producing that good, while (μ_i) denotes the module-firm-specific markup premium (MFMP). It is important to note that both components can vary over time, and the module-firm-specific markup premium μ_i can increase or decrease the overall markup measure.

We use granular pricing data to identify the firm-specific markup premium. Specifically, we estimate the following regression:

(3) $$\log p_{i,j,t} = \alpha_{j,t} + \log \mu_{i,j,t}$$

In this model, $p_{i,j,t}$ is the price of a good produced by firm i in module j at time t. We include fixed effects for module by time, , which account for all common shocks and characteristics affecting goods within that module during that quarter. The fixed effect captures demand, supply, and cost shocks that are shared across all firms producing goods in that module, as well as the average markup for that module. Additionally, it also absorbs any common retailer markup measure. We argue that the residual from this model corresponds to the module-firm-specific markup premium ($\log \mu_{i,j,t}$).

We validate our measurement in two primary ways. First, we narrow our focus to the sample of publicly listed firms and compare our estimates of the firm-level markup premium to the traditional "production approach," which calculates markup at the firm level using accounting data. Next, leveraging on the entire NielsenIQ dataset, which includes data for private firms, we demonstrate that the firm-level markup premium exhibits the expected relationships with market share, concentration, and size.

4. Validation and Properties

In subsection 4.1, we provide validation of our module-firm-level markup premium by comparing it to established measures of markups. In subsection 4.2, we examine the properties of firms within modules, exploring how factors like market share and firm size relate to markup premiums. In subsection 4.3, we analyze the characteristics of modules themselves, focusing on the effects of market concentration and size on markup levels and dispersion. Finally, in subsection 4.4, we investigate the time series properties of our markup premium measure to understand its behavior over time.

4.1. Validation

We validate our measure of module-firm-specific markup premium by comparing it with established alternatives. The estimation of markups has a long-standing history in both industrial organization and international trade. Traditionally, markups were estimated by analyzing demand systems along with assumptions on pricing behavior, an approach that requires detailed market-level data—such as prices, quantities, and product characteristics—and can be computationally intensive. This "demand approach" is typically applied to individual markets(e.g, Miller et al. (2021) for the US beer industry).[3]

More recent studies, inspired by Hall (1986), propose an alternative method based on firm-level balance sheet data, which is less computationally demanding (see De Loecker and Eeckhout (2018) and De Loecker et al. (2020)). Following this production-based approach, we compare our MFMP measure for public listed firms to the markup estimation from De Loecker et al. (2020), referred to as the DLEU measure. Since our measure operates at the module-firm level, we aggregate it to the firm level using module sales as weights.

Our comparison focuses on the 288 publicly listed firms in our NielsenIQ sample. Figure 1 presents a visual comparison between our MFMP markup premium measure and the DLEU markup estimates under two specifications, PF1 and PF2. The key distinction between the two is that PF2 includes overhead costs (SG&A) as a production input, while PF1 does not. [4] Each panel shows a positive relationship between the two measures, with the MFMP on the y-axis and the DLEU estimates on the x-axis. The correlation coefficients are 0.22 for PF1 and 0.20 for PF2, suggesting a meaningful alignment across methodologies.

The observed level difference is expected, as DLEU estimates firm-specific markups, while

[3] An exception is the work of Döpper et al. (2022) which examines multiple markets but does not focus on the firm dimension.

[4] PF1 assumes a production technology using variable inputs and physical capital. PF2 additionally incorporates overhead expenditures in the construction of markups. In both cases, we extend the DLEU markup estimates by holding output elasticities fixed at their final 2016 values.

our MFMP measure captures the markup premium at the module level within each firm. The positive correlation suggests that MFMP aligns with DLEU in capturing meaningful cross-firm variation, providing initial validation of our measure.

It is important to note that a perfect correlation is not anticipated due to several factors. First, to construct a firm-level measure, we aggregate our module-firm level MFMP using NielsenIQ sales data, which may not fully represent total firm sales since some products may not be captured in our sample. Additionally, while DLEU does not account for differences in markups across various segments of a firm, our MFMP measure does.

next, we conduct a more rigorous regression analysis to further examine the relationship between MFMP and DLEU measures. The regression results presented in Table 3 show the relationship between our MFMP measure and the DLEU markup estimates under the two specifications. In columns (1) and (2), the log of the DLEU markup under PF1 is positively correlated with our MFMP measure, with coefficients of 0.394 and 0.290, respectively, both significant at the 1% and 5% levels. This suggests a positive relationship between the two measures, confirming the alignment of MFMP with DLEU markups under this specification. Column (3) includes firm-fixed effects and shows a lower coefficient (0.178), which remains significant at the 10% level. Columns (4) to (6) report the regressions using DLEU markups under PF2. The coefficients are again positive, with values of 0.359, 0.295, and 0.218 in models (4), (5), and (6), respectively, all of which are statistically significant at varying levels.

Overall, the positive and significant coefficients across models suggest that our MFMP measure aligns with DLEU in capturing cross-firm markup variation, providing validation of our approach. The inclusion of firm and year-fixed effects, along with clustering by firm, indicates a robust model specification, reinforcing the observed relationship between MFMP and DLEU markups.

4.2. Properties of Firms within Modules

In this subsection, we analyze the relationship between the module-firm-specific markup premium (MFMP) and key variables such as market share and firm size. The MFMP measure is calculated using the methodology outlined earlier. For each firm, we define market share as the firm's sales in a given module relative to total sales within that module. Firm size is measured as the logarithm of the firm's total sales across all modules in which it operates. Importantly, while the previous subsection compared our MFMP measure to DLEU markup estimates using a restricted sample of publicly listed firms, for the rest of this section we leverage on NielsenIQ data alone. As a result, we expand our analysis to include over 25,000 firms.

Panel A of Table 4 shows the relationship between lagged market share and the markup premium. A one-unit increase in market share (which, given that market share is between 0 and 1, means a change from, say, 0.20 to 0.21) is associated with an approximate 25.7% increase in the markup premium. This result is robust even after controlling for time-module and module-firm fixed effects. In columns (3) and (4), where we also control for the previous level of the markup premium (a proxy for firm quality in that module), we find that a unit increase in market share leads to a 7.1% increase in excess markups.

Next, we evaluate whether larger firms, measured by their sales, have higher excess markups. Columns (5) to (8) examine the impact of firm size on the markup premium. The results show that larger firms do indeed have higher markups, although the magnitude is relatively small. Specifically, after controlling for the lagged level of the markup premium, a 1% increase in sales is associated with only a 0.005% increase in excess markups.

Panel B of Table 4 introduces an interaction term between market share and firm size to demonstrate that market share is not merely capturing firm size. In column (8), the results show that a one-unit increase in market share leads to a 21% increase in markups. While the relationship between firm size and markups remains positive, it weakens as market share increases. In other words, the effect of firm size on markups diminishes for firms with larger market shares.

Overall, the measure of markup premium displays the expected relationships. Market share in the previous period has a strong and positive effect on markups, indicating that firms with a larger market share can command higher markups, likely due to increased pricing power. The lagged dependent variable (markup) is highly significant in both panels, showing that markups are persistent over time. Firms with high markups tend to maintain them. Although firm size positively affects markups, this effect is smaller compared to the impact of market share. Moreover, the interaction term in Panel B shows that this effect diminishes for larger firms, meaning that the size-driven effect on markups is weaker for firms with a dominant market position.

4.3. Properties of Modules

In this subsection, we analyze the effects of market concentration (measured by the Herfindahl-Hirschman Index, HHI) and market size (measured by total sales) on both the level and dispersion of markup premiums across different modules. To capture these dynamics, we aggregate the markup premium within each module by calculating both the average (sales-weighted) markup premium and the interquartile range (IQR) of markups. Results are presented in Table 5.

In Panel A, we observe that market concentration (HHI) is positively associated with the

markup premium. In more concentrated markets, firms are able to charge higher markups, as indicated by the significant and positive relationship between HHI and markups in columns (1) and (4). For example, in column (1), the coefficient of 0.070 indicates that a one-unit increase in HHI is associated with a 7.0% increase in the markup premium. This suggests that firms in concentrated markets possess more pricing power due to reduced competition, allowing them to increase their markups. However, when controlling for market size (as seen in columns (3) and (6)), the effect of HHI becomes insignificant. For instance, in column (3), the coefficient on HHI drops to 0.028 and is no longer statistically significant, implying that market size plays a stronger role in determining competition than concentration alone when both are considered. The negative and significant relationship between log(Sales) and markup across columns (3), (5), and (6) shows that as the size of the market increases, competition intensifies, leading to lower markups. For example, in column (3), the coefficient of -0.025 on sales suggests that a 1% increase in sales is associated with a 2.5% decrease in markup premiums. This aligns with economic theory: in a perfectly competitive market, firms cannot raise prices significantly, and markup premiums should be close to zero.

