Common Ownership, Markups, and Corporate Governance

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Abstract

The "common ownership" hypothesis posits that shareholders with stakes in multiple firms within the same industry may reduce firm incentives to compete. While a substantial body of empirical work lends some support to this theory, other scholars suggest that measures of common ownership do not reliably predict indicators of market power. In this article, I provide novel evidence backing the hypothesis by refining the methodologies and datasets employed in current studies. In contrast to the literature which frequently relies on market-level measures of market power and common ownership, I derive firm-level measures for these key variables. This approach includes structurally estimating firm-level markups from data on firm investments, costs, and sales, and calculating firm-specific "profit weights" using a unique dataset that includes data on blockholders. The results indicate a positive association between common ownership and increased markups, a finding that becomes more pronounced when I use S&P 500 index inclusions to introduce quasi-exogenous variation in common ownership levels. Furthermore, by mapping my dataset to a historical record of corporate votes and focusing on the influence of pivotal voters, I observe a significant amplification of my treatment effects. Overall, my findings reinforce existing work suggesting that common ownership may induce anti-competitive outcomes.

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1 Introduction

The "common ownership" hypothesis suggests that when shareholders own shares in multiple firms within the same industry, those firms may have reduced incentives to compete (Rubinstein et al. (1983); Rotemberg (1984)). The theory posits that common ownership could encourage firms to soften competition through various means, such as by raising prices, lowering output, scaling back on investment, or diminishing innovation efforts. While firm decision-making power is ordinarily vested in its board of directors and managers, shareholders may wield a considerable degree of influence over firm conduct by virtue of their legal rights to appoint or remove these key personnel (Kraakman et al. (2017)). As a firm under common ownership is assumed to consider the impact of its competitive decisions on rival firms, the phenomenon also challenges the assumption in neo-classical economics that firms take actions that maximize their own profits (Friedman (1953); Moskalev (2019)).

Although scholars have known about the potential for such anti-competitive effects for a long time (Rubinstein et al. (1983); Rotemberg (1984); Hart (1979)), common ownership has only recently begun to draw significant scholarly attention. This renewed interest appears to stem from major shifts in the composition of capital markets over the past few decades. In 1950, institutional investors owned about 7% of all public companies in the United States. Today, they hold almost 70% of the same (Azar (2017)). In Europe, the influence of institutional investors is similarly pronounced, with Blackrock emerging as the dominant shareholder in a third of the top-tier companies listed on the UK and German stock exchanges (Weche and Wambach (2021)). This trend towards greater institutional ownership has intensified the prevalence of common ownership (Backus et al. (2021b)), sparking a vigorous debate regarding the need for regulatory actions to mitigate its potential anti-competitive consequences (Elhauge (2015); Posner et al. (2017); Hemphill and Kahan (2019)).

While a significant amount of empirical research lends support to the "common ownership" hypothesis (Azar et al. (2018); Boller and Scott Morton (2020); Newham et al. (2018); Ederer and Pellegrino (2022); Saidi and Streitz (2021)), other scholars argue that common ownership metrics do not consistently serve as reliable predictors of market power indicators (Antón et al. (2023); Aslan (2023)). For instance, while Azar et al. (2018) has linked increased common ownership concentration on specific flight routes to higher airline ticket prices, Dennis et al. (2021) has suggested that the positive correlation between common ownership and ticket prices stems from the market share component of the common ownership measure, not its ownership and control components. In a similar vein, scholarly skepticism extends to the generalizability of such findings across different industries. Koch et al. (2021), analyzing a broad panel of firms from 1985 to 2012, failed to find a consistent positive relationship between common ownership and industry profitability or output prices, as would be expected if common ownership were to reduce competition. At the same time, Backus et al. (2021a) found that own-firm profit maximization was more consistent with data in the Ready-to-Eat Cereal Industry, challenging the notion that common ownership significantly influences competitive behavior.

Given that the effects of common ownership on firm-level outcomes are likely to be heterogeneous across different types of industries and ownership structures, these contrasting findings should not come as a surprise. Bindal and Nordlund (2022), for instance, observed that common ownership's effects differ based on a firm's product market traits, with more pronounced price and profitability increases where product offerings are less distinct. Similarly, Charoenwong et al. (2023) found that when compared to their passive counterparts, active mutual funds who are common owners not only achieve better risk-adjusted returns, but also tend to vote more frequently against executive bonus plans and in favor of appointing directors who hold positions in competing companies. These results are consistent with the broader literature on the role of corporate governance in mediating the effects of common ownership, where scholars like Morley (2018) and Bebchuk and Hirst (2019) have noted systemic reasons preventing agents of common owners from intervening in the business strategies of their portfolio companies, including significant information costs and the risk of fiduciary liability.

In this article, I provide novel evidence backing the "common ownership" hypothesis by refining the methodologies and data sources employed in current studies, which frequently contend with challenges due to incomplete data, sub-optimal identification strategies, and measurement difficulties. My work aims to tackle four specific issues identified in existing studies. First, in contrast to much of the literature that relies on *market-level* indicators of market power and common ownership, I utilize *firm-specific* measures for both key variables. De Loecker et al. (2020) have criticized common market power metrics like the Herfindahl-Hirschman Index (HHI) for their market scope sensitivity and the challenges they pose in cross-industry and longitudinal market power analysis. Similar complications arise with market-level assessments of common ownership. For example, Backus et al. (2021b) critique the Modified-Herfindahl-Hirschman Index (MHHI) (O'Brien and Salop (1999); Bresnahan and Salop (1986)), a standard market-level common ownership measure, for its reliance on the Cournot competition assumption and the necessity to delineate product markets. This critique aligns with Dennis et al. (2021), who attribute observed ticket price increases in their study to market shares rather than common ownership.[1]

[1]This critique by Dennis et al. (2021) mirrors the conventional wisdom in the Industrial Organization literature. For instance, Berry et al. (2019) note that "regressions with an outcome such as markups or profits on the left-hand

To procure a firm-level measure of market power, I follow Hall (1988), De Loecker and Warzynski (2012) and De Loecker et al. (2020) in structurally estimating firm-level markups from data on firm investments, costs, and sales. Similarly, to obtain a firm-level measure of common ownership, I compute firm-level "profit weights" as per Backus et al. (2021b) and Amel-Zadeh et al. (2022), a measure representing the extent to which a firm would internalize its rivals' profits within a given industry.

Second, diverging from the common reliance on the Thomson Reuters (TR) institutional holdings dataset in much of the existing literature, I opt for a dataset developed by Amel-Zadeh et al. (2022) that addresses several of the TR database's reliability concerns. As pointed out by Backus et al. (2021b), the TR dataset is plagued by coverage gaps and discrepancies when compared to their source documents. Furthermore, as Amel-Zadeh et al. (2022) highlight, the TR dataset is based on 13-F filings that capture ownership holdings by large institutional investors, but often miss similar holdings by smaller activist funds, corporate insiders, and non-institutional investors. For example, they note significant individual stakes such as Elon Musk's ownership of over 16.7% in Tesla and Jeff Bezos's more than 9.8% in Amazon in 2021, which would be overlooked by analyses relying solely on 13-F filings. Additionally, 13-F data presents ownership at the individual fund level, without accounting for the consolidation of ownership rights at the management company level within a fund family (Morley (2018); Morley (2013)). To overcome these issues, I utilize a comprehensive dataset from Amel-Zadeh et al. (2022) that extracts and processes all ownership records from the SEC's EDGAR system for 2003-2019, covering all single-class firms in the S&P 500. I further refine this data by consolidating ownership figures at the fund-family level.

Third, the inherent endogeneity of ownership (and thus, common ownership) necessitates the use of identification strategies to uncover exogenous shifts in institutional ownership which are not influenced by market power. The endogeneity of ownership stems from its potential dependency on factors like profitability and markups, indicating that ownership can both impact and be impacted by competitive forces (Dennis et al. (2021); Boller and Scott Morton (2020)). This concept is supported by a large body of literature in corporate governance, which outlines the mechanisms through which investors may exercise their influence either through their control rights (through voting, engagement) or by simply selling their shares (Li et al. (2022); Broccardo et al. (2022); Levit et al. (2019)). In contrast to much of the existing literature, I employ an identification strategy pioneered by Boller and Scott Morton (2020) and employed by Antón et al. (2023), where index entries to the S&P 500 are used to identify quasi-exogenous changes in common owner-

side and a measure of market concentration on the right-hand side… face severe measurement problems and worse conceptual problems". Among other issues, Berry et al. (2019) note that concentration is econometrically endogenous.

ship.[2] As I will detail later, harnessing index strategies to identify changes in common ownership has significant advantages over competing identification strategies such as analyzing mergers among institutional shareholders or the reconstitution of Russell indices. Furthermore, index entries provide a canonical framework where the impact of treatment on firms is distributed over time, allowing me to harness contemporary methodologies in identifying staggered treatment effects (Baker et al. (2022); Goodman-Bacon (2021); Sun and Abraham (2021); De Chaisemartin and d'Haultfoeuille (2020); Callaway and Sant'Anna (2021)).

Finally, few scholars have empirically demonstrated the specific mechanisms which might lead to potentially anti-competitive effects. While Azar et al. (2018) and Elhauge (2021) have highlighted possible ways investors might sway corporate decisions, such as through voting, engagements, or by structuring executive compensation frameworks, the paucity of evidence in this area has prompted Federal Trade Commmission[er] (FTC) Noah J. Phillips to to emphasize the need for a "clear mechanism of harm" to be established before reconsidering the FTC's stance on common ownership. To that end, recent work by Antón et al. (2023) posits that common owners might foster anti-competitive conditions by endorsing compensation schemes for executives that are detached from performance, while Eldar et al. (2023) has observed a correlation between common ownership across industry peers and an increased likelihood of shared directorships.[3] By mapping my dataset to a historical record of corporate votes from Institutional Shareholder Services (ISS), my work contributes to this discourse by examining the voting mechanism, traditionally viewed as a principal means through which investors may direct corporate behavior (Azar et al. (2018); Shekita (2021)). Crucially, the firm-level profit weights in my analysis allow for a modification of the "proportional control" assumption within the model's structure, allowing me to assess a counterfactual in which firm managers are assumed to focus on the influence of pivotal voters.

By refining the methodologies and data sources as discussed above, I find a strong and positive association between common ownership and firm-level markups. As changes in costs may also induce changes in markups (De Loecker et al. (2020)), I control for firm overhead expenditures in most of my specifications.[4] These findings are buttressed by results indicating a positive "av-

[2] In Sections 3.2, 6.2 and 6.3, I delve deeper into the possible threats to identification.

[3] Nili (2019) posits that the existence of shared directorships might contravene Section 8 of the Clayton Act as well as Section 5 of the Federal Trade Commission Act. However, he also observes that formal legal proceedings have not been pursued by the FTC or the Department of Justice (DOJ) in response to these potential violations. Instead, these entities have relied on self-policing and behind-the-scenes actions to pressure violators.

[4] This problem is particularly salient in common ownership, as common ownership may reduce costs if it leads to information spillovers (López and Vives (2019); He and Huang (2017); Aslan (2023); Gibbon and Schain (2023)). Note that I also control for overhead expenditures in an alternative production function specification (see Section 2.2).

erage treatment effect for the treated" (ATT) when I use S&P 500 index inclusions to introduce a quasi-exogenous increase in common ownership levels. Notably, the magnitude of these treatment effects is intensified when I employ adjusted "control weights" which emphasize the role of pivotal voters. Furthermore, the positive association between common ownership and increased markups remains consistent across a variety of robustness checks, including different configurations of fixed effects and standard errors, the application of propensity score matching methods, and the use of an instrumental variables framework.

My article contributes to several strands of the literature. First, it builds on the extensive research exploring the impact of common ownership on firm decisions and industry outcomes (Boller and Scott Morton (2020); Azar et al. (2018); Newham et al. (2018); Xie and Gerakos (2020); Dennis et al. (2021); Azar et al. (2022); Backus et al. (2021b); Backus et al. (2021a); Lewellen and Lowry (2021); Saidi and Streitz (2021); Gibbon and Schain (2023); Ederer and Pellegrino (2022); Ruiz-Pérez (2019); Banal-Estañol et al. (2022)). As detailed earlier, the evidence is mixed and heterogenous across varying datasets, industries, outcome variables, and the methodologies used. Among the relevant literature, the work of Gibbon and Schain (2023) and Banal-Estañol et al. (2022) is most closely related to mine, as both studies investigate the relationship between firm-level markups and common ownership. However, my study diverges by focusing on a dataset of S&P 500 companies, using index entries to address endogeneity concerns associated with common ownership. In contrast, Gibbon and Schain (2023) examine European manufacturing firms, analyzing heterogeneity in technological spillovers across firms and utilizing a distinct identification strategy. Meanwhile, Banal-Estañol et al. (2022) assume ownership is driven solely by investor characteristics and apply a 2SLS specification for their identification approach.

Second, my article also builds on the growing work regarding the mechanisms through which common ownership might influence corporate decision-making, despite the starting presumption that such decisions are primarily the purview of a company's directors and managers (Elhauge (2021); Hemphill and Kahan (2019); Antón et al. (2023); Eldar et al. (2023); Geng et al. (2022); Shekita (2021); Gilje et al. (2020)). Insofar as these papers are concerned, Gilje et al. (2020) presents research most similar to mine, as they also attempt to map ownership data to voting data from ISS. However, Gilje et al. (2020) use a measure of common ownership that restricts voting control to binary managerial decisions. Backus et al. (2021b) highlight that this approach precludes the potential for strategic interactions and, consequently, most models of market power.[5] In contrast,

[5]In Gilje et al. (2020), managers of a firm are constrained to selecting a policy $x_n \in \{0, 1\}$, where choosing $x_n = 1$ leads to a *deterministic* positive or negative externality on other firms m ($n \neq m$). On the other hand, Backus et al. (2021b) provide a framework where firm managers have the ability to *directly alter* the firm's objective function to reflect its competitive incentives arising from common ownership. See Section 8.

the measure of common ownership I adopt, in line with Backus et al. (2021b), is fully general. Accordingly, the measure allows for a "microfounded" modification of the "proportional control" assumption within the model's structure, even in the presence of market power.