In contrast, Panel B evaluates the dispersion of markups, as measured by the interquartile range (IQR), and shows a consistently negative and significant relationship between HHI and the IQR of markups. In more concentrated markets, firms not only charge higher markups (as seen in Panel A) but also exhibit less variation in pricing strategies, resulting in a narrower IQR. For instance, in column (1), the coefficient of -0.140 indicates that a one-unit increase in HHI is associated with a 14.0% decrease in the IQR of markups, suggesting that firms adopt more uniform pricing strategies in concentrated markets. This reduction in markup variability implies that concentrated markets may experience less price competition, as firms with greater market power maintain similar pricing structures, leading to a smaller IQR.

The role of market size (log(Sales)) in Panel B is more nuanced. While the relationship between market size and IQR is positive and significant in some specifications (columns (1) and (3)), indicating that larger markets exhibit greater variation in pricing strategies, this relationship is not always statistically significant. For example, in column (1), the coefficient of 0.012 suggests that a 1% increase in total sales is associated with a 1.2% increase in the IQR of markups. This implies that firms in larger markets may adopt more diverse pricing strategies due to increased competition or market segmentation, resulting in a wider IQR. However, this effect is weaker and less consistent compared to the strong impact of market concentration on reducing markup dispersion.

In summary, results in Table 5 show that more concentrated markets have higher markup premiums, but market size mitigates this effect by promoting competition, driving down markups in larger markets. Panel B reveals that concentrated markets also lead to more

uniform pricing (narrower IQR), while larger markets sometimes promote greater pricing variation. Taken together, these results suggest that market concentration increases both pricing power and uniformity, while market size fosters more competition and diverse pricing strategies.

4.4. Time Series Properties

Using a production-based approach, De Loecker et al. (2020) document a rise in aggregate markups since 1980, largely driven by firms in the upper tail of the distribution. They also observe a shift in market share from low to high markup firms, predominantly within industries. While we cannot analyze average markups directly, as our focus is on markup premiums, we can examine tail behaviors, which reflect firm-level deviations from the average. Additionally, our findings do not address the overall distribution of markups or expenditure allocation but rather the distribution of "consumer product types" and grocery store expenditure patterns.

Figure 2 presents a decomposition of the average sales-weighted markup premium over time, normalized to 2007Q1. In Panel A, the solid red line shows the observed evolution of the average markup premium paid by consumers, weighted by firm-product sales. We observe a modest but persistent decline over the sample period leading up to 2020. To unpack the drivers of this trend, we construct two counterfactual series: the blue dashed line holds expenditure weights fixed at their initial (2007Q1) levels while allowing firm markups to vary, capturing changes in individual pricing behavior; the green dotted line fixes firm-level markups at their initial levels and allows expenditure weights to vary, isolating the effect of consumers shifting spending across products and firms.

The comparison across these series shows that the overall decline is driven primarily by compositional changes—consumers increasingly shifted their expenditures toward lower-markup firms and product categories. This demand-side reallocation accounts for a larger share of the decline than any within-firm reductions in pricing premiums. Panel B repeats the decomposition at the module level. The observed pattern is similar but attenuated, suggesting that while within-category dynamics matter, the bulk of the decline is explained by cross-category and cross-firm shifts in consumer spending.

5. Capital structure and markups

In this section, we investigate how firms' financial structure shapes their markup premiums. Our methodology, which enables measurement of markups for both publicly listed and private firms, allows for a comprehensive comparison across ownership types. In Subsection 5.1,

we compare markup premiums between public and private firms. Subsection 5.2 examines how these differences evolved during the 2021–2022 inflation surge following the COVID-19 pandemic. We then explore the mechanisms behind public firms' pricing behavior during this period in Subsection 5.3,

5.1. Public versus Private Firms

We begin by examining how markup premiums differ between public and private firms at a granular product level. To identify the effect of public listing on markups, we exploit the staggered timing of firms transitioning from private to public status (and vice versa). Our empirical strategy combines propensity score matching with a stacked difference-in-differences (DiD) design.

Following Fracassi et al. (2022), we implement propensity score matching at the product-module level. For each firm that transitions to public status, we match its product modules to those of five firms that remain private. Matching is performed over an eight-quarter pre-treatment window, ending one year prior to the transition. Firms are matched based on their pre-treatment markup premium, market share, firm size, and total sales within the product module.

To account for the staggered timing of firms' transitions to public ownership, we implement a stacked difference-in-differences (DiD) framework using the initial public offering (IPO) date as the treatment event. This approach addresses concerns about potential bias in traditional two-way fixed effects DiD estimators when treatment is staggered across units and time (Callaway and Sant'Anna, 2021; Cengiz et al., 2019; Goodman-Bacon, 2021; Gormley and Matsa, 2011; Sun and Abraham, 2021), and yields consistent estimates of the causal effect of public listing on markup premiums.

For each treated firm—that is, a firm that undergoes an IPO during the sample period—we construct a matched control group of private firms based on observed characteristics. Matching is performed at the firm–module level, ensuring comparability in both firm and product dimensions. Each treatment–control cohort c consists of one treated firm–module pair $i^T j^T$ and N matched control firm–module pairs $i_n^C j_n^C$, for $n = 1, 2, \ldots, N$. In our baseline specification, we set $N = 5$.

Although the number of IPO events in our sample is relatively small—23 firms went public over the sample period—we leverage the granularity of our data, specifically the firm–module structure, to generate a large number of comparison groups. The firms that went publicly listed span 282 modules and are matched with 880 private firms. This allows us to exploit within-product variation in pricing behavior across firms, increasing statistical power and enabling a more precise estimation of the effects of public listing on markups.

We calculate firm characteristics for matching by averaging them over a pre-treatment window defined as $[t_c - 5 - W, t_c - 5]$, where t_c denotes the quarter in which the treatment firm in cohort c goes public, and W is the length of the matching window. In the baseline specification, we set $W = 8$. For example, if a treatment firm went public in 2012Q4, we compute its average characteristics—as well as those of all potential control firm-modules—over the period from 2009Q3 to 2011Q3.

The distance between a treatment firm-module and each potential control firm-module is computed as the sum of standardized differences across all matching variables. For each treated firm-module, we retain the N closest matches as its control group. In the baseline, we set $N = 5$.

After stacking the matched treatment and control firm-modules, we restrict the analysis window to 8 quarters before and 12 quarters after the treatment event for each firm-module cohort c. Let h denote the number of quarters relative to the treatment, with $h = 0$ corresponding to the quarter of the IPO.

To estimate the impact of going public on firm markup premiums, we estimate the following specification:

$$\log(\mu_{cih}) = \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih}, \tag{4}$$

where $\log(\mu_{cih})$ denotes the log markup premium of firm-module i in cohort c at relative time h, as estimated in the framework described in the previous section. The interaction term $\text{Post}_{ch} \times \text{Treat}_{ci}$ captures the causal effect of going public, where Post_{ch} is an indicator for post-treatment periods, and Treat_{ci} is a dummy equal to 1 for treated firm-modules.

The specification includes cohort-by-date fixed effects α_{ch}, which control for time-specific shocks and relative time trends common to all firms in the same product module cohort. This ensures that identification is not driven by aggregate trends or macroeconomic shocks affecting all firms around the IPO window. In addition, cohort-by-firm fixed effects δ_{ci} account for time-invariant differences across firm-modules. As a result, the estimated effect is identified from within-cohort, within-module deviations around the IPO event.

Table 6 presents the estimation results. We find that markup premiums increase following a firm's transition to public ownership. In Column (1), the estimated coefficient of 0.034 indicates that treated firms raise their markups by approximately 3.4% relative to their matched private-firm controls. When we weight observations by log(sales), the effect rises to 3.8%, as shown in Column (2). The larger effect in the sales-weighted specification suggests that markup increases are concentrated in firms' most economically significant

products—where pricing decisions carry the greatest aggregate impact.

This result is particularly striking given that one might expect the opposite: firms typically experience lower financing costs and improved capital access after going public, which under competitive conditions could lead to lower prices or smaller markups. Instead, our findings suggest that public listing may amplify incentives to raise margins—possibly due to heightened pressure from shareholders, margin-focused performance targets, or equity-linked managerial compensation. These results underscore how financial structure can shape pricing behavior in ways that reinforce, rather than dampen, firm-level pricing power.

Next, we examine the dynamic evolution of markup premiums around the time of a firm's IPO. To do so, we plot the average markup premium (MFMP) for treated and control firms after removing cohort-by-date and cohort-by-firm-module fixed effects. As shown in Figure 3, there is no significant difference between the treated and control groups in the pre-treatment period, supporting the parallel trends assumption. Following the IPO, however, markup premiums rise steadily for treated firms, while remaining flat for their matched controls. The divergence begins shortly after the IPO and persists throughout the post-treatment window, suggesting a sustained shift in pricing behavior after firms become publicly listed.

5.2. Capital Structure and Markups During the 2021–2022 Inflation Surge

Building on our earlier finding that firms systematically increase their markup premiums after going public, we now examine whether public and private firms responded differently during the 2021–2022 inflation surge. Public firms may face stronger incentives to expand margins in inflationary environments—driven by investor expectations, equity-linked compensation, or greater pricing discretion.

To explore this, we compare the markup behavior of public and private firms between 2018 and 2022. We restrict the treatment group to firms that went public before 2020Q1 and construct matched control groups of private firms based on observable characteristics measured over the four quarters preceding the inflation surge. Given the shorter post-2021 sample period, we adopt a shorter matching window than in our IPO analysis.

Figure 4 illustrates the time-series dynamics of markup premiums (MFMP) for public and matched private firms, after controlling for cohort-by-date and cohort-by-firm-module fixed effects. The right axis overlays the Consumer Price Index (CPI) for food-at-home goods, measured using the Fisher Price Index. Before 2021, markup trends across the two groups closely track each other. But beginning with the inflation surge in early 2021, public firms show a sharp and sustained increase in markup premiums, while private firms' markups remain largely stable. This divergence suggests that public firms were more aggressive in expanding margins during the inflationary period.

To formally quantify this shift, we estimate the following difference-in-differences specification:

$$\log(\mu_{cih}) = \beta \cdot \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih}, \tag{5}$$

where $\log(\mu_{cih})$ is the log markup premium of firm-module i in cohort c at time h, Treat_{ci} indicates public firms, and Post_{ch} is a dummy for periods after 2020Q1. The model includes cohort-by-date fixed effects (α_{ch}) and cohort-by-firm-module fixed effects (δ_{ci}) to absorb common shocks and time-invariant differences. Standard errors are clustered at the firm level.

Table 7 reports the estimation results. Column (1) shows that public firms increased their markup premiums by 0.018 log points—roughly 1.8%—more than comparable private firms during the inflation surge. Column (2) confirms the result holds when weighting by log(sales), indicating that markup expansion was more pronounced in high-revenue product lines. Columns (3)–(6) examine heterogeneity by estimating the same model on subsamples. Specifically, we classify modules based on their Herfindahl-Hirschman Index (HHI) and the share of sales by public firms, both measured in 2019Q4. Modules with above-median HHI are classified as high-concentration modules (Columns (3) and (4)), while those with above-median public share are classified as high-public share modules (Columns (5) and (6)). In both settings, the markup response among public firms is significantly larger, suggesting that financial structure and market dominance jointly amplify firms' ability to raise prices during inflationary shocks.

To assess whether these markup increases translated into actual consumer price growth, we replicate the difference-in-differences design using the Fisher Price Index as the dependent variable. Table 9 presents the results. Column (1) shows that public firms raised prices by 0.6 percentage points more than matched private firms after 2020Q1, with the effect remaining statistically significant when weighting by log(sales) in Column (2). This provides direct evidence that margin expansion was passed through to consumers, reinforcing the interpretation that public firms not only absorbed inflationary cost shocks, but actively amplified them. Economically, this suggests that financial structure—not just input costs—plays a critical role in shaping firm-level inflation transmission.

5.3. Unpacking the Mechanisms Behind Public Firm Pricing Behavior

To better understand why public firms expanded their markups more aggressively during the inflation surge, we examine whether this behavior varies systematically with firm char-

acteristics that proxy for investor pressure, managerial incentives, and financial flexibility. In our empirical design, we match public and private firms on a rich set of pre-period observables, including firm size, market share, and sales. Given that these key operational characteristics are held constant, the primary distinction between public and private firms lies in their ownership structure and access to capital markets. This motivates our next step: testing whether pressures associated with being publicly listed—such as shareholder demands, stock-linked compensation, or financing advantages—help explain the differential markup response.

Specifically, we split the sample of public firms based on the median value of several pre-determined variables.

To capture capital market pressure, we consider *Retail Share*, the proportion of a firm's equity held by retail investors (based on Form 13F filings), and *Market Value Loss*, defined as the firm's stock return in 2020Q1. These proxies reflect investor composition and the extent of early-pandemic performance shocks.

To proxy for managerial incentives, we use several compensation-related measures. *SBC (Stock-Based Compensation)* is total stock-based pay (Compustat item `STKCO`) scaled by sales. *Delta* measures the sensitivity of executive wealth to changes in stock price, and *Wealth Sensitivity* (or inside equity) reflects the fraction of managerial wealth held in firm equity. Both are constructed following Coles et al. (2006), based on the methodology of Core and Guay (2002).

To assess financial flexibility, we include the *Quick Ratio*, calculated as current assets minus inventory over current liabilities, and *Leverage*, defined as total debt divided by total assets. These proxies reflect a firm's liquidity position and reliance on external financing.

All variables are measured prior to the inflation surge—primarily in 2019, with the exception of *Market Value Loss*, which is from 2020Q1. By comparing firms with high versus low values along each dimension, we assess whether specific features of public firms' financial and governance structures are associated with differential markup behavior during the inflationary period.

Table 8 compares the public firms in our NielsenIQ sample to the broader universe of listed firms from Compustat along key sorting variables. This comparison helps assess whether the firms for which we observe detailed product-level pricing data are representative of the full public firm population.

Overall, the NielsenIQ sample exhibits similar patterns to the full Compustat sample across most dimensions. Retail ownership is slightly higher on average in the NielsenIQ sample (28.4% vs. 26.3%), and Market Value Loss in 2020Q1 is somewhat lower (8.95% vs. 11.2%), suggesting that firms in the NielsenIQ sample may have been less exposed to

early-pandemic financial distress. Compensation-related measures—including stock-based pay (SBC), Delta, and Wealth Sensitivity—are also broadly in line, although SBC as a share of sales is lower in the NielsenIQ sample, likely reflecting industry composition.

In terms of financial flexibility, firms in the NielsenIQ sample appear slightly more conservative, with a lower Quick Ratio (1.31 vs. 2.39) and slightly higher Leverage (0.37 vs. 0.33), suggesting they are more reliant on debt and less liquid on average. These comparisons indicate that while our analysis is based on a selected sample of public firms, it captures a meaningful and diverse subset of the public firm universe, spanning a range of investor exposures, incentive structures, and balance sheet conditions.

Figure 5 presents the results of this heterogeneity analysis. For each characteristic, we estimate the same difference-in-differences specification as in Equation (5), using the same fixed effects and control structure. Specifically, we run the regression separately for firms above and below the median of each sorting variable. The figure reports the estimated treatment effects and 90% confidence intervals across these subsamples.

The results reveal that firms with higher exposure to retail investors, greater stock price declines in 2020Q1, and stronger equity-based incentives exhibit significantly larger increases in markup premiums during the inflation surge. For example, the markup response is notably higher among firms with above-median *Retail Share*, *Market Value Loss*, and *Stock-Based Compensation*. These patterns are consistent with the hypothesis that capital market pressure and stock-linked managerial incentives intensified firms' responsiveness to inflationary conditions.

In contrast, the differences in markup responses across subsamples split by financial flexibility—as proxied by the *Quick Ratio* and *Leverage*—are more muted. While some variation is present, these results suggest that access to internal liquidity or debt capacity played a less central role than ownership and incentive structures in driving firms' pricing behavior. Taken together, these findings reinforce the idea that pressures associated with public listing—rather than operational fundamentals alone—shaped firms' markup strategies during the post-pandemic inflation surge.

To further explore the interaction between managerial incentives and investor pressure, Figure 6 presents results from a double-sorted analysis. For each of the three incentive measures—Delta (Panel A), Wealth Sensitivity (Panel B), and Stock-Based Compensation (Panel C)—we divide firms into high and low groups based on the median value of the incentive variable. Within each group, we then split the sample again based on Market Value Loss during 2020Q1, yielding four categories: High-High, High-Low, Low-High, and Low-Low.