My article is organized as follows. In Section 2, I discuss my data sources, the construction of firm-level markups, and the construction of firm-level common ownership "profit weights". In Section 3, I present empirical results documenting a positive association between common ownership and markups, as well as some other results exploring the heterogeneity of this association across investor characteristics. Additionally, I harness S&P 500 index inclusions to introduce a quasi-exogenous increase in common ownership levels, and demonstrate a positive ATT on markups. In Section 4, I present empirical results under a corporate governance model where a modified "control weight" (which emphasizes the role of pivotal voters) is applied to the voting data. Section 5 concludes. Finally, an Appendix (Section 6) includes a variety of robustness checks, while an Online Appendix (Section 8) provides detailed derivations for the microfoundations of my common ownership and markup measures.

2 Data and Measures

2.1 Data Sources

I procure my data from three distinct sources. The initial set of ownership data comes from Amel-Zadeh et al. (2022)'s dataset, which extracts and processes all ownership records from the SEC's EDGAR system for the years 2003-2019. The dataset encompasses all single-class companies listed in the S&P 500, and includes data from filings by 13-F, 13-D, 13-G holders, as well as Form 3/4/5 filings by blockholders and insiders.[6] However, as Amel-Zadeh et al. (2022) provides only partial coverage for my variables of interest, I engage in further scraping of the SEC's EDGAR database for investor names corresponding to the unique investor-level identifiers (i.e., an investor's "CIK" number) in Amel-Zadeh et al. (2022)'s dataset. Where fund investors are involved, I further refine the data by consolidating ownership figures at the fund-family level, using ISS's categorization of fund-families as a reference point.[7] As Morley (2018) has explained, this consolidation step is crucial, due to the SEC's data representation at the individual fund level, which overlooks the

[6]Note that the dataset includes single-class companies which were listed in the S&P 500 for only part of the sample years (2003-2019).

[7]For instance, holdings associated with a Blackrock fund, such as the "iShares US Index Fund", are combined and attributed to the overarching entity, "Blackrock Inc."

legal reassignment of ownership rights from individual funds to their respective management companies within a fund family. In practice, control rights are typically exercised by investment management companies that vote on behalf of all the funds under their control, thereby wielding influence that spans across their entire portfolio of funds (Iliev and Lowry (2015)). Accordingly, a failure to consolidate holdings may lead researchers to underestimate the true scale of ownership and common ownership. Ownership data is reported at the Investor-Firm-Quarter level.

The second set of data required to estimate firm-level markups is procured from the CRSP-Compustat-Merged (CCM) database. The structural estimation of markups necessitates data on a firm's variable inputs, gross output, capital stock, and investments (as a proxy variable for productivity), and these variables are available for most of my firms on the CCM database.[8] In addition, the CCM database also supplies data on firm-level control variables (e.g., Firm Size, Leverage Ratio, Tobin's Q, etc.).[9] While the CCM database offers data at both Firm-Quarter and Firm-Year levels, I elect to procure CCM data at the Firm-Year level, aligning with prevalent practices in the markup estimation literature (De Loecker et al. (2020); De Loecker and Warzynski (2012); Baqaee and Farhi (2020)).

The third component of my data comes from the "Voting Analytics" database by ISS, which contains mutual fund voting records at the Investor-Firm-Meeting-Proposal-Year level. Although the ISS database encompasses a wide array of variables related to fund voting records (e.g., binary indicators for whether the vote followed a shareholder/management proposal), I focus on data that details the total number of votes cast in favor, against, or abstaining on specific proposals within individual meetings of a particular firm.[10] Additionally, the dataset includes the aggregate number of votes cast for each proposal[11] and records how individual funds voted on these proposals.[12]

Aside from the voting data, all other data is merged and collapsed to the Firm-Year level. For example, when dealing with data that was initially at the Investor-Firm-Quarter level, the information is first aggregated to the Firm-Quarter level, where characteristics specific to each fund (e.g., the percentage of a firm owned by Blackrock Inc.) are aggregated for each Firm-Quarter

[8] A more detailed description of how firm-level markups are derived from cost-minimization, as well as details on the estimation procedure are available in Online Appendixes 8.1 and 8.2.

[9] Further information about these variables can be found in Table A1.

[10] For instance, a proposal at Kansas City Southern on May 2, 2013, to "initiate the necessary actions to restructure the Board of Directors into a single class, with each director standing for election annually, and to finalize this reorganization within one year" received 28,220 affirmative votes.

[11] The votes from investors who do not engage in shareholder meetings are thus omitted from this metric of voting participation.

[12] Investors who are not required to disclose their voting records are thus excluded from my analysis. See Section 4.

using each fund's ownership weights (Brav et al. (2024)). Subsequently, this data is further aggregated to the firm-year level.

2.2 Construction of Firm-Level Markups

A markup, often defined as the ratio of a firm's price to its marginal cost,[13] may serve as an indicator of the firm's market power, albeit with certain caveats.[14] Nevertheless, calculating markups across a wide array of firms presents challenges due to the lack of readily accessible data on marginal costs and prices. As De Loecker et al. (2020) note, there are three distinct approaches to measure markups. The first, frequently referred to as the "accounting approach", depends on directly observable profit margins. However, the accounting approach relies on strong assumptions, including the notion that marginal and average production costs are equal, production operates under constant returns to scale, there are no fixed costs, and all production factors are perfectly substitutable. This methodology is employed in some segments of the common ownership literature. For instance, Koch et al. (2021) calculates accounting markups as the ratio of firm revenues to the difference between firm revenues and earnings before interest and taxes. Similarly, Saidi and Streitz (2021) define accounting markups as the difference between total firm revenues and the total cost of goods sold.

The second approach, often termed the "demand approach", relies on the specification of a demand system which yields price elasticities of demand (Berry et al. (1995)). This approach is particularly valuable in contexts where detailed consumer data for a specific industry is available (Backus et al. (2021a)). However, the main challenge with this approach lies in the absence of granular data on prices and quantities at the product level for a broad panel of firms spanning various industries. For example, as detailed in Section 2.1, the dataset features firms spanning a broad spectrum of industries, covering dozens of unique sectors.

To circumvent these difficulties, I rely on a third approach – the "production approach". This technique is grounded in the idea that markups can be derived from the cost minimization of a variable input in the production process (Hall (1988); De Loecker and Warzynski (2012); De Loecker et al.

[13] Markups may also be defined as $\frac{p-mc}{p}$, as indicated by Lerner (1934).

[14] As noted earlier in Section 1, changes in costs may also induce changes in markups. De Loecker et al. (2020) suggest that markups may be high because overhead costs or fixed costs are high. In this case, the firm charges prices well above marginal costs to cover its fixed costs. Additionally, advancements in innovation could also contribute to elevated markups, especially if such innovations result in reduced marginal costs for the firm (Syverson (2019)). However, it is generally expected that these innovations would also entail an increase in fixed costs. Accordingly, to examine the impact of market power (as opposed to cost-driven factors) on markups, I control for firm overhead expenditures in most of my specifications as a proxy for fixed costs (De Loecker et al. (2020)).

(2020)). The production approach utilizes data from the firm's financial statements (available on the CCM database), and is advantageous insofar as it does not require any assumptions on demand and how firms compete. Nevertheless, the production approach necessitates specifying a production function to ascertain the output elasticities of at least one variable input.

Following Olley and Pakes (1996) and Ackerberg et al. (2015), I estimate firm-level markups by assuming a Cobb-Douglas production function. The production function of firm i in year t for output y_{it} includes the inputs capital k_{it}, variable input v_{it}, controls c_{it}, unobserved productivity ω_{it}, and a measurement error ε_{it}, such that $y_{it} = \alpha + v_{it}\beta + \mathbf{x}_{it}\boldsymbol{\gamma} + \omega_{it} + \varepsilon_{it}$, where $\mathbf{x}_{it}$ is a vector encompassing k_{it} and c_{it}. Like De Loecker et al. (2020) and Baqaee and Farhi (2020), the baseline set of controls c_{it} denotes the sales share for each firm at the 4-digit SIC industry level. In my primary production function, the variable input relates to the firm's cost of goods sold (COGS), which aggregates all costs directly linked to the production of the goods that the firm sells. This encompasses expenses for materials and intermediate inputs, labor costs, among others.[15] In an alternative production function specification, I include overhead (SG&A) as an additional input in the production function.[16]

I consider time-varying production function parameters, so that individual production functions are estimated for each year and each two-digit NAICS code.[17] I use 5-year rolling windows so that the elasticity estimates from years $t-2$ up to $t+2$ are assigned to year t. The estimation process involves two stages. In the first stage, y_{it} is regressed on a 3-rd degree polynomial of capital, variable input, proxy for productivity, and control variables to obtain fitted values for productivity (ω_{it} and ω_{it-1}) in different periods.[18] In the second stage, output elasticities relative to the variable input θ^v_{it} are determined by fitting an AR(1) process for productivity to the data using GMM, incorporating the correction technique from Ackerberg et al. (2015).[19] Given values of θ^v_{it}, we can compute firm-level markups as:

$$\mu_{it} = \frac{\theta^v_{it}}{\alpha_{it}}$$

[15]While this measure of variable costs does not directly report a breakdown of the expenditure on variable inputs, such as labor, intermediate inputs, electricity, and others, it excludes any imputation for capital costs.

[16]A more detailed description of how firm-level markups are derived from cost-minimization, as well as details on the estimation procedure are available in Online Appendixes 8.1 and 8.2.

[17]As De Loecker et al. (2020) note, this setup allows technology to vary over time and across different sectors.

[18]See Online Appendix 8.2. As I note in the Section, the first stage involves the non-parametric estimation of a "control function" (Petrin and Train (2010)).

[19]See Online Appendix 8.2. Given that productivity is not directly observable, I utilize the fitted values of productivity (obtained from the first stage) to estimate the error term $\xi_{it}(\theta_t)$ in the AR(1) process. This error term is subsequently harnessed to ascertain output elasticities via GMM estimation.

where μ_{it} represents the markup of firm i in year t, θ_{it}^{v} denotes the relevant elasticity of output, and $\alpha_{it} = \frac{J_{it}V_{it}}{P_{it}Y_{it}}$ is the variable input share of total output. The product of output prices and quantities $P_{it}Y_{it}$ is observed as total sales in the dataset, while the product of variable input prices and quantities $J_{it}V_{it}$ is reflected as the total cost of goods sold (COGS).

Figure 1 presents a time series of average estimated markups. The trend shown in the figure indicates an overall increase in markups during the sample period, with a discernible peak occurring around 2017 to 2018, followed by a subsequent decline. Meanwhile, Figure 2 offers a juxtaposition of estimated markups derived from two different production function models against the markups estimated by De Loecker et al. (2020), assuming constant values for θ_{it}^{v} post 2016.[20] As demonstrated in Figure 2, the distributions of these markups are strikingly similar.

2.3 Construction of Common Ownership Measures

I follow Backus et al. (2021b) in their definition and computation of firm-level profit weights. They build on earlier work by Rotemberg (1984), O'Brien and Salop (1999), and Bresnahan and Salop (1986). This approach posits that an investor s holds a proportional claim, denoted by β_{fs}, to the profits π_f of firm f, where β_{fs} represents the share of firm f owned by investor s. An investor is a common owner if $\beta_{fs} > 0$ for multiple firms. The profits of a common owner can thus be defined as the sum of its profits from its portfolio investments weighted by its cash flow rights[21]:

$$v_s = \sum_{\forall g} \beta_{gs}\pi_g$$

The fundamental assumption adopted by Backus et al. (2021b) is that managers in firm f will place a Pareto weight γ_{fs} on the portfolio profits of investor s and maximize the Pareto-weighted sum of their investors' profits. These "Pareto weights" may be interpreted as "control weights," reflecting the influence of each investor's profits in the firm's decision-making process. In Section 2.1, I explore the adaptation of these Pareto weights using a dataset of corporate voting records.

Given the aforementioned assumptions, Backus et al. (2021b) show that the objective function

[20] De Loecker et al. (2020) provide open access to their estimated output elasticities covering the period from 1955 to 2016. Conlon et al. (2023), applying contemporary data, employ these elasticity estimates to measure the correlation between the change in firm level markups and the change in industry level prices , "holding estimated output elasticities fixed at the final values (from 2016) in De Loecker et al. (2020)".

[21] A more detailed description of how common ownership weights are derived is available in Online Appendix 8.1.

of the firm may be rewritten as a weighted portfolio of rival profits, where firm f attempts to maximize the expression:

$$\pi_f + \sum_{\forall s} \frac{\sum\limits_{\forall s} \gamma_{fs}\beta_{gs}}{\sum\limits_{\forall s} \gamma_{fs}\beta_{fs}} \pi_g$$

where $\frac{\sum_{\forall s} \gamma_{fs}\beta_{gs}}{\sum_{\forall s} \gamma_{fs}\beta_{fs}}$ represents the implied profit weight $\kappa_{fg}(\gamma_{fs}, \beta)$ arising from common ownership. These profit weights embody various potential behaviors of firms in different contexts. For instance, when $\kappa_{fg} = 0$, firm f is solely maximizing its own profits without regard for firm g's profits. At the opposite end of the spectrum, much of the industrial organization literature assumes that in the case of a merger between firms f and g, the merged entities are under unified control, implying that both κ_{fg} and κ_{gf} are equal to 1 post merger. The derivation of κ_{fg} is very general and does not depend on whether firm g is a competitor of firm f within the same industry. Indeed, the underlying premise of the model is that managers aim to maximize a sum of profits that is weighted by investors' interests, which can encompass profits from firms across different industries.