The results reveal a consistent pattern across all three panels: markup responses are

strongest among firms with both high managerial incentive alignment and high investor pressure. For example, in Panel A, firms with high Delta and large stock price losses exhibit significantly larger markup increases than those in other bins. Similar results hold for Wealth Sensitivity and Stock-Based Compensation in Panels B and C, respectively. These findings suggest a complementary role between internal incentive structures and external capital market shocks in shaping firm pricing behavior.

In contrast, firms with low incentive sensitivity or minimal investor pressure (the Low-Low groups) display muted or near-zero markup adjustments. This asymmetry highlights that neither managerial incentives nor market losses alone are sufficient to explain markup expansion—rather, it is their interaction that appears to drive more aggressive margin-setting during the inflationary period.

Figure 7 provides important context for interpreting our results. It shows that public firms' market share—measured by total sales in each module (Panel A) and by the number of active firms (Panel B)—declined steadily after 2020Q1. This downward trend suggests that the observed increase in markup premiums among public firms is not driven by an increasing market footprint. If anything, public firms became relatively less prominent during the inflationary period. These patterns reinforce our interpretation that the disproportionate markup expansion observed among public firms is driven by differences in incentives and pricing behavior, rather than by structural shifts in market share.

In sum, our results show that public firms expanded their markups more aggressively than private firms during the 2021–2022 inflation surge, despite losing relative market share. This behavior cannot be explained by differences in size, product mix, or market position alone. Instead, the evidence points to incentive structures unique to public firms—particularly the combination of equity-linked compensation and exposure to capital market pressure—as key drivers of this differential response. These findings highlight the role of firm financial structure in shaping pricing behavior during inflationary episodes and suggest that firm responses to macroeconomic shocks may depend as much on governance and incentives as on cost fundamentals.

6. Is It Just Public Pressure? The Case of Private Equity

To assess whether the pricing behavior we observe among public firms reflects broader capital market dynamics or is uniquely driven by public listing and managerial incentives, we conduct a complementary analysis of firms receiving private equity (PE) or venture capital (VC) funding. Using deal-level data from PitchBook, we identify 220 firms in the NielsenIQ sample that received at least one PE/VC transaction between 2006 and 2023, matched using

firm names and ZIP codes. On average, these firms received six deals, with a mean deal size of approximately $170 million.

We construct matched control groups of non-PE firms based on observable characteristics measured over a four-quarter window preceding the first PE/VC deal. The matching is conducted at the firm-module level and balances key dimensions: log markup premiums, product-level market share, total firm sales, and firm-module sales. We then estimate the following difference-in-differences specification:

$$\log(\mu_{cih}) = \beta \cdot \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih}, \tag{6}$$

The results, reported in Table 10 and visualized in Figure 8, show that markup premiums increase significantly following PE/VC transactions. The estimated effect—approximately 2.8 to 3.5%—is comparable to the increase observed after firms go public. This suggests that access to equity capital, even outside public markets, can be associated with greater pricing power.

However, when we examine markup behavior during the 2021–2022 inflation surge, the pattern diverges. As shown in Table 11 and Figure 9, PE-backed firms do not significantly increase markups relative to matched private firms over the same period. This stands in contrast to the behavior of publicly listed firms, as documented in Table 7 and Figure 4, which expanded their markup premiums more aggressively during the inflationary shock. These findings suggest that public ownership—rather than the mere presence of outside capital—is more strongly associated with inflation-period pricing adjustments.

Our findings are consistent with those of Fracassi et al. (2022), who show that PE ownership is associated with strategic product line restructuring and long-run pricing changes. However, our contribution lies in analyzing short-run markup dynamics during macroeconomic shocks. While PE-backed firms increase markups following investment, they do not display the same responsiveness to inflationary conditions as public firms. A likely explanation is that valuation pressures in public markets are more immediate and observable, with consequences for managerial compensation and investor expectations. In contrast, performance signals in PE-owned firms are more opaque and evolve over longer horizons, reducing the immediacy of the incentive to raise prices.

Taken together, these results reinforce the interpretation that it is not just the presence of outside investors that drives differential markup behavior, but the real-time governance environment of public markets. Firms listed on public exchanges face heightened performance visibility and incentive alignment pressures that appear to amplify their responsiveness to

macroeconomic shocks.

7. Conclusion

This paper develops a new granular measure of firm-product-level markup premiums and applies it to analyze how financial structure and managerial incentives shape pricing behavior—particularly during the 2021–2022 inflation surge.

We show that financial structure plays a central role in explaining variation in markups. Firms that go public systematically raise markups relative to comparable private firms, and publicly listed firms expanded margins more aggressively during the inflationary period. These effects are concentrated in firms with greater retail investor ownership, significant equity-based compensation, and large stock price declines during the COVID-19 crisis—highlighting the influence of capital market pressure and executive incentives.

Importantly, these markup increases were not merely accounting artifacts: public firms also passed through higher prices to consumers, contributing disproportionately to inflation. In contrast, private equity–backed firms—while showing similar post-investment markup increases—did not exhibit the same inflationary price response, underscoring the distinctive governance dynamics of public markets.

Our findings suggest that public listing amplifies firms' responsiveness to macroeconomic shocks, not just through capital access but via real-time investor scrutiny and incentive structures. More broadly, they highlight the need to incorporate ownership and governance features into models of inflation dynamics and pricing behavior.

For policymakers, this suggests that corporate governance environments—especially those shaped by public capital markets—can meaningfully affect how firms transmit macroeconomic shocks into consumer prices.

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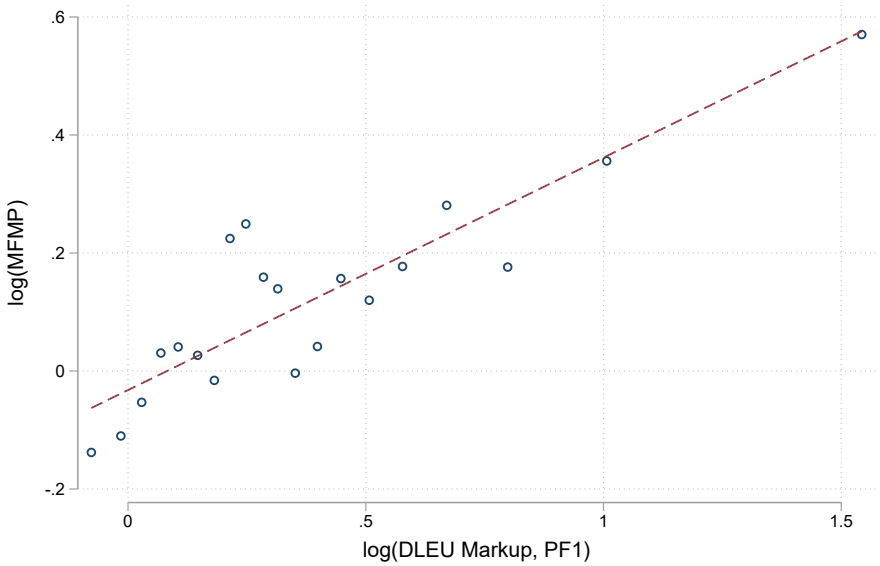
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I. Figures

Figure 1: Relationship Between MFMP and DLEU Markups

Figure 1 presents binned scatter plots of MFMP (vertical axis) against two firm-level markup measures from De Loecker et al. (2020) (DLEU markups, horizontal axis). Panel A shows PF1, which assumes a production technology that uses variable inputs and physical capital. Panel B shows PF2, which additionally accounts for overhead expenditure in markup construction. The data covers 2007 to 2022.

Panel A: Relationship Between MFMP and DLEU Markup, PF1



Panel B: Relationship Between MFMP and DLEU Markup, PF2

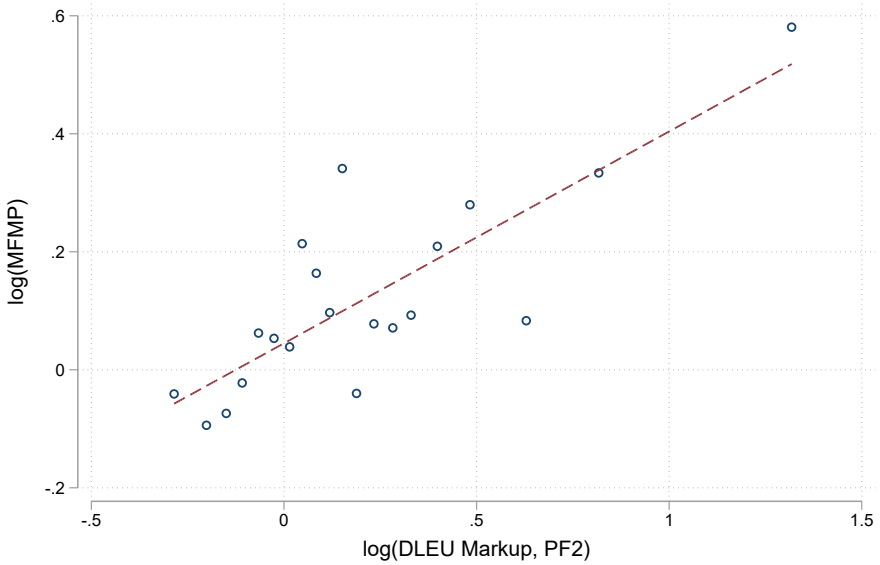


Figure 2: Decomposition of Aggregate MFMP Over Time

We plot the decomposition of aggregate MFMP over time. In panel A, the solid red line shows the average sales-weighted MFMP. The dashed blue line holds sales fixed at the initial value (2007Q1) and varies MFMP over time. The dotted green line holds MFMP fixed at the initial value (2007Q1) and varies sales weights over time. To distinguish between between-module and within-module trends, in Panel B, we first calculate average sales-weighted MFMP at the module level. We then follow a similar procedure as in Panel A to calculate initial-weight (dashed blue line) and intial-markup (dotted green line) average MFMP using sales and MFMP at the module level.

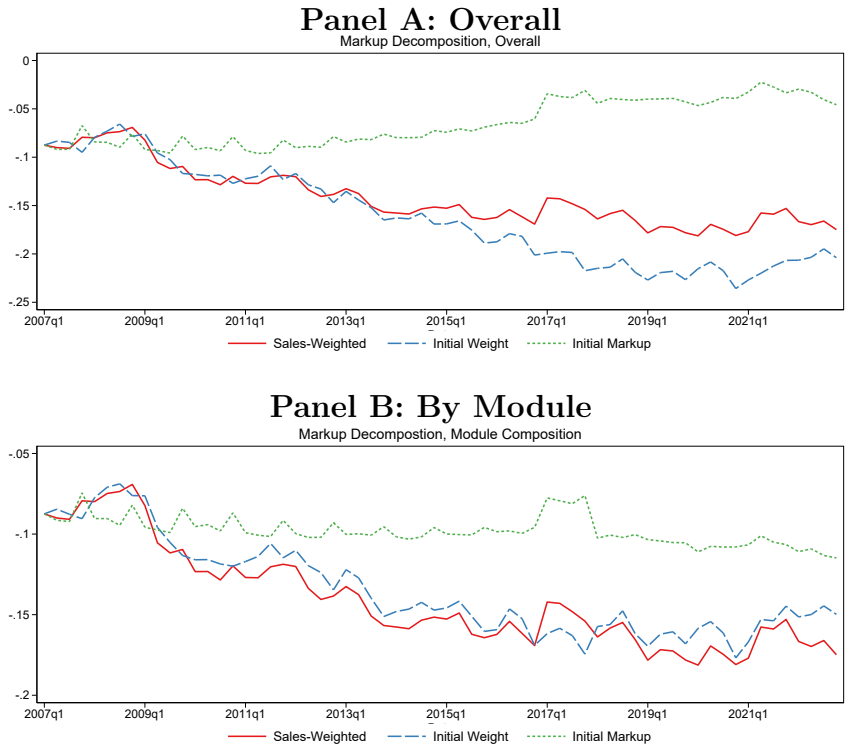


Figure 3: MFMP Around IPO

The figure shows the time series dynamics of MFMP around the time a treated firm went public. we plot the average MFMP of the treated and control firms after removing the cohort-by-date and cohort-by-firm-module fixed effects. The figure shows the 90% confidence interval bands.

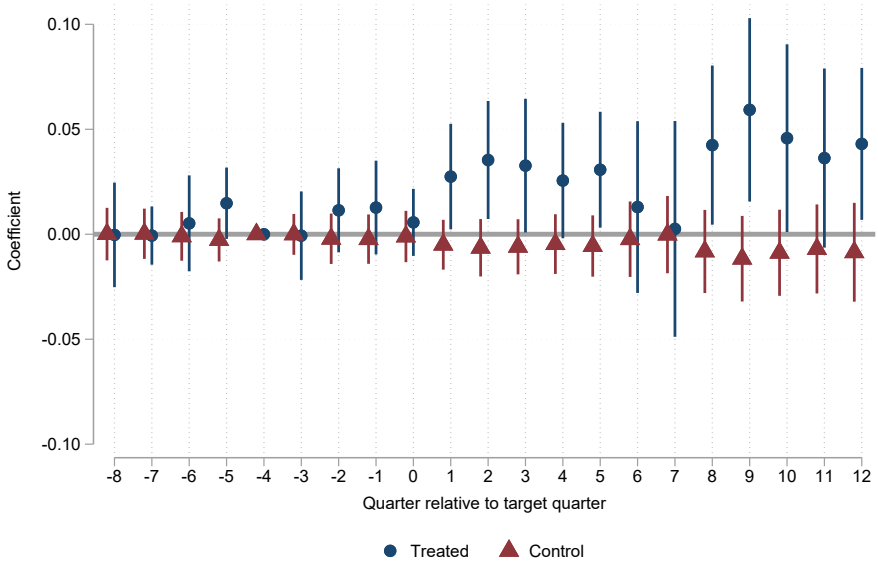


Figure 4: MFMP During 21/22 Inflation Surge, Public and Private Firms

The figure shows the time series dynamics of MFMP of public firms and their matched peers around 21/22 inflation surge. we plot the average MFMP of the treated and control firms after removing the cohort-by-date and cohort-by-firm-module fixed effects. The gray dashed line plots CPI: Food at Home on the right axis. The figure shows the 90% confidence interval bands.

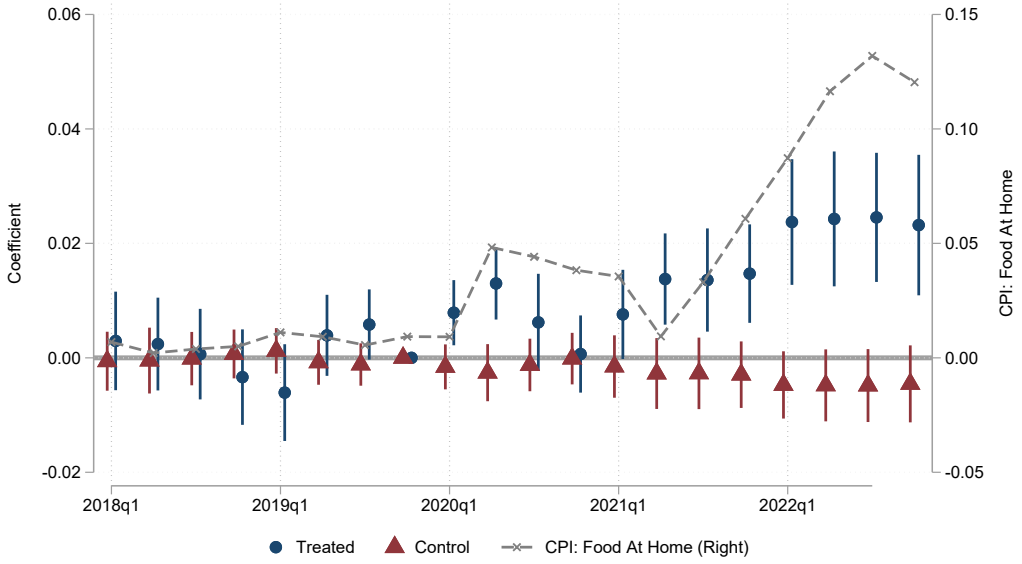


Figure 5: MFMP of Public Firms During 21/22 Inflation Surge, Subsamples

The table shows how public firms adjust their markups during 21/22 inflation surge compared with their private peers. We estimate the following specification on different subsamples:

$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih}$$

where $\log(\mu_{cih})$ is the log MFMP of firm-module i within the cohort c for event time h. The figure shows coefficients estimates β with 90% confidence interval bands. Post_{ch} is a dummy that takes the value of 1 after 2020Q1. Treat_{ci} is a dummy that takes the value of 1 for the public firms in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. For each group, we split the sample into two equal-sized subsamples based on the median of each key characteristic. Retail Share is the proportion of a firm's equity held by retail investors, based on Form 13F filings. Market Value Loss is negative returns in 2020Q1. SBC is Stock Compensation Expense (Compustat item `STKCO`) scaled by sales. Delta (pay-performance sensitivity) and Wealth Sensitivity (inside equity) are calculated by Coles et al. (2006) based on methodology developed in Core and Guay (2002). Quick Ratio is current assets net of inventory scaled by current liabilities. Leverage is the sum of short-term and long-term debt divided by total assets. All characteristics are from 2019 with the exception of Market Value Loss.