In Amel-Zadeh et al. (2022), the authors build on this insight by suggesting that "universal owners" (i.e., owners who own more than 95% of a given firm) could potentially induce their portfolio firms to internalize some of their negative environmental and social externalities (Hart and Zingales (2017)). However, insofar as the anti-competitive effects of common ownership are concerned, the profit-weights of firm-pairs outside a given industry should be excluded. This assumption stems from two key considerations. First, insofar as a firm's competitive strategy is concerned, firm managers are more inclined to consider the financial externalities exerted on competitor firms within the same industry rather than those imposed on firms across various industries (Amel-Zadeh et al. (2022)).[22] Second, the notion that firm managers might optimize a weighted sum of their investors' portfolios across all firms may be unrealistic, considering the possible limitations on the attention spans of firm managers (Gilje et al. (2020)). Focusing on a more limited subset of these portfolios – specifically those with holdings in direct competitors – would mitigate such concerns.

In Panel A of Figure 3, I compare two scenarios: (1) "industry profit weights", where all profit-weights of firm-pairs outside a 4-digit SIC industry are omitted, and (2) "universal profit weights",

[22] Note that Pellegrino (2019) presents a notable deviation from this argument in a general equilibrium context. Nevertheless, Pellegrino (2019) focuses on pecuniary externalities exerted on competitor firms with similar Hoberg-Phillips scores.

which include all profit weights without restrictions. As is evident in Figure 3, profit weights in the first scenario are significantly higher than in the second, consistent with findings reported by Amel-Zadeh et al. (2022).

An assumption of proportional control rights would imply that $\gamma_{fs} = \beta_{fs}$. Under this assumption, κ_{fg} may be decomposed into two components:

$$\kappa_{fg} = \cos\left(\beta_f, \beta_g\right) \cdot \sqrt{\frac{\left\|\beta_g\right\|^2}{\left\|\beta_f\right\|^2}}$$

with the former cosine term representing the degree of "overlapping ownership" and the latter term, relative investor concentration (RIHHI) representing the relative "price" of investor control in firm f vis-à-vis firm g (Backus et al. (2021b)).[23] As Backus et al. (2021b) note, the latter term has intuitive comparative statics. Holding all other factors constant, firms with a concentrated investor base are inclined to prioritize their own profits over those of competitors, given that $\left\|\beta_f\right\|^2$ features in the denominator. However, if firm g has a concentrated investor base, $\left\|\beta_g\right\|^2$ will be large, control rights (in firm g) will be relatively more costly, and κ_{fg} smaller.[24] In Panel B of Figure 3, I illustrate how most of the variation in common ownership is attributable to a growing similarity in ownership structures, rather than fluctuations in the relative investor concentrations across firms.

Finally, since κ_{fg} is defined at the firm-pair level, to obtain firm-level profit weights, I aggregate profit weights across all firms g ($\forall g \neq f$). As Backus et al. (2021b) note that weighting the observations by either market capitalization or revenue does not qualitatively change the results, I focus on the equal weight average moving forward.

2.4 Summary Statistics

Table 1 presents summary statistics for the key variables in my dataset, absent voting data. Summary Statistics are presented for S&P 500 firms with at least 2 firms in the same industry, defined at a 4-digit SIC level. The dataset covers a total of 630 unique firms, across 128 industries (de-

[23]As β_f represents the fraction of firm f owned by s, $\left\|\beta_f\right\|^2$ is the Herfindahl-Hirschman Index (HHI) for the investors in firm f, which Backus et al. (2021b) label as the $IHHI_f$.

[24]A more detailed description of the economic intuition behind these components is available in Online Appendix 8.1.

fined at the 4-digit SIC level) and 186 sectors (defined at the 5-digit NAICS level), from 2003 to 2019. The table indicates that, on average, each investor holds a relatively small ownership share. However, the "13F Ownership" metric, which reflects most of the (aggregated) institutional ownership data from SEC filings, exhibits a substantially higher value. This shift towards increased institutional ownership and reduced individual investor shares underscores a broader trend towards more diversified ownership structures, as discussed by Backus et al. (2021b). Furthermore, Table 1 illustrates a wide range of firm sizes and markups, aligning with the observations made by De Loecker et al. (2020), who point out a marked increase in the markups of the largest firms, even as most firms experience no growth in markups and a decline in market share. In addition, regarding variables at the investor level, the table points to a significant diversity in 13-F ownership data, suggesting a variety of ownership structures across different firms.

3 Results

3.1 Panel Regressions

In this section, I explore the relationship between common ownership and markups. My baseline panel analysis uses the following specification:

$$\mu_{ijt} = \alpha + \kappa_{ijt-1}\beta + X_{ijt-1}\xi + \varphi_{ijt} + \theta_i + \nu_t + \varepsilon_{ijt} \tag{1}$$

where i indexes firms, j indexes industries, X is a vector of controls[25], while θ_i and ν_t represent firm and year fixed effects, respectively. Meanwhile, μ_{ijt} represents (log-values of) firm-level markups. In my baseline model, I harness markups derived from a production function without the use of overhead (SG&A) as a specific input, which I term "Production Function 1". Meanwhile, φ_{ijt} is a firm-specific variable that accounts for a firm's overhead, booked under selling, general, and administrative expenses (SG&A). As De Loecker et al. (2020) have noted, high markups may not directly indicate market power if a firm incurs substantial overhead expenses. In these situations, firms might set prices significantly above marginal costs to cover their fixed expenses. By controlling for overhead costs in my analysis, I aim to isolate the impact of common ownership on markups.

κ_{ijt-1} represents my principal variable of interest – a measure of common ownership. In my

[25] Further information about these variables can be found in Table A1.

baseline model, I utilize "industry profit weights" as the requisite measure of common ownership. These weights are determined by excluding the profit weights of firm pairs that do not share the same 4-digit SIC industry as firm i. As detailed earlier in Section 2.3, when compared to "universal profit weights", "industry profit weights" are more likely to reflect the incentives of a common owner to internalize the pecuniary externalities between its portfolio firms competing in the same industry. To ensure that my results are not driven by outliers, I winsorize all continuous variables at the 1% level. Following Abadie et al. (2023), I cluster all standard errors at the firm level.

I report some of these results in Table 2. As is evident in the table, the coefficient on κ_{ijt-1} is positive and statistically significant at the 1% level when overhead (i.e., SG&A) is not included as a control variable, but remains positive and statistically significant at the 5% level when I control for overhead costs (column (4)). The coefficient associated with overhead costs is also insignificant at the 10% level. This finding is consistent with the results of De Loecker et al. (2020), who suggest that the increase in markups cannot be solely ascribed to a rise in overhead costs, as firms charge an excess markup that more than compensates for overhead.[26] Additionally, the regressions in columns (2), (3), (5), and (6) explore the link between common ownership components and markups, revealing that variations in common ownership are largely driven by the "cosine" component rather than the "RHHI" component. This finding aligns with the patterns depicted in Figure 3, Panel B. The results from column (4) also indicate that a one-unit rise in a firm's industry profit weight is asociated with a 13.7% increase in its markup ratios. Putting this into perspective, average profit weights have seen a rough increase of 0.2 in the past twenty years, leading to an approximate 2.74% growth in markup ratios across S&P 500 firms. All regressions in Table 2 use firm fixed effects to remove firm-invariant characteristics and time fixed effects to account for trends in common ownership which may change over time.

Table 3 reports results for specification (1) where markups are regressed on "industry" and "universal" profit weights. In columns (1) to (3), markups are regressed on "industry profit weights". The baseline specification, implemented previously in column (4) of Table 2 and reiterated in column (1) of Table 3, employs firm fixed effects. Columns (2) and (3) substitute firm fixed effects with industry fixed effects, with column (3) further controlling for overhead costs. The results indicate that the coefficients in columns (2) and (3) are notably higher than those in column (1), highlighting the significant role of incorporating between-firm variation into the analysis. For instance, the results in column (3) suggest that a one-unit rise in a firm's industry profit weight is associated with a 22.7% increase in its markup ratios.[27] In columns (4) to (6), I shift my focus to

[26] Autor et al. (2020) and De Loecker et al. (2020) find that such excess markups are especially pronounced for large firms. This finding is highly relevant to my study, which focuses on firms listed in the S&P 500.

[27] Putting this into perspective, average profit weights have seen a rough increase of 0.2 in the past twenty years,

"universal profit weights". While the coefficient in column (4) lacks statistical significance at the 10% level, it achieves significance at the 5% level in column (5), and again shows significance at the 10% level in column (6). This pattern mirrors the findings from the "industry profit weights" analysis, where the coefficient on κ_{ijt-1} increases with the use of industry fixed effects in lieu of firm fixed effects.

Table 4 provides a potential explanation for the results presented in Table 3. In Table 4, I provide a variance decomposition of four variables of interest: "industry" profit weights, "universal" profit weights, markups constructed from a production function without the inclusion of overhead (SG&A) costs, and markups that account for these costs. Given that these variables vary both over time and between different firms, I evaluate the proportion of variation attributed to temporal changes within a single firm ("within-firm" variation) and the proportion resulting from differences across various firms ("between-firm" variation). As Table 4 reveals, "between-firm" variation contributes a large portion of variation in markups. This observation aligns with expectations given the methodology for estimating markups, as discussed in Section 2.2. Given that the pertinent output elasticities (θ^v_{it}) are derived from production functions tailored to specific sub-industries and time frames, the primary source of variation in firm-specific markups stems from α_{it}, the share of output attributed to variable inputs, rather than from θ^v_{it}. Additionally, while "industry" and "universal" profit weights display more "within-firm" variation relative to the markups in Table 4, the table indicates that the predominant source of variation in these profit weights stems from "between-firm" variation. As employing firm fixed effects in specifications eliminates all between-firm variation, specifications which rely solely on firm fixed effects may lead to more conservative estimates.

Table 5 reports results for specification (1) where different variants of markups are regressed on "industry profit weights". The baseline specification, as described in Table 2 and repeated in column (1), uses markups calculated from a production function excluding overhead (SG&A) costs.[28] In contrast, columns (2) and (3) feature markups from an alternative production function that incorporates overhead expenses, which I term "Production Function 2". Although the coefficients in these columns are marginally lower than in column (1), they retain statistical significance at the 5% level. In column (4), I utilize markups defined in Section 2.2 but where the relevant output elasticities (θ^v_{it}) are assumed to take on a *constant* value of 0.85, in line with De Loecker et al. (2020)'s estimation of the median output elasticity over time. The resulting coefficient of interest is closely aligned with that in column (1). Finally, column (5) adopts accounting markups as determined by Koch et al. (2021), who define these markups as the ratio of firm revenues to the

leading to an approximate 4.54% growth in markup ratios across S&P 500 firms.

[28]However, note that Overhead is included as a control variable in the specification.

difference between firm revenues and earnings before interest and taxes. The coefficient in this column is notably lower compared to those derived from production function-based markups, emphasizing the critical role of the assumptions inherent in employing accounting markups.[29]

In Table 6, I examine heterogeneity across investor characteristics within my dataset. Prior research suggests that large institutional investors may adopt a "rationally passive" approach to corporate governance due to specific incentives (Morley (2018); Bebchuk and Hirst (2019); Gilson and Gordon (2013)). To investigate this, I estimate specification (1) while incorporating two additional variables of interest: $\kappa_{ijt-1} \times C_{ijt-1}$ and C_{ijt-1}. The variable C_{ijt-1} captures distinct investor characteristics, such as the level of "Big-Three Ownership" or an "Indexing Measure," as defined by Backus et al. (2021b), which estimates the extent of index fund investments in a firm.[30] Additional characteristics include levels of "Form 3/4/5 Ownership," "13D Ownership," and "13G Ownership".

The coefficients on the interaction term $\kappa_{ijt-1} \times C_{ijt-1}$ reflect the *marginal* impact of common ownership linked to specific investor characteristics. While the coefficient on κ_{ijt-1} remains positive and statistically significant across all variants of C_{ijt-1} in Table 6, column (1) indicates that the interaction between κ_{ijt-1} and the indicator for Big Three Ownership is negative and statistically significant at the 5% level. In contrast, the interaction terms in columns (2) to (6) are not statistically significant at the 10% level, suggesting that these specific investor characteristics are not a key driver of the positive relationship between common ownership and estimated markups.

While further research is needed to fully understand these results, the findings suggest that the potential anti-competitive implications of common ownership may not be as pronounced among the largest institutional investors.[31] Instead, these effects might be more noticeable among smaller investors, who, despite having less voting power, might be more motivated to engage in active governance. Indeed, prior theory posits that activist investors often have a symbiotic relationship with large, typically passive institutional investors, who are willing to respond to governance pro-

[29]Moreover, the coefficient on overhead costs is negative and reaches statistical significance at the 1% level, a finding that diverges from economic theory. Most scholars are of the view that higher fixed or overhead costs should be associated with increased markups, as firms must implement a positive markup to compensate for these fixed expenses (Joskow and Klevorick (1979); De Loecker et al. (2020)). This result highlights the limitations of relying on accounting-based markups as indicators of market power or profitability.