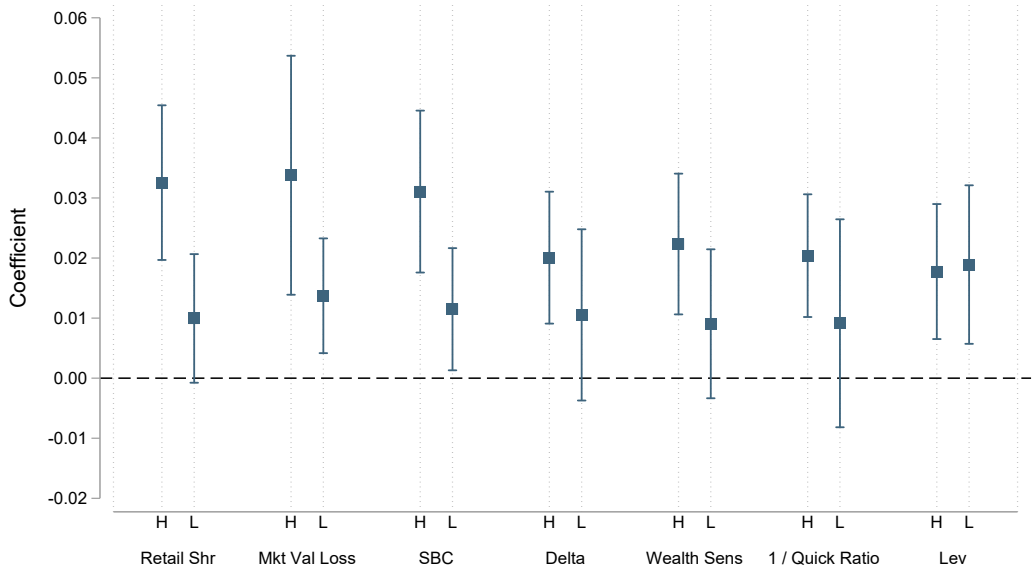


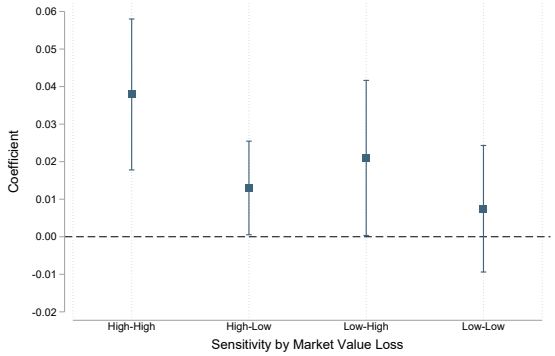
Figure 6: MFMP of Public Firms During 21/22 Inflation Surge, Sensitivity by Market Value Loss

The table shows how public firms adjust their markups during 21/22 inflation surge compared with their private peers. We estimate the following specification on different subsamples:

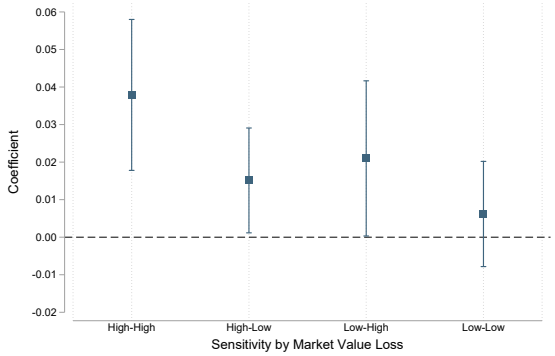
$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih}$$

where $\log(\mu_{cih})$ is the log MFMP of firm-module i within the cohort c for event time h. The figure shows coefficients estimates β with 90% confidence interval bands. Post_{ch} is a dummy that takes the value of 1 after 2020Q1. Treat_{ci} is a dummy that takes the value of 1 for the public firms in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. We consider three managerial incentive measures: Delta (pay-performance sensitivity) in Panel A, Wealth Sensitivity (inside equity) in Panel B, and Stock-Based Compensation scaled by sales in Panel C. Delta and Wealth sensitivity are calculated by Coles et al. (2006) based on methodology developed in Core and Guay (2002). First, we divide the sample into two equal-sized subsamples based on the median value of each sensitivity measure. Then, within each sensitivity subsample, we further split observations into two equal-sized groups based on Market Value Loss, measured as negative returns in 2020Q1.

Panel A: Delta



Panel B: Wealth Sensitivity



Panel C: Stock-Based Compensation

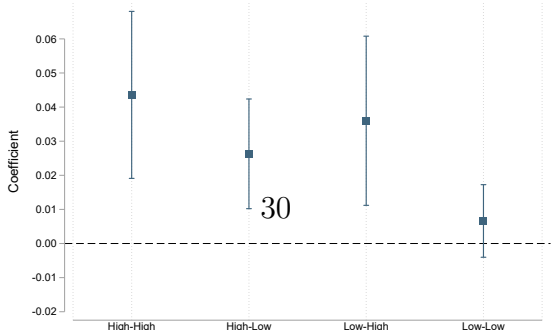


Figure 7: Public Share during 21/22 Inflation Surge

The figure shows the dynamics of public firm market share during 21/22 inflation surge. Public share is defined as total sales by public firms divided by total sales in each module (Panel A), or total number of public firms divided by total number of firms in each module (Panel B). We fit separate linear trends to these market share measures before and after 2020Q1 in our scatter plots.

Panel A: Market Share, Sales



Panel B: Market Share, Number of Firms

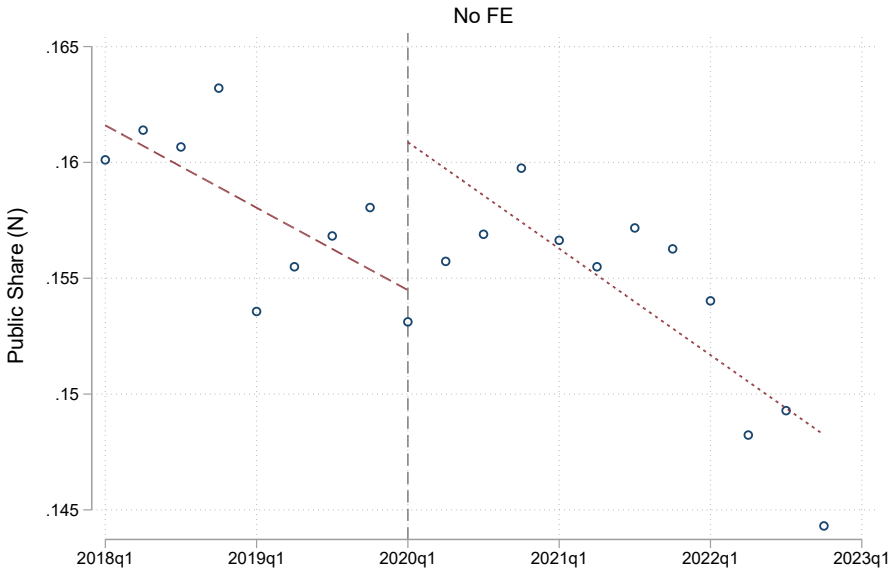


Figure 8: MFMP Around PE Deals

The figure shows the time series dynamics of MFMP around the time a treated firm received a PE deal. we plot the average MFMP of the treated and control firms after removing the cohort-by-date and cohort-by-firm-module fixed effects. The figure shows the 90% confidence interval bands.

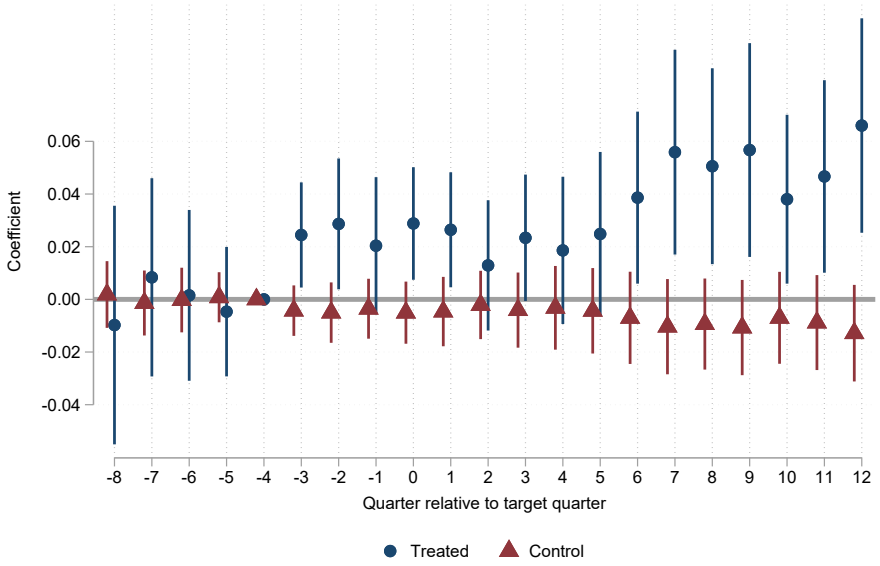
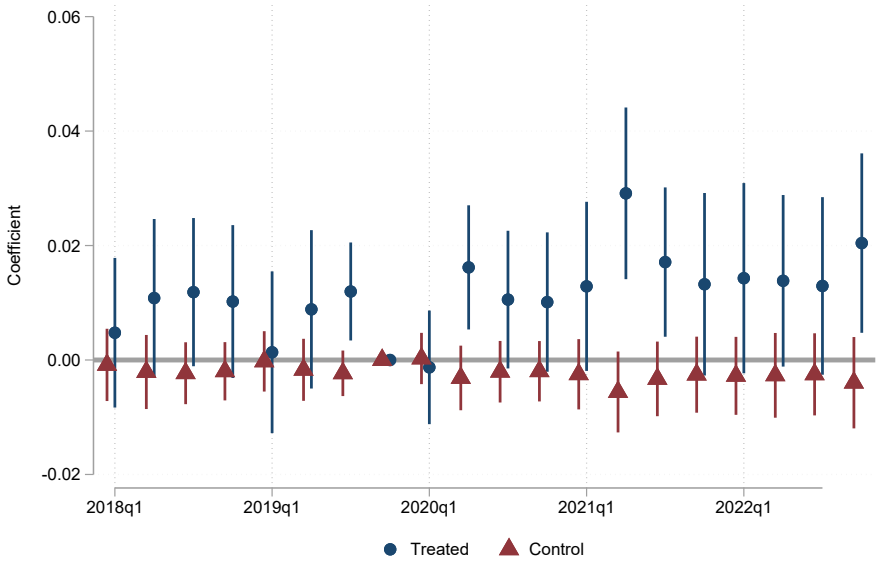


Figure 9: MFMP During 21/22 Inflation Surge, PE-Backed and Private Firms

The figure shows the time series dynamics of MFMP of PE-backed firms and their matched peers around 21/22 inflation surge. we plot the average MFMP of the treated and control firms after removing the cohort-by-date and cohort-by-firm-module fixed effects. The figure shows the 90% confidence interval bands.



II. Tables

Table 1: Sales and Firms Across Departments

The table reports the dataset's coverage. We compute total sales and the number of firms in each department each quarter, then average them over the entire sample.

	Full Sample		Public Firms	
	Avg. Sales ($MM)	No. of Firms	Avg. Sales ($MM)	No. of Firms
Health & Beauty Care	1.6	4,075	26.3	108
Dry Grocery	1.9	10,691	86.9	135
Frozen Foods	1.1	3,200	19.5	71
Dairy	1.4	2,113	20.2	45
Deli	0.7	1,630	9.9	50
Packaged Meat	1.7	976	33.9	24
Fresh Produce	1.0	1,563	3.1	27
Non-Food Grocery	1.8	4,126	42.2	112
Alcoholic Beverages	1.5	2,456	36.1	35
General Merchandise	0.5	6,116	7.2	180
Total		25,294		298

Table 2: Summary Statistics

The table reports summary statistics for key variables across two levels of analysis. Panel A presents firm-module-level price index and log of markup premium. Panel B presents module-level Herfindahl-Hirschman Index (by sales) and public firm sales share.

	Mean	Sd	Min	Max
Panel A: Full Sample				
π^F	0.998	0.178	0.341	1.791
$\log \mu$	0.002	0.759	-2.280	2.095
Observations	2,935,240			
Panel B: Module Sample				
HHI	0.462	0.270	0.070	1.000
Public Share	0.402	0.356	0.000	1.000
Observations	70,423			

Table 3: Relationship Between MFMP and DLEU Markups

The table compares the MFMP measure against firm-level markup measures from De Loecker et al. (2020), PF1 and PF2. We calculate firm-year level MFMP by calculating the sales-weighted average. PF1 assumes a production technology that uses variable inputs and physical capital. PF2 which additionally accounts for overhead expenditure in markup construction. t-statistics are in parentheses. Standard errors are clustered at the firm level. The data covers 2007 to 2022. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

	log(MFMP)					
	(1)	(2)	(3)	(4)	(5)	(6)
log(DLEU Markup, PF1)	0.394***	0.290**	0.178*			
	(3.85)	(2.52)	(1.87)			
log(DLEU Markup, PF2)				0.359***	0.295**	0.218**
				(3.29)	(2.50)	(2.08)
Observations	2732	2732	2703	2732	2732	2703
R-Squared	0.048	0.180	0.768	0.039	0.180	0.769
Year × Industry		Yes			Yes	
Firm			Yes			Yes
Year			Yes			Yes
Clustered by	Firm	Firm	Firm	Firm	Firm	Firm

Table 4: Market Share, Firm Size, and Markup

The table shows the relationship between the firm's market share and size and MFMP. We report coefficients from

$$\begin{aligned}\log \mu_{imt} =& \beta \text{Market Share}_{imt-1} + \gamma \log(\text{Firm Sale}_{it-1}) + \delta \text{Market Share}_{imt-1} \times \log(\text{Firm Sale}_{it-1}) \\ &+ \text{Controls}_{imt} + \varepsilon_{imt},\end{aligned}$$

where $\log \mu_{imt}$ is the MFMP, $\text{Market Share}_{imt-1}$ is lagged market share for firm i in module m in quarter $t-1$, $\log(\text{Firm Sale}_{it-1})$ is lagged log sales for firm i across all modules in quarter $t-1$. In different specifications we include lagged MFMP, time fixed effects, module-by-firm fixed effects, and time-by-module fixed effects as controls. t-statistics are in parentheses. Standard errors are clustered at the firm level. The data covers 2007 to 2022. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

Panel A: Baseline

	$\log(\mu_t)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Market Share}_{t-1}$	0.257***	0.212***	0.071***	0.061***				
	(8.41)	(7.17)	(6.37)	(5.63)				
$\log(\text{Firm Sale}_{t-1})$					0.019***	0.016***	0.006***	0.005***
					(20.66)	(18.22)	(14.75)	(13.00)
$\log(\mu_{t-1})$			0.731***	0.726***			0.730***	0.725***
			(209.24)	(191.94)			(207.18)	(190.69)
Observations	2927327	2927314	2711067	2710936	2927327	2927314	2711067	2710936
R-Squared	0.829	0.840	0.922	0.927	0.830	0.840	0.922	0.927
Time	Yes		Yes		Yes		Yes	
Module × Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Module		Yes		Yes		Yes		Yes
Clustered By	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Panel B: Interaction terms

	$\log(\mu_t)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Market Share}_{t-1}$	0.179***	0.141***	0.049***	0.041***	0.359**	0.297**	0.216***	0.210***
	(5.86)	(4.81)	(4.43)	(3.83)	(2.35)	(2.03)	(3.35)	(3.31)
$\log(\text{Firm Sale}_{t-1})$	0.018***	0.016***	0.005***	0.005***	0.018***	0.016***	0.005***	0.005***
	(20.18)	(17.89)	(14.37)	(12.69)	(20.14)	(17.83)	(14.27)	(12.54)
$\log(\text{Firm Sale}_{t-1}) \times \text{Market Share}_{t-1}$					-0.011	-0.009	-0.010***	-0.010***
					(-1.19)	(-1.07)	(-2.67)	(-2.68)
$\log(\mu_{t-1})$			0.730***	0.725***			0.730***	0.725***
			(207.23)	(190.74)			(207.20)	(190.72)
Observations	2927327	2927314	2711067	2710936	2927327	2927314	2711067	2710936
R-Squared	0.830	0.840	0.922	0.927	0.830	0.840	0.922	0.927
Time	Yes		Yes		Yes		Yes	
Module × Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Module		Yes		Yes		Yes		Yes
Clustered By	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Table 5: Competition, Market Size, and MFMP