[30]As Backus et al. (2021b) note, for each period, one can construct $\bar{w}_f = \sum_s \beta_{fs} / \sum_{f,s} \beta_{f,s}$ that represents the market porfolio. One can then compare the normalized porfolio weights for each investor s, $w_{fs} = \beta_{fs} / \sum_f \beta_{fs}$ and measure the similarity of each investor's portfolio to the market portfolio. In Table 6, I use a cosine similarity measure, where $L_2(w_s, \bar{w}) = \cos(w_s, \bar{w})$.

[31]For example, activist hedge funds may play a significant role in driving higher markups in commonly-owned firms (Brav et al. (2008)). However, due to the lack of data identifying activist hedge funds, this hypothesis cannot be tested in the current analysis.

posals but do not initiate them (Gilson and Gordon (2013)). This interpretation is also consistent with the findings of Eldar et al. (2023), who show that common ownership across firms in the same industry is associated with a higher likelihood of shared directors, except when the "Big Three" fund families are involved.

The findings from Tables 2 through 6 indicate a positive association between markups and common ownership profit weights across multiple specifications, diverging from previous studies that questioned the consistency of common ownership metrics as indicators of market power (Antón et al. (2023); Aslan (2023); Koch et al. (2021); Dennis et al. (2021)). Even after controlling for various potential confounders, a unit increase in a firm's lagged profit weight is associated with an estimated 2.7 to 4.5% rise in the firm's markup. However, the employment of lagged values of κ_{ijt} to mitigate endogeneity issues does not fully resolve them, particularly if the lagged variables remain correlated with their unlagged counterparts (Reed (2015)). In the next Section, I explore quasi-exogenous variations in κ_{ijt} to further address these concerns.

3.2 Quasi-Exogenous Variations in Common Ownership

As alluded to in Section 1, ownership may depend on factors like profitability and markups, indicating that ownership can both impact and be impacted by competitive forces (Dennis et al. (2021); Boller and Scott Morton (2020)). For instance, lower markups and profitability may lead investors to sell their shares, which might induce changes in the level of common ownership. Indeed, a large body of literature in corporate governance suggests that investors often elect between mechanisms of "voice" (i.e., voting, engagement) or "exit" (i.e., the sale of shares) (Li et al. (2022); Broccardo et al. (2022); Levit et al. (2019)). Accordingly, the panel regression coefficients in Section 3.1 should not be interpreted simplistically to imply that common ownership directly results in higher markups. To investigate whether the observed correlations can be causally linked, my analysis employs a methodology that considers the impact of exogenous shocks to common ownership, specifically those resulting from the inclusion of competing firms in the S&P 500 index. This approach focuses on discerning whether the positive relationship between common ownership and markups remains when analyzing only the variations in common ownership attributed to the index inclusions of industry competitors.

Although the use of index inclusions as an instrumental shock to institutional ownership has become a common practice in empirical research, concerns have been raised about potential violations of the exclusion restriction, particularly in relation to common ownership. For example, Lewellen and Lowry (2021) illustrate that when a firm is added to the S&P 500, there is not only an increase in common ownership among index constituents, but also an increase in overall institutional ownership, alongside a reduction in block ownership.[32] This complexity introduces a challenge in attributing effects solely to common ownership. In this scenario, if block ownership is positively associated with the outcome variable of interest (e.g., profitability or markups), then the observed relationship between markups and index entry could actually be driven by changes in institutional ownership, rather than common ownership.

To avoid these concerns, I employ a variant of this identification strategy, pioneered by Boller and Scott Morton (2020) and later utilized by Antón et al. (2023). This method leverages the inclusion of a new firm, k, into the S&P 500, treating it as a quasi-exogenous event that affects the common ownership "industry profit weights" of its industry competitors, i, who are already members of the S&P 500. An index entry event does not alter the ownership structure (both institutional and block ownership) of these incumbent firms within the index. However, the industry profit weights κ_{ik} that the investors of these competitors i put on their newly added rival k do change (Boller and Scott Morton (2020)). As Boller and Scott Morton (2020) and Antón et al. (2023) have explained, these changes in industry profit weights are induced by the fact that index funds that already own shares in index incumbents are compelled to purchase shares in the index entrant as well. Accordingly, index incumbents sharing an industry with the index entrant experience a resulting increase in industry profit weights, while control firms outside the industry do not experience a change in industry profit weights. Meanwhile, the index entrant k is deliberately excluded from the analysis altogether.

Figure 4 highlights the effect of an industry competitor's addition to the index, indicating a rightward shift in the distribution of the average industry profit weight, κ_i, for treated firms, illustrated in red. This shift is in comparison to the distribution for the control group of firms, represented in blue. Furthermore, the figure also reveals a parallel rightward shift in the distribution of the average cosine similarity for these treated firms, emphasizing the contrast with the control group.

Index entries occur sequentially, leading to a staggered inclusion of firms in the treatment group over time. For example, when firm f_1 is added to the S&P 500 index in 2005, its industry peers are considered treated. Subsequently, in 2007, the entry of another firm, f_2, into the index results in its industry peers being similarly classified as treated. I assume that once a firm is treated in a given year t_0, it remains treated in subsequent years ($t_0 + t$, where $t > 0$). This identification strategy has the advantage of preserving a control group of "never-treated" firms that did not undergo index inclusions within the sample period, thereby avoiding potential biases that two-

[32]The commonly referenced threshold for defining a blockholder in the context of corporate ownership is owning at least 5% of a company's shares (Dasgupta et al. (2021)).

way fixed effects difference-in-differences (DID) analyses might introduce.[33] Such distortions often arise in scenarios with staggered treatments over time and the presence of heterogeneous treatment effects (Baker et al. (2022); Goodman-Bacon (2021); Sun and Abraham (2021); Callaway and Sant'Anna (2021)).[34] Additionally, this method sidesteps the need for the somewhat arbitrary assumption required in models where treatment effects can "switch off," which posits that any increase in common ownership following index inclusion is temporary (De Chaisemartin and d'Haultfoeuille (2020)). Nevertheless, this approach comes with the drawback of diminished statistical power due to the inability to use treated firms as "controls" in situations where the industry of a treated firm undergoes multiple index inclusions.

Given this assumption, the process of index entries mirrors a canonical panel event study where treatment is staggered over time. To estimate the Average Treatment on the Treated firms (ATT) in this setting, I begin with the specification:

$$\mu_{it} = \alpha + \sum_{j=2}^{J} \beta_j (Lag_j)_{it} + \sum_{k=1}^{K} \gamma_k (Lead_k)_{it} + X_{it-1}\xi + \theta_i + \nu_t + \varepsilon_{it} \tag{2}$$

where μ_{it} relates to (log-values of) firm-level markups, i indexes firms, X is a vector of controls[35], while θ_i and ν_t represent firm and year fixed effects, respectively. I denote as $Event_i$ a variable recording the time period t in which firm i is treated – that is, when firm i shares the same industry as the index entrant k in year t. Accordingly, lags and leads to the event of interest are defined as follows:

$$(Lag\ J)_{it} = \mathbf{1}\left[t \leq Event_i - J\right]$$

$$(Lag\ j)_{it} = \mathbf{1}\left[t = Event_i - j\right] \text{ for } j \in \{1, ..., J-1\}$$

$$(Lead\ k)_{it} = \mathbf{1}\left[t = Event_i + k\right] \text{ for } j \in \{1, ..., K-1\}$$

$$(Lead\ K)_{it} = \mathbf{1}\left[t \geq Event_i + K\right]$$

where $\mathbf{1}$ is a binary indicator variable that is 1 when the specified time conditions are met, and 0 otherwise. The terms *Lag J* and *Lead K* represent the periods before and after the event, respec-

[33] Boller and Scott Morton (2020) and Antón et al. (2023) use a standard two-way fixed effects DID model, with a singular "post-event" indicator for all periods following the treatment in my baseline specification.

[34] Intuitively, Sun and Abraham (2021) note that "with variation in treatment timing across units, the coefficient on a given lead or lag can be contaminated by effects from other periods, and apparent pretrends can arise solely from treatment effects heterogeneity."

[35] Further information about these variables can be found in Table A1.

tively, extending to the furthest defined lags and leads.[36] The intermediary lags (j) and leads (k) capture specific single periods before and after the event. To account for the baseline difference when the event occurs versus when it does not, one lag term (where $j = 1$) is excluded. Thereafter, the ATT is usually reported as the simple average of all estimated (post-event) coefficients, γ_k.

Unlike the single-coefficient model that uses a singular "post-event" indicator ($Post_{it} = \mathbf{1}[t \geq Event_i]$) for all periods following the treatment, Specification (2) reveals two crucial insights not discernible in the single-coefficient approach. First, estimating event lags allows for the inspection of parallel trends between the control and treatment groups in the pre-treatment period. Second, by including event lags and leads, Specification (2) facilitates the examination of the treatment effects' dynamics, allowing for an assessment of whether these effects intensify or diminish over time.[37]

As Sun and Abraham (2021) note, β_j and γ_k in specification (2) are unreliable measures of dynamic treatment effects in the presence of heterogeneous treatment effects. Therefore, I use the estimator in Callaway and Sant'Anna (2021) for my baseline specifications, although I also include the treatment effects from a two-way fixed effects specification.[38] Callaway and Sant'Anna (2021) suggest that the ATT may be consistently estimated by weighting observations in relation to a treatment group g, where a group is defined by when units are first treated (i.e., firms in 2003 and 2009 are in distinct groups). The Callaway and Sant'Anna (2021) estimator then compares observations from the control group and group g, omitting other groups, before up-weighting control group observations with similar characteristics to group g, while down-weighting control group observations with characteristics that diverge from group g.

The results from these baseline specifications are detailed in Table 7. In column (1), row (1), I estimate the ATT for markups, derived from "Production Function 1", using the approach recommended by Callaway and Sant'Anna (2021), without incorporating any extra weighting beyond their specified methodology.[39] The ATT estimate is positive and significant at the 1% level, indicating that, on average, index entry is associated with a 5.04% rise in markups for treated firms. In column (2), row (1), the ATT on markups is estimated by applying additional weights to give more

[36] Accordingly, final lags (*Lag J*) and leads (*Lead K*) "accumulate" lags or leads beyond J and K periods.

[37] Specification (2) does not specify the number of lags or leads, and I do not restrict this number in my estimations.

[38] Beyond Callaway and Sant'Anna (2021) and Sun and Abraham (2021), a long line of literature has suggested how the standard coefficient in a two-way fixed effects specification is not guaranteed to recover the causal parameter of interest (Baker et al. (2022); Goodman-Bacon (2021); De Chaisemartin and d'Haultfoeuille (2020)).

[39] In this setting, I report the ATT as the simple average of all estimated ATTs across groups g and time periods t post-treatment (Callaway and Sant'Anna (2021)).

significance to firms with higher control weights in the analysis.[40] Here, control weights are defined as the sum of ownership shares present in my dataset for each firm ($\gamma_{ft} = \sum_{\forall s} \gamma_{fst} = \sum_{\forall s} \beta_{fst}$).[41] Similar to column (1), the ATT for markups remains positive and statistically significant at the 1% level, albeit slightly lower than the estimate in column (1). In columns (3) and (4) of row (1), I replicate the analysis for markups derived from "Production Function 2." The results are consistent with the ATTs reported in columns (1) and (2). However, the ATT estimate in column (4) is significant only at the 5% level. Finally, in row (2), I present results from a two-way fixed effects specification as outlined in specification (2). These findings closely mirror those obtained using the Callaway and Sant'Anna (2021) methodology in the baseline specifications.

Coefficient plots for my baseline specifications are displayed in Figures 5 and 6. Figure 5 illustrates the dynamic treatment effects from a two-way fixed effects model without weights (Panel A), a Callaway and Sant'Anna (2021) model without weights (Panel B), and a Callaway and Sant'Anna (2021) model incorporating probability weights based on each firm's control weights, assuming proportionate control (Panel C). These plots provide evidence of parallel trends between the control and treatment groups before the treatment and indicate an increasing treatment effect on markups over time, except in the final year of the dataset, where the treatment effect is not statistically significant. Similarly, Figure 6 focuses on the results corresponding to columns (3) and (4) of Table 7, using the Callaway and Sant'Anna (2021) model for markups derived from "Production Function 2."

The results in this Section suggest a positive relationship between markups and quasi-exogenous increases in common ownership profit weights, reinforcing the observations documented in Section 3.1. Under an assumption of proportional control, my results show that index inclusions typically lead to a 4.4 to 5.0% markup increase for firms within the same industry as the index entrant. In the following Section, I will examine the robustness of these findings against a control weight measure that departs from the proportional control assumption.

[40] In a weighted least squares context, weights are assigned such that the estimation of parameters is achieved through minimizing the sum of the weighted squared residuals.

[41] Note that $\sum_{\forall s} \beta_{fst} \neq 1$, as the variable βfst does not capture the ownership stakes held by retail investors and institutional investors who are exempt from disclosure requirements stipulated by securities regulations. See Table A1.

4 Extension to Voting Data

Thus far, I have assumed a model of proportional control in my analysis, where $\beta_{fs} = \gamma_{fs}$.[42] To explore a model of corporate control that diverges from this proportional framework, I construct new values for γ_{fs} which are informed by historical voting records. However, integrating the ownership data from Amel-Zadeh et al. (2022) with the ISS Voting Analytics dataset is challenging due to the absence of a common identifier linking the two (see Section 2.1). To address this, a combination of manual and fuzzy-matching techniques is employed to combine the datasets. The results of this matching process are illustrated in Figure 7, which displays a histogram: grey bars indicate the distribution of ownership stakes as per the original dataset, red bars show the distribution of ownership stakes successfully matched using the combined matching techniques, and blue bars represent the distribution of ownership stakes that could not be matched. As detailed in Section 1, voting records are available only for mutual funds that are subject to N-PX filing requirements under Section 30 of the Investment Company Act of 1940[43]; high-net-worth individuals like Elon Musk are excluded from these disclosure obligations. Despite the absence of these records, Figure 7 reveals that the distribution of matched ownership values closely aligns with the distribution of ownership values utilized in Sections 3.1 and 3.2, suggesting that the unmatched values are unlikely to significantly impact the analysis.

To motivate a model of control that incorporates historical voting records, I posit that firm managers allocate greater Pareto weights to shareholders with a history of prevailing in past elections. This approach aligns with numerous voting models where "pivotal voters" are deemed more influential (Palfrey and Rosenthal (1983); Palfrey and Rosenthal (1985); Downs (1957); Mulligan and Hunter (2003)). To achieve this, I adopt a specific functional form for γ_{fst}:

$$\gamma_{fst} = \frac{1}{J} \sum_{j} \left[\left[\frac{1}{t-1} \sum_{1}^{t-1} \left[1 - (2\left|x_{jt} - 0.5\right|)^{p} \right] \right] \left[\frac{1}{t-1} \sum_{1}^{t-1} \left[k_{jst} \right] \right] \right] \tag{3}$$

where f indexes firms, j indexes proposals,[44] s indexes investors, and t indexes years. Meanwhile, x_{jt} represents the proportion of votes out of participating votes that determined the proposal's outcome, and k_{jst} represents the share of votes by investor s in the winning coalition.[45] Since my voting data is observed at the Investor-Firm-Meeting-Proposal-Year level (see Section 2.1),

[42] Note that I omit the time subscript t for simplicity, as $beta_{fs}$ values vary over time.
[43] See also Sections 13 and 15(d) of the Securities Exchange Act of 1934.
[44] Note that each shareholder meeting may involve one or several proposals.
[45] Accordingly, $k_{jst} = 0$ if investor s is not in a winning coalition.

expression (3) essentially aggregates the data to the Investor-Firm-Year level. The parameter $0 < p < 1$ is an exogenous factor indicating the degree to which firm managers are sensitive to proposal closely contested around the majority threshold. In my baseline specification, I assume that $p = 1$. The control weights for each firm f, denoted by γ_{ft}, are computed by summing all investor control weights γ_{fst} in expression (3), in contrast to the approach outlined in Section 3.2, which assumed $\gamma_{ft} = \sum_{\forall s} \beta_{fst}$.

The components specified in expression (3) are economically meaningful. The first term in the expression, $\left[\frac{1}{t-1}\sum_{1}^{t-1}\left[1-(2\left|x_{jt}-0.5\right|)^{p}\right]\right]$, represents the historical average probability that proposals in a particular firm were tightly contested. As the voting outcome approaches 0.5, the majority threshold, the value of this expression increases. For instance, when $x_{jt} = 0.5$, the expression $[1 - 2|x_{jt} - 0.5|]$ reaches its maximum value of 1.[46] Conversely, at the extremes, when $x_{jt} = 1$ or $x_{jt} = 0$, this expression drops to its minimum value of 0. Meanwhile, at $x_{jt} = 0.3$, the expression yields a value of 0.6, indicating a value between the maximum and minimum. While this theoretical assumption is motivated by existing work in political science (Mulligan and Hunter (2003)), it is also supported by empirical work within the realm of corporate voting. For instance, Michaely et al. (2021) demonstrates that mutual funds tend to modify their voting patterns when their vote has a higher chance of being decisive, aligning with the notion that firm managers might give more weight to closely fought elections.[47]

The second term in the expression, $\left[\frac{1}{t-1}\sum_{s=1}^{t-1} k_{jst}\right]$, represents the historical average probability of an investor being in a winning voting coalition for different proposals within a particular firm, while also accounting for the relative significance of the investor's vote within these coalitions. The underlying assumption here is that firm managers tend to reward those who are on the winning side of votes and penalize the losers, driven by concerns for their own careers (Matvos and Ostrovsky (2010)). Many studies indicate that company managers often implement proposals that attract substantial shareholder support even when they are not binding on the company (Ertimur et al. (2010), Thomas and Cotter (2007); Renneboog and Szilagyi (2011); Kahan and Rock (2009); Buchanan et al. (2010)). These studies further reveal that companies disregarding successful proposals frequently face adverse consequences, including financial underperformance, negative media coverage, lowered ratings from governance rating agencies, and inclusion on CalPERS's "focus list" for subpar governance. Consequently, it may be disadvantageous for firm managers to disregard the voting preferences of influential shareholders.

[46] As indicated earlier, in my baseline specification, I assume that $p = 1$.

[47] This term also aids in reducing the negative impact of"Big Three Ownership" on markups as outlined in Table 7, as the "Big-Three" fund-families typically support management in elections when the outcomes are not tightly contested (Bubb and Catan (2022); Brav et al. (2024); Bolton et al. (2020)).

After reconstituting the control weights as outlined above, I re-estimate the ATT for markups derived from both production functions using the approach proposed by Callaway and Sant'Anna (2021), while applying additional weights to give more significance to firms with higher control weights in the analysis like in Section 3.2.[48] The outcomes of this revised estimation are displayed in Table 8. In column (1), I estimate the ATT for markups derived from "Production Function 1" with the reconstituted control weights. The ATT estimate is positive and significant at the 1% level. This suggests that, on average, index entries are associated with a 6.87% increase in markups for the treated firms. This result is notably higher compared to the baseline estimate under the model of proportional control presented in Table 7, column (2), which indicated only a 4.59% increase in markups. Similarly, in column (2), the ATT for markups from "Production Function 2," also re-estimated with the updated control weights, is positive and significant at the 1% level. Here, index inclusion is linked to a 6.85% markup increase for treated firms, surpassing the baseline estimate of a 4.44% increase shown in Table 7, column (4). Coefficient plots for these specifications are displayed in Figure 8, which visually represents the ATTs from Table 8, plotted over time. In Panel A, markups are generated from "Production Function 1", while in Panel B, markups are generated from "Production Function 2". Like Figures 6 and 7, Figure 8 provides support for the existence of parallel trends prior to the intervention, and indicates a growing impact of the intervention on markups over time.

5 Conclusion

In this Article, I present new evidence supporting the hypothesis that common ownership is associated with higher markups by enhancing the methods and data used in existing research. My primary findings reveal a significant relationship between common ownership and markups across a wide array of industries. This finding is validated further by utilizing S&P 500 index additions as a means to introduce quasi-exogenous shifts in common ownership levels. My analysis reveals that, even after controlling for various potential confounders, a unit increase in a firm's profit weight is tied to an estimated 2.7 to 4.5% rise in the firm's markup. In addition, my results show that index inclusions typically lead to a 4.4 to 5.0% markup increase for firms within the same industry as the index entrant under an assumption of proportional control. These increases are even more pronounced, reaching around 6.8%, when adopting a stylized voting model that assumes firm managers place extra emphasis on the votes of pivotal shareholders.

[48]In a weighted least squares context, weights are assigned such that the estimation of parameters is achieved through minimizing the sum of the weighted squared residuals.

While there has been considerable exploration into how common ownership might facilitate anti-competitive behaviors (Eldar et al. (2023); Antón et al. (2023)), more detailed work is required to understand the nuanced effects of different voting dynamics on firm-specific outcomes like markups and operational costs. In the stylized model I proposed in Section 4, each proposal is equally weighted, but the corporate governance literature indicates that the significance of proposals can vary greatly across firms (Bubb and Catan (2022); Bolton et al. (2020); Brav et al. (2024)). Also, the assumption that all shareholders have uniform motives for influencing firm decisions overlooks the documented diversity in how activist investors target specific firms (Bebchuk et al. (2020)). These areas offer rich opportunities for future research to delve deeper into such complex dynamics.

6 Appendix

In this Section, I provide a series of robustness tests which reinforce the validity of my findings in Section 3.

6.1 Variations of Fixed Effects and Standard Errors

As detailed in Section 3, Tables 2, 3, and 5 demonstrate a significant and positive correlation between markups and industry profit-weights across various specifications. In Table 9, I find that this association is robust to an array of alternative fixed effects and standard errors.[49] Column (1) of Table 9 reports the baseline specification for markups generated by "Production Function 1", initially outlined in column (4) of Table 2. Column (2) modifies this model to include industry-year fixed effects instead of year fixed effects, adhering to the approach suggested by Antón et al. (2023). As demonstrated in the Table, the coefficient on industry profit-weights is positive and significant at the 5% level. In column (3), I report the baseline specification for markups generated by "Production Function 2", previously described in column (3) of Table 5. Column (4) reports the same specification but with industry-year fixed effects in place of year fixed effects, mirroring the modification in column (2). Again, the coefficient of interest is positive and significant at the 5% level. Finally, in column (5), I report the specification from column (3) with an adjustment to include industry fixed effects instead of firm fixed effects, leading to an augmented and statistically significant coefficient at the 1% level.

[49]For the standard approach, I cluster all standard errors at the firm-level. The p-values from these standard errors are reported in curly parentheses.

In addressing the selection of standard errors, I modify all specifications to ensure that standard errors are doubly clustered at the firm-year level, diverging from the previous approach of clustering solely by firm (Antón et al. (2023)). The p-values from these standard errors are reported in square parentheses. Table 9 clearly illustrates that the positive association present in all my specifications remains consistent, regardless of the standard error clustering method employed.

6.2 Propensity Score Matching

The discussion in Section 3.2 presupposes that firms within the treatment group (specifically, incumbent firms within the same industry as the entrant to the index) possess characteristics comparable to those in the control group (namely, incumbent firms outside the industry of the index entrant), with the exception of their common ownership profit-weights. For causal inference to be considered valid in this context, it is necessary that index entry induces changes in firm behavior *through* changes in common ownership, as opposed to alternative channels which may drive a positive association between markups and treatment.[50] As detailed in Section 3.2, if firms under treatment are consistently linked with higher levels of institutional ownership compared to control firms (Lewellen and Lowry (2021)), then higher markups may be driven by the presence of institutional ownership, not common ownership.

To mitigate the possibility that the observed higher markups might be influenced by such confounding variables, I estimate propensity scores for both the treatment and control groups. These scores represent the likelihood of a firm being assigned to the treatment group, based on a range of observed characteristics, denoted by x_{it}. By incorporating these propensity scores into the analysis, I ensure that the treatment and control groups are essentially equivalent, with no systematic differences between them, aside from their common ownership profit-weights.[51] In a first stage, I estimate a probit regression to predict the likelihood of treatment based on a set of (lagged) covariates (x_{it-1}) listed in Table A1:

$$P(T = 1|x_{it-1}) = y_{it} = \Phi(x_{it-1}\beta) \tag{4}$$

where y_{it} relates to the binary treatment variable assigned to each firm i at time t and Φ represents the CDF of the standard normal distribution. After deriving the propensity scores

[50] This is a necessary condition for the exclusion restriction to hold.

[51] In the context of common ownership, Gibbon and Schain (2023) also harness propensity score matching to address the endogeneity of ownership. The key assumption here is the "unconfoundedness" assumption, which suggests that there are no unmeasured confounders that both affect the treatment assignment and the outcome.

$p(x_{it}) = \Phi(x_{it-1}\hat{\beta})$ by estimating the coefficients $\hat{\beta}$ in specification 4[52], I follow Rosenbaum (1987) in computing an inverse probability of treatment weight (IPTW), where the IPTW w_{it} is defined as:

$$w_{it} = \frac{y_{it}}{p(x_{it})} + \frac{1 - y_{it}}{1 - p(x_{it})} \tag{5}$$

As the IPTW is equal to the inverse of the observation's probability of receiving the treatment, weighting a regression model with IPTWs allows for a specification that consistently estimates the true treatment effect (Joffe et al. (2004)).

In Table 10, I report variants of specification 1, weighted by the IPTWs computed in specification 5. Column (1) of Table 9 reports the baseline specification for markups generated by "Production Function 1", initially outlined in column (1) of Table 2 but this time adjusted using IPTWs. Relative to its unweighted counterpart, the coefficient of interest – industry profit weights – in this revised model shows an increase and is statistically significant at the 5% level. Similarly, the coefficient of interest in a revised specification where overhead is included as a control (column (2)) is also positive and statistically significant at the 5% level. In column (3), I present the specification from column (2), with the modification of incorporating industry fixed effects in lieu of firm fixed effects. In column (4), the adjustment involves replacing year fixed effects with industry-year fixed effects for the same model. Similar to the results presented in columns (1) and (2), the coefficients of interest in these adjusted models are positive and achieve statistical significance, at the 1% level for column (3) and at the 10% level for column (4).

Column (5) of Table 9 reports analogous results for markups generated by "Production Function 2", initially detailed in column (3) of Table 5, now modified to incorporate IPTWs. This result, similar to the revised specfications for "Production Function 1," reveals a positive and statistically significant coefficient at the 10% level. Columns (6) and (7) of Table 9 extend these adjustments in a manner akin to columns (4) and (5), with the coefficients in these models also being positive and statistically significant, at the 1% level for column (6) and at the 10% level for column (7). Collectively, these results reinforce the robustness of my results in Section 3.2.

[52] Following the propensity score matching of treatment and control groups, none of the observable variables' mean differences are statistically significant from zero.

6.3 2SLS and the Potential Endogeneity of Index Entries

The methods employed in Section 6.2 aim to mitigate the issue of mistakenly attributing the effects of common ownership to other observable factors that could lead to increased markups. However, this approach does not address the potential endogeneity of index inclusion. For instance, there is a remote possibility that decisions regarding S&P 500 inclusions could be influenced by factors like profitability or firm size, which may also be associated with common ownership (Robertson (2019)). To counter these concerns, I employ an alternative strategy: using index inclusions as an instrumental variable. This strategy operates under the assumption that while index inclusions are positively correlated with common ownership, they are uncorrelated with higher markups *except* through their effect on treated firms. Assuming these conditions are met, a "two-stage least squares" (2SLS) methodology will be able to determine the causal impact of common ownership on markups. The method involves a two-step process. In the first stage, I regress industry profit-weights κ_{it} on the binary treatment variable assigned to each firm (y_{it} in Section 6.2), as well as a set of control variables outlined in Table A1. In the second stage, I execute specification 1 with the common ownership variable substituted by the predicted values of $\hat{\kappa_{it}}$ obtained from the initial stage, while also incorporating the same control variables identified in that first stage.

I report the results from these estimations in Table 11. The focal coefficients on "Index Entrant (y_{it})" from the first stage regressions are presented in columns (1), (3), (5), and (7). Across all models, these findings suggest a link between index entrants and a rise in common ownership, as indicated by the consistently positive and statistically significant coefficients on "Index Entrant" at the 5% significance level.

From the second stage regressions, the coefficients on "Kappa (Industry) ($\hat{\kappa_{it}}$)" are detailed in columns (2), (4), (6), and (8) of Table 11. Each specification varies based on the chosen dependent variable and fixed effects. Column (2) introduces a model utilizing "Production Function 1" markups with industry and year fixed effects, where the coefficient of interest is positively significant at the 5% level. Column (4) presents a similar model but substitutes industry fixed effects with firm fixed effects, rendering the coefficient of interest positive, yet not statistically significant at the 10% level, albeit with a p-value nearing 0.10. Column (6) features a model using "Production Function 2" markups accompanied by industry and year fixed effects, where the coefficient of interest remains positively significant at the 5% level. Conversely, in column (8), replacing industry fixed effects with firm fixed effects yields a positive and statistically significant coefficient for $\hat{\kappa_{it}}$, in contrast to the findings in column (4). These findings underscore the robust positive association between common ownership and firm-level markups.

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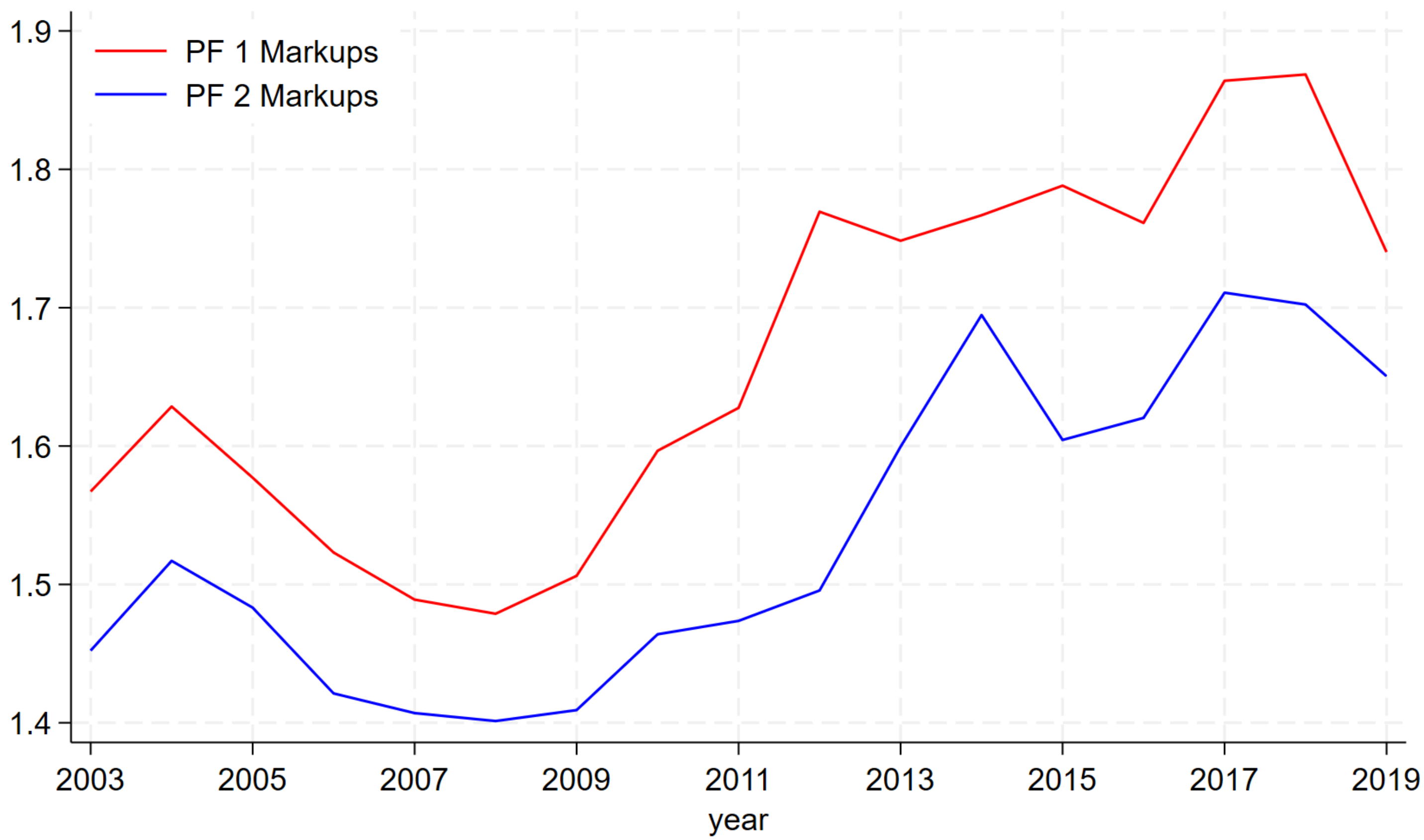
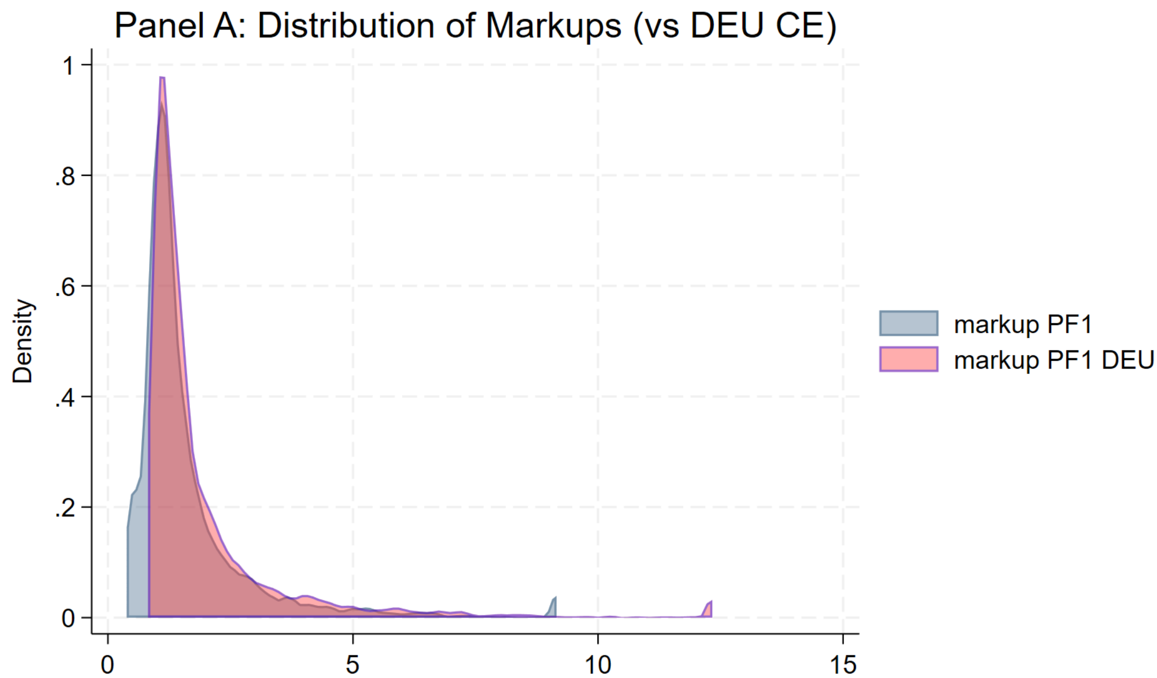
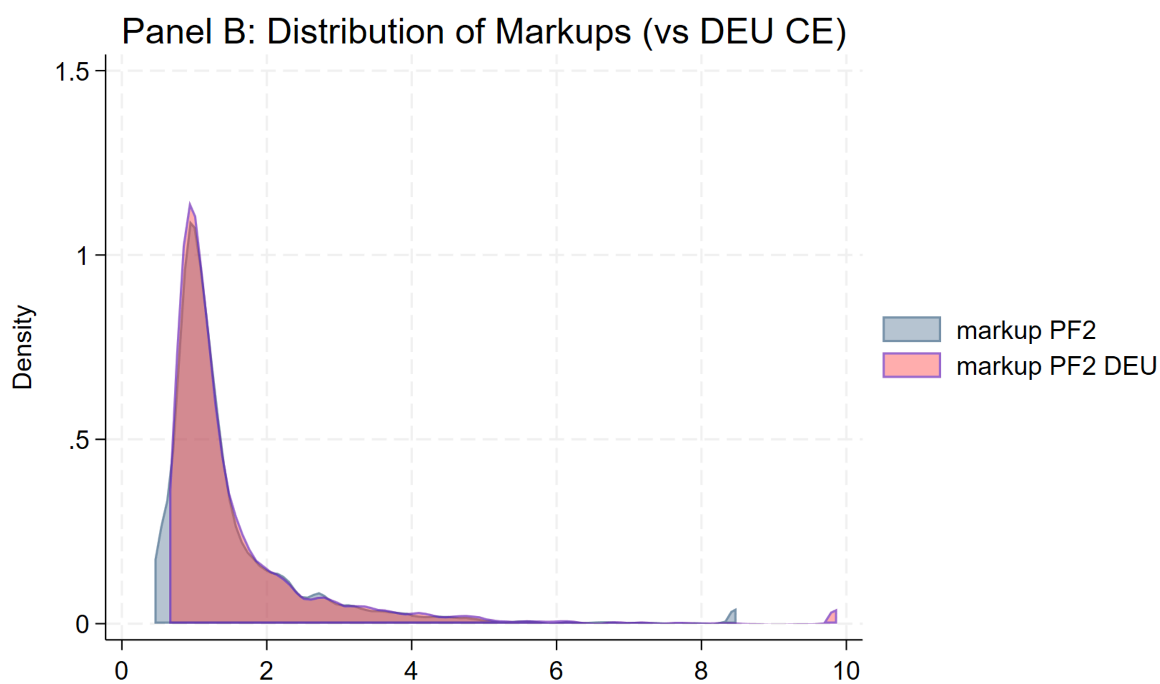
Figure 1: Markups over Time



Note: This figure provides a time series of firm-level markups from 2003 to 2019. The red line represents estimated markups derived from "Production Function 1", where Overhead (SG&A) is not used as an input. The blue line represents estimated markups derived from "Production Function 2", where Overhead (SG&A) is employed as an additional input.

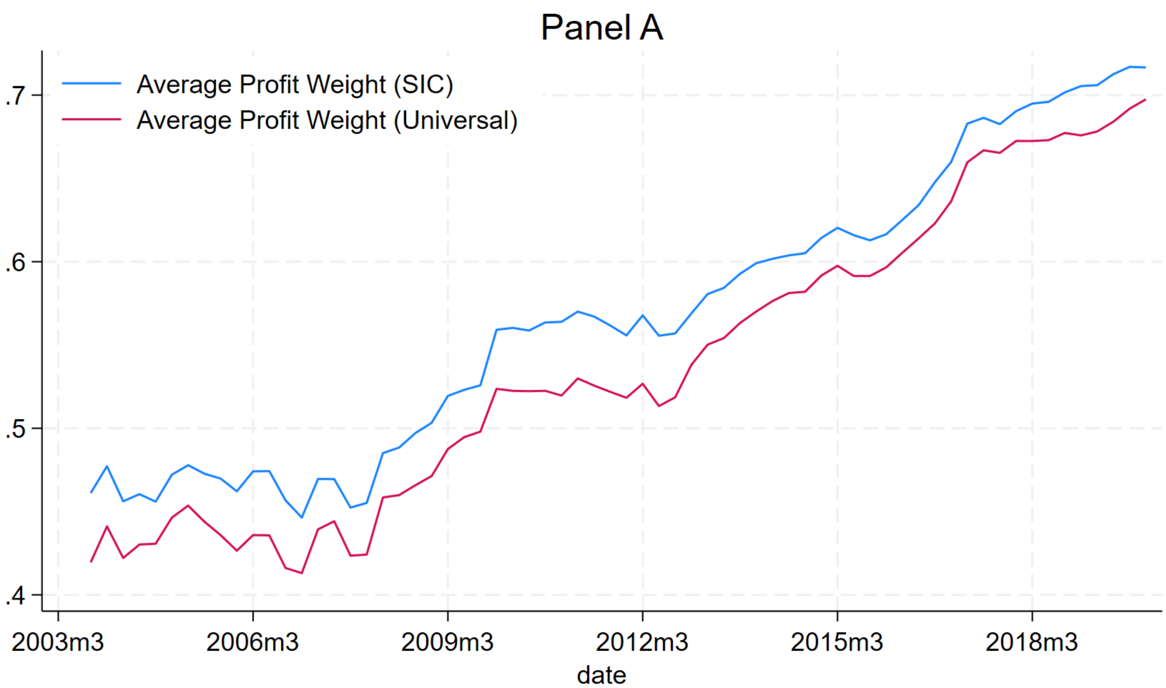
Figure 2: Markup Distributions

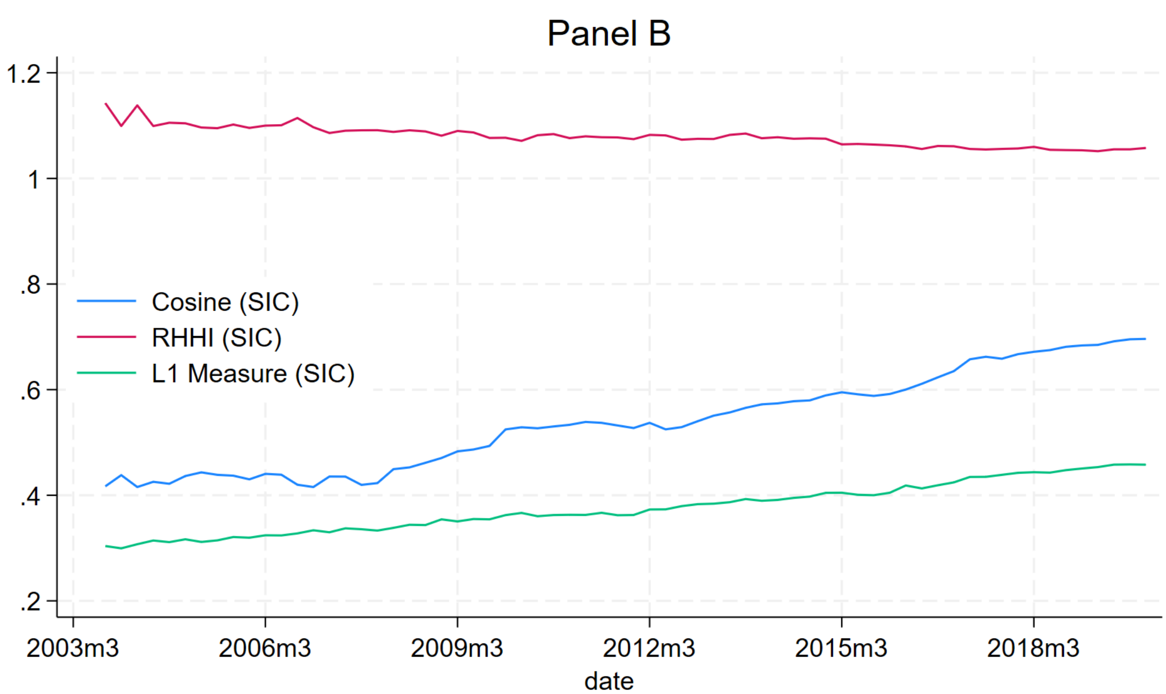




Note: Panel A offers a juxtaposition of estimated markups derived from "Production Function 1" and markups from De Loecker et al. (2020) (assuming 2016 elasticities), while Panel B offers a juxtaposition of the same with regard to markups derived from "Production Function 2".

Figure 3: Common Ownership Measures over Time





Note: Panel A provides a time series of "Universal" and "Industry" profit-weights from 2003 to 2019, while Panel B does the same for decomposed components of the "Industry" profit weights in Panel A.

Table 1: Summary Statistics

	Mean	1Q	Median	3Q	N	Standard Deviation
Ownership (per Investor)	0.002	0.001	0.002	0.002	5,793	0.001
L2 Var for Indexing	0.576	0.532	0.581	0.628	5,793	0.075
Big Three Ownership	0.130	0.071	0.136	0.177	5,793	0.059
Captured Ownership	0.812	0.718	0.823	0.915	5,793	0.139
13F Ownership	0.779	0.685	0.796	0.884	5,793	0.141
Form 3/4/5 Ownership	0.021	0.002	0.005	0.012	5,793	0.048
13D Ownership	0.007	0.000	0.000	0.000	5,793	0.030
13G Ownership	0.129	0.054	0.118	0.190	5,793	0.096
Retail Ownership	0.193	0.087	0.178	0.282	5,793	0.131
Firm Size	9.828	8.771	9.700	10.704	5,792	1.412
Leverage Ratio	0.253	0.125	0.238	0.353	5,770	0.172
Tangibility	0.264	0.055	0.154	0.446	5,741	0.259
Tobin's Q	2.015	1.172	1.567	2.404	5,791	1.235
RoA	0.057	0.018	0.050	0.093	5,792	0.070
Kappa (Industry)	0.558	0.386	0.541	0.720	5,793	0.239
Kappa (Universal)	0.529	0.367	0.514	0.680	5,793	0.221
PF1 Markups	1.758	0.974	1.257	1.886	5,790	1.483
PF2 Markups	1.624	0.900	1.169	1.777	5,790	1.346
Overhead	7.487	6.605	7.419	8.248	4,589	1.251

Note: This Table presents Summary Statistics for S&P 500 firms with at least 2 or more firms in the same industry, defined at a 4-digit SIC level. The dataset covers a total of 630 unique firms, across 128 industries (defined at the 4-digit SIC level) and 186 sectors (defined at the 5-digit NAICS level), from 2003 to 2019. Voting data is not included in the Summary Statistics reported here.

Table 2: Markups on Industry Profit Weights (Firm FEs)

	(1)	(2)	(3)	(4)	(5)	(6)
Kappa (Industry)	0.139***			0.137**		
	(0.006)			(0.018)		
Cosine		0.140**			0.129*	
		(0.031)			(0.071)	
RHHI			0.051*			0.051
			(0.070)			(0.102)
Overhead				0.051	0.052	0.051
				(0.317)	(0.309)	(0.319)
Constant	0.362	0.321	0.307	0.514*	0.475*	0.455
	(0.146)	(0.198)	(0.218)	(0.066)	(0.090)	(0.105)
Observations	5046	5046	5046	3999	3999	3999
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.844	0.844	0.844	0.843	0.843	0.843
F Statistic	5.922	5.893	5.804	4.715	4.686	4.721

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable relates to Log Markups (generated from "Production Function 1"). All profit weights, their components, and firm-fund-controls are lagged by one period. Standard errors are clustered at the firm-level.

Table 3: Markups on Industry and Universal Profit Weights (Firm and Industry FEs)

	(1)	(2)	(3)	(4)	(5)	(6)
Kappa (Industry)	0.137**	0.237***	0.227***			
	(0.018)	(0.000)	(0.001)			
Kappa (Universal)				0.079	0.171**	0.152*
				(0.266)	(0.013)	(0.074)
Overhead	0.051		0.126***			0.110***
	(0.317)		(0.000)			(0.001)
Constant	0.514*	0.345**	0.736***	0.326	0.298*	0.625***
	(0.066)	(0.042)	(0.001)	(0.111)	(0.058)	(0.002)
Observations	3999	5095	4047	6478	6519	5368
Firm FE	Yes	No	No	Yes	No	No
Industry FE	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.843	0.625	0.616	0.853	0.650	0.651
F Statistic	4.715	8.587	7.550	6.917	8.433	7.473

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable relates to Log Markups (generated from "Production Function 1"). All profit weights and firm-fund-controls are lagged by one period. Standard errors are clustered at the firm-level.

Table 4: Decomposition of Between and Within-Entity Variation

(1) Variable		(2) Mean	(3) Standard Deviation
Kappa (Industry)	Overall	0.558103	0.2387147
	Between		0.1918117
	Within		0.1478649
Kappa (Universal)	Overall	0.523955	0.2170018
	Between		0.1790601
	Within		0.1320557
PF1 Markups	Overall	0.389584	0.4866072
	Between		0.4505892
	Within		0.1850866
PF2 Markups	Overall	0.243794	0.5493206
	Between		0.5039828
	Within		0.2152175

Note: This table decomposes the variable x_{it} (shown in column (1)) into a between ($\overline{x_i}$) and within ($x_{it} - x_i + \overline{\overline{x}}$) components, where $\overline{\overline{x}}$ relates to the global mean of the variable for commensurability.

Table 5: Variants of Markups on Industry Profit Weights

	(1) PF1 Markups	(2) PF2 Markups	(3) PF2 Markups	(4) Median Elasticity Markups	(5) Average Cost Markups
Kappa (Industry)	0.137**	0.115**	0.124**	0.137**	0.040**
	(0.018)	(0.041)	(0.015)	(0.023)	(0.031)
Overhead	0.051	0.052		0.072	-0.053***
	(0.317)	(0.318)		(0.187)	(0.005)
Constant	0.514*	0.338	0.249	0.351	0.387***
	(0.066)	(0.224)	(0.331)	(0.267)	(0.000)
Observations	3999	3999	5046	3999	4001
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.843	0.842	0.839	0.856	0.757
F Statistic	4.715	5.608	6.945	4.760	18.164

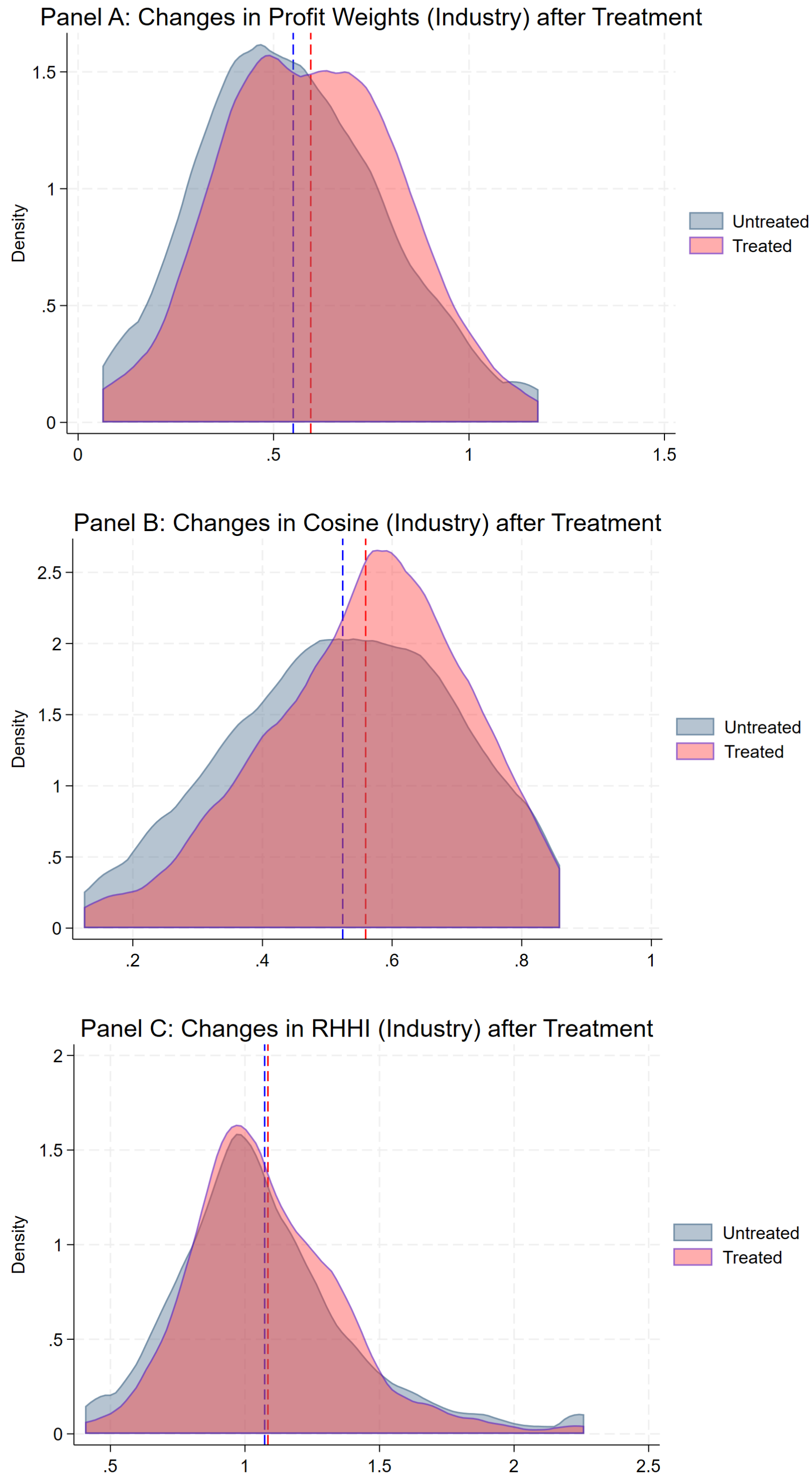
Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. The dependent variable in column (1) is Log Markups based on "Production Function 1," while columns (2) and (3) use Log Markups from "Production Function 2." Column (4) employs Log Markups derived from Section 2.2 where the relevant output elasticities (θ^{v}_{it}) are assumed to take on a constant value of 0.85, and column (5) uses average-cost markups. All profit weights and firm-fund-controls are lagged by one period. Standard errors are clustered at the firm-level.

Table 6: Heterogeneity across Investor Characteristics

	(1)	(2)	(3)	(4)	(5)
Kappa (Industry)	0.396***	0.597**	0.226***	0.237***	0.262***
	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)
Kappa (Industry) × Big Three	-1.393**				
	(0.029)				
Kappa (Industry) × Indexing Measure		-0.661			
		(0.149)			
Kappa (Industry) × Form 3/4/5 Ownership			1.273		
			(0.286)		
Kappa (Industry) × 13D Ownership				-0.172	
				(0.867)	
Kappa (Industry) × 13G Ownership					-0.307
					(0.321)
Constant	0.272	0.022	0.336**	0.345**	0.341**
	(0.117)	(0.920)	(0.047)	(0.042)	(0.045)
Observations	5095	5095	5095	5095	5095
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.626	0.626	0.625	0.625	0.625
F Statistic	8.380	7.439	7.940	7.922	8.046

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. All profit weights and firm-fund-controls are lagged by one period. Coefficients for C_{ijt-1}, which capture distinct investor characteristics such as "Big-Three Ownership," "Indexing Measure," and "13D Ownership," are not reported. The dependent variable relates to Log Markups (generated from "Production Function 1"). Standard errors are clustered at the firm-level.

Figure 4: Quasi-Exogenous Variations in Common Ownership



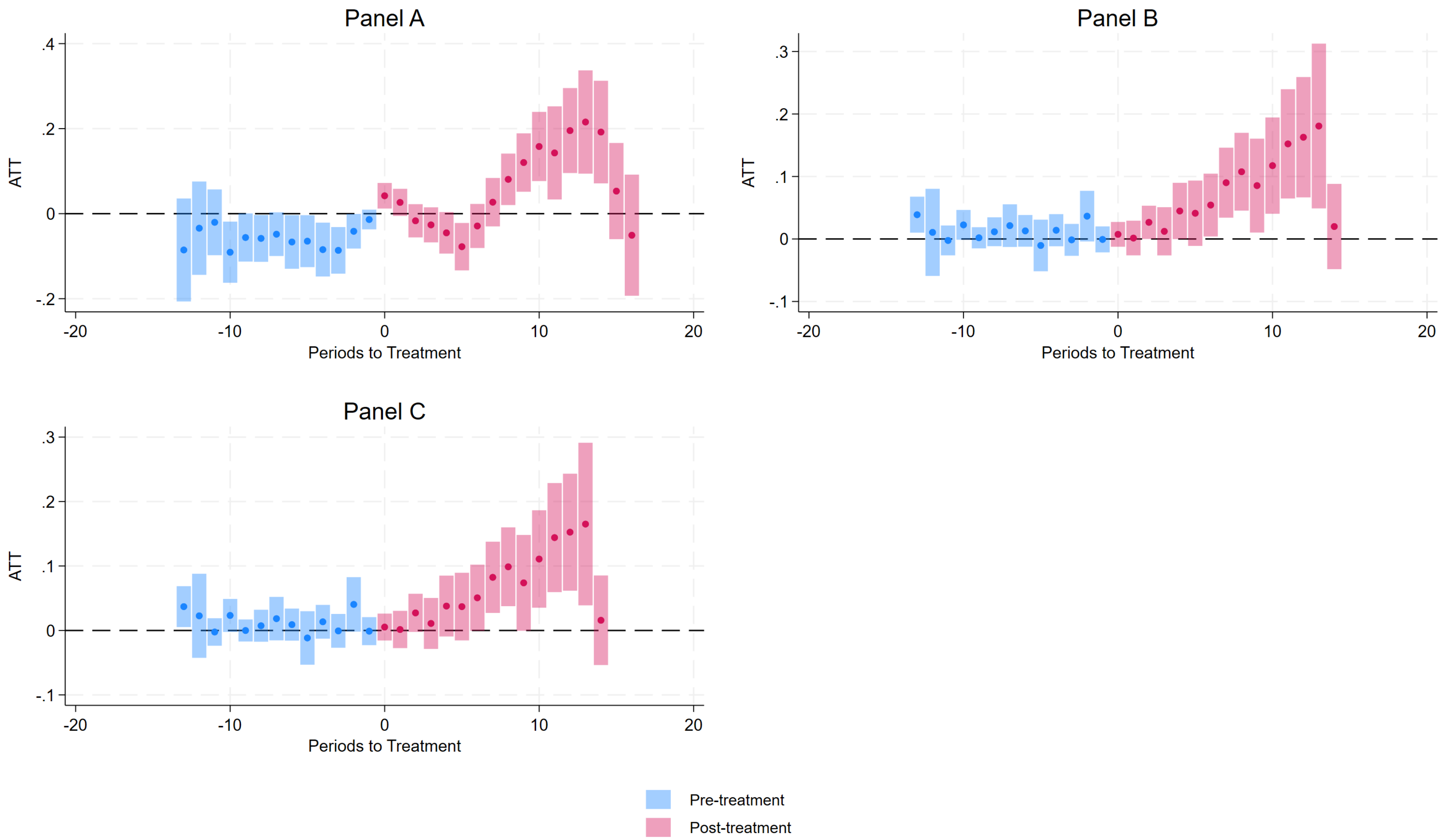
Note: Panel A illustrates the differences in industry profit weights between "treated" firms which share the same industry as the index-entrant, and "control" firms which do not. Index entrants are excluded from the analysis and are neither in the treatment nor the control group. Panels B and C illustrate the same for components of the industry profit weights.

Table 7: Panel Event Study: Index Entries in the S&P 500 (Proportional Control)

		(1) PF1 Treatment (Unweighted)	(2) PF1 Treatment (Proportionate Weights)	(3) PF2 Treatment (Unweighted)	(4) PF2 Treatment (Proportionate Weights)
(1)	Average Treatment Effect on Treated (C&S)	0.0504148***	0.0459577***	0.04804***	0.0444482**
		(0.001)	(0.002)	(0.006)	(0.014)
(2)	Average Treatment Effect on Treated (TWFE)	0.049898***	0.0453897***	0.0360991**	0.0212936**
		(0.002)	(0.003)	(0.007)	(0.015)

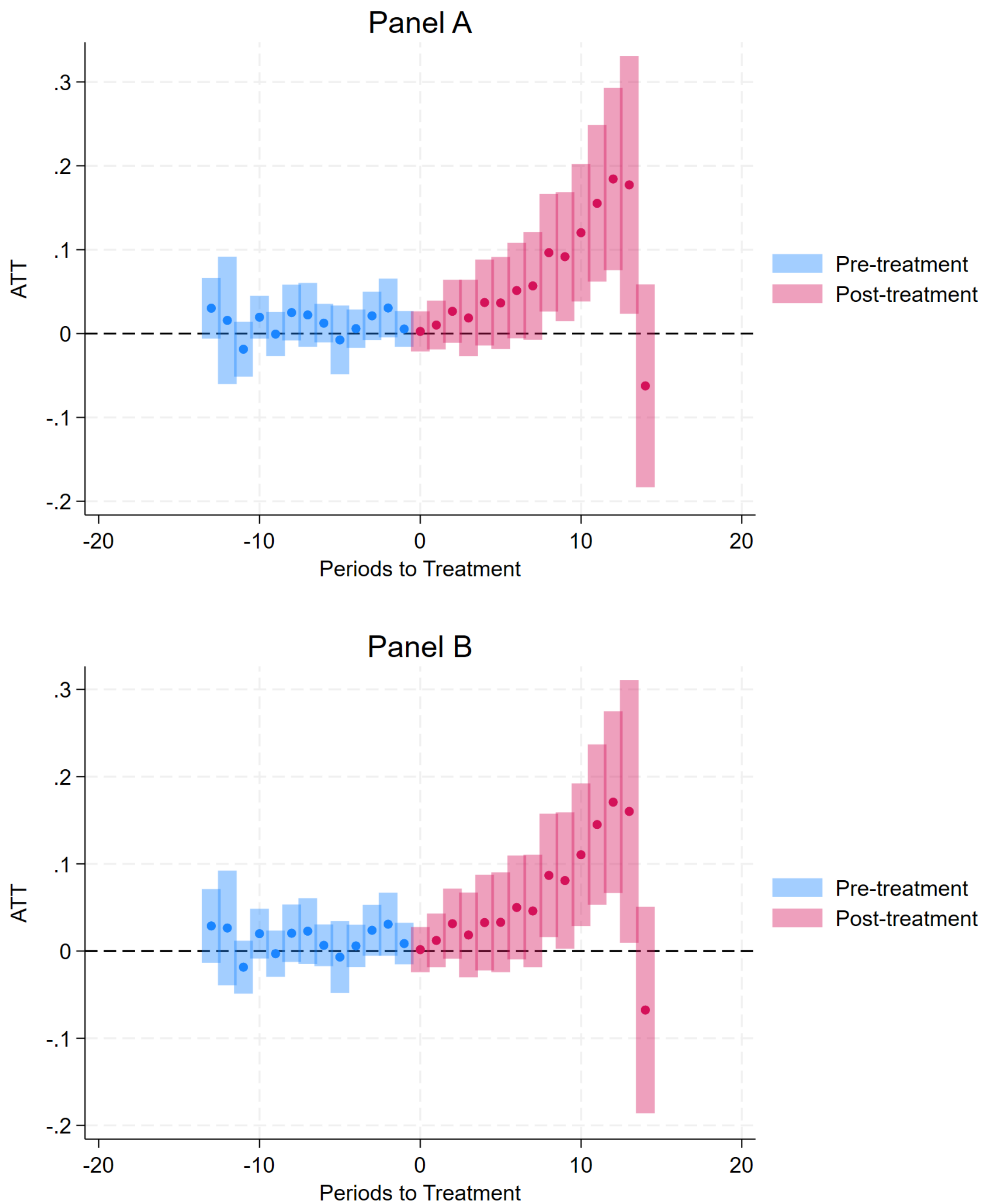
Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. Row (1) presents ATTs re-weighted using a generalized propensity score following Callaway and Sant'Anna (2021), while row (2) reports ATTs from a standard two-way fixed effects model detailed in specification (2). Columns (1) and (3) do not apply any additional probability weights, while Columns (2) and (4) incorporate probability weights based on each firm's control weights, assuming proportionate control. Firm-fund-controls (including overhead) are included and are lagged prior to treatment as per Antón et al. (2023). Standard errors are clustered at the firm-level.

Figure 5: Coefficient Plots over Time (PF 1) (Proportionate Control)



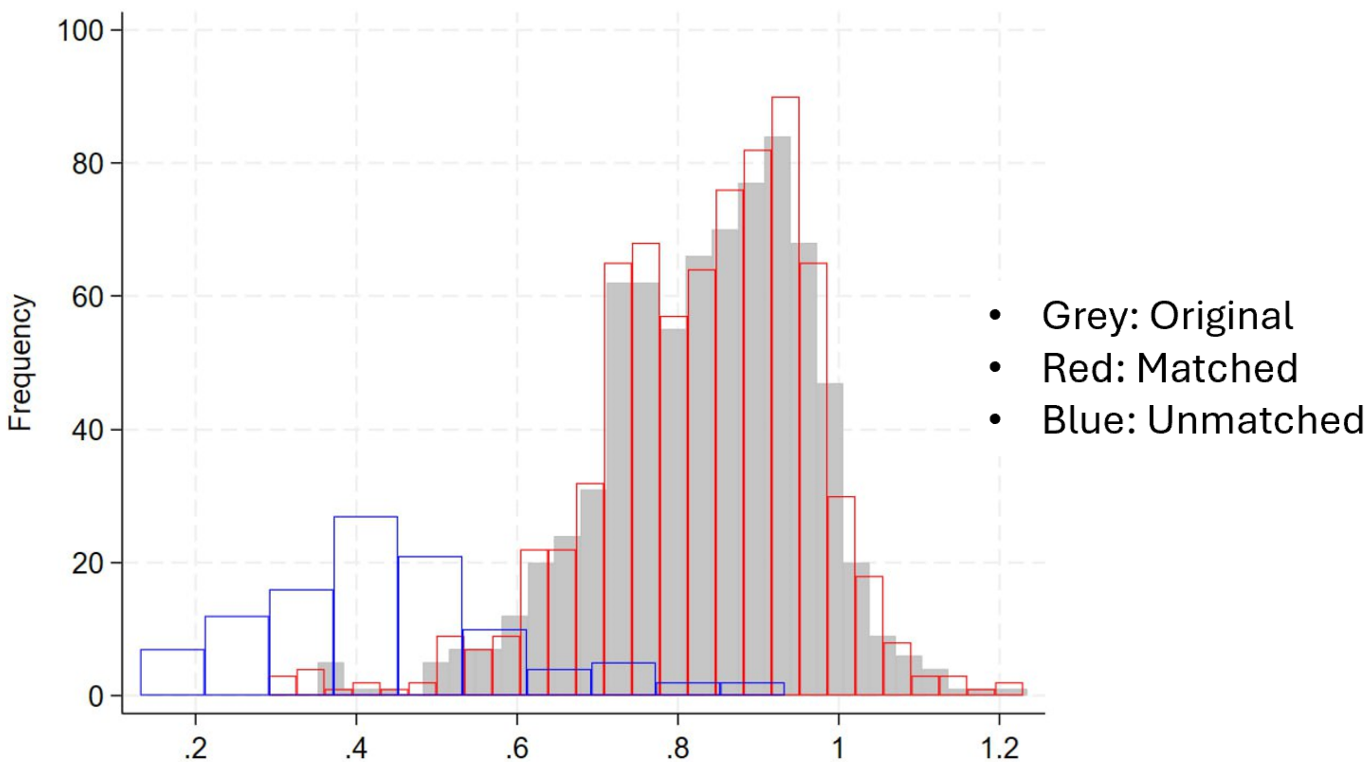
Note: Panel A shows the coefficients for the Average Treatment Effects on the Treated (ATTs) over time from a two-way fixed effects model without probability weights. Panel B displays results from a Callaway and Sant'Anna (2021) model without probability weights, while Panel C uses a Callaway and Sant'Anna (2021) model with probability weights based on each firm's control weights, assuming proportionate control. Markups are derived from Production Function 1.

Figure