The table shows the relationship between module-level HHI, sales, and average MFMP or the dispersion of MFMP. We report coefficients from

$$y_{mt} = \beta \text{HHI}_{mt-1} + \gamma \log(\text{Module Sale}_{mt-1}) + \epsilon_{mt},$$

where y_{mt} is sales-weighted MFMP in Panel A and the IQR of MFMP in panel B. t-statistics are in parentheses. Standard errors are clustered at the module level. The data covers 2007 to 2022. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

Panel A: Sales-Weighted MFMP

	$\log(\mu_t)$, Sales-Weighted					
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	0.070*		-0.028	0.074**		-0.025
	(1.89)		(-0.66)	(1.98)		(-0.59)
$\log(\text{Module Sale}_{t-1})$		-0.024***	-0.025***		-0.025***	-0.026***
		(-7.42)	(-6.87)		(-7.48)	(-6.90)
Observations	70423	70423	70423	70423	70423	70423
R-Squared	0.002	0.021	0.021	0.006	0.026	0.026
Time				Yes	Yes	Yes
Clustered By	Module	Module	Module	Module	Module	Module

Panel B: IQR of MFMP

	$\log(\mu_t)$, IQR					
	(1)	(2)	(3)	(4)	(5)	(6)
HHI_{t-1}	-0.140***		-0.118**	-0.140***		-0.118**
	(-2.67)		(-2.20)	(-2.67)		(-2.20)
$\log(\text{Module Sale}_{t-1})$		0.012**	0.008		0.012**	0.008
		(2.04)	(1.31)		(2.02)	(1.30)
Observations	67858	67858	67858	67858	67858	67858
R-Squared	0.004	0.002	0.005	0.004	0.003	0.005
Time				Yes	Yes	Yes
Clustered By	Module	Module	Module	Module	Module	Module

Table 6: IPO and Markups

The table shows how firms adjust their markups after going public compared with their private peers. We estimate the following specification:

$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih},$$

where $\log(\mu)_{cih}$ is the log markups of firm-module i within the cohort c for event time h. Post_{ch} is a dummy that takes the value of 1 for the period after the treated firm went public in cohort c. Treat_{ci} is a dummy that takes the value of 1 for the firm-module i that went public in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. The table shows t-statistics in parentheses, standard errors are clustered at the firm level. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

	$\log(\mu)$	
	(1)	(2)
Post × Treat	0.034*	0.038*
	(1.75)	(1.82)
Observations	31300	31300
R-Squared	0.917	0.925
FEs	Yes	Yes
Clustered By	Firm	Firm
Weighted		log(Sales)

Table 7: MFMP of Public Firms During 21/22 Inflation Surge

The table shows how public firms adjust their markups during 21/22 inflation surge compared with their private peers. We estimate the following specification:

$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih},$$

where $\log(\mu_{cih})$ is the log MFMP of firm-module i within the cohort c for event time h in Panels A and B. Post_{ch} is a dummy that takes the value of 1 after 2020Q1. Treat_{ci} is a dummy that takes the value of 1 for the public firms in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. Columns (1) and (2) show the baseline full-sample regression results. We further estimate the same regression on subsamples composed of modules with higher-than-median HHI or public firm market share. Results are reported in Columns (3) through (6) The table shows t-statistics in parentheses, standard errors are clustered at the firm level. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

	Baseline		High HHI		High Public Share	
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treat	0.018***	0.015***	0.031***	0.029***	0.019***	0.017***
	(3.46)	(3.20)	(4.00)	(4.02)	(3.15)	(3.04)
Observations	456859	456859	126905	126905	294622	294622
R-Squared	0.924	0.938	0.920	0.932	0.927	0.940
FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered By	Firm	Firm	Firm	Firm	Firm	Firm
Weighted		log(Sales)		log(Sales)		log(Sales)

Table 8: Summary Statistics of Sorting Variables

The table presents summary statistics of variables used to split the sample, comparing the Full Compustat Sample with the Nielsen IQ subsample. Retail Share is the proportion of a firm's equity held by retail investors, based on Form 13F filings. Market Value Loss is negative returns in 2020Q1. SBC is Stock Compensation Expense (Compustat item `STKCO`) scaled by sales. Delta (pay-performance sensitivity) and Wealth Sensitivity (inside equity) are calculated by Coles et al. (2006) based on methodology developed in Core and Guay (2002). Quick Ratio is current assets net of inventory scaled by current liabilities. Leverage is the sum of short-term and long-term debt divided by total assets. All variables are from 2019 with the exception of Market Value Loss.

	Full Compustat Sample			NielsenIQ Sample		
	Obs	Mean	SD	Obs	Mean	SD
Retail Share (%)	1,946	26.29	26.44	147	28.39	24.00
Market Value Loss (%)	2,433	11.19	11.92	156	8.95	9.69
Stock-Based Compensation / Sales (%)	4,221	23.38	121.47	165	0.95	1.25
Delta ($k)	1,553	300.57	689.66	125	450.93	771.78
Wealth Sensitivity ($mn)	1,553	26.25	64.80	125	36.57	72.29
Quick Ratio	2,398	2.19	2.42	156	1.31	1.50
Leverage	2,443	0.33	0.25	158	0.37	0.22

Table 9: Price Growth of Public Firms During 21/22 Inflation Surge

The table shows how public firms adjust their prices during 21/22 inflation surge compared with their private peers. We estimate the following specification:

$$\pi^f_{cih} = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih},$$

where π^f_{cih} is the Fisher Price Index of firm-module i within the cohort c for event time h in Panels A and B. Post_{ch} is a dummy that takes the value of 1 after 2020Q1. Treat_{ci} is a dummy that takes the value of 1 for the public firms in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. The table shows t-statistics in parentheses, standard errors are clustered at the firm level. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

Panel C: Inflation

	π^f	
	(1)	(2)
Post × Treat	0.006***	0.005***
	(2.64)	(2.83)
Observations	460693	460693
R-Squared	0.425	0.452
FEs	Yes	Yes
Clustered By	Firm	Firm
Weighted		log(Sales)

Table 10: PE Deals and Markups

The table shows how firms adjust their markups after getting a private equity deal compared with their private peers. We estimate the following specification:

$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih},$$

where $\log(\mu)_{cih}$ is the log markups of firm-module i within the cohort c for event time h. Post_{ch} is a dummy that takes the value of 1 for the period after the treated firm get the first PE deal in cohort c. Treat_{ci} is a dummy that takes the value of 1 for the firm-module i that got PE deals in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. The table shows t-statistics in parentheses, standard errors are clustered at the firm level. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

	$\log(\mu)$	
	(1)	(2)
Post × Treat	0.035*	0.028*
	(1.84)	(1.78)
Observations	35676	35676
R-Squared	0.901	0.916
FEs	Yes	Yes
Clustered By	Firm	Firm
Weighted		log(Sales)

Table 11: Markups of PE-backed Firms During 21/22 Inflation Surge

The table shows how PE-backed firms adjust their markups during 21/22 inflation surge compared with their private peers. We estimate the following specification:

$$\log(\mu_{cih}) = \beta \text{Post}_{ch} \times \text{Treat}_{ci} + \alpha_{ch} + \delta_{ci} + \epsilon_{cih},$$

where $\log(\mu)_{cih}$ is the log markups of firm-module i within the cohort c for event time h. Post_{ch} is a dummy that takes the value of 1 after 2020Q1. Treat_{ci} is a dummy that takes the value of 1 for the PE-backed firms in the cohort c. α_{ch} represents the cohort-by-event time fixed effects and δ_{ci} cohort-by-firm-module fixed effects. The table shows t-statistics in parentheses, standard errors are clustered at the firm level. Significance levels are indicated by * (10%), ** (5%), and *** (1%).

	$\log(\mu)$	
	(1)	(2)
Post × Treat	0.009	0.009
	(1.10)	(1.26)
Observations	196778	196778
R-Squared	0.930	0.940
FEs	Yes	Yes
Clustered By	Firm	Firm
Weighted		log(Sales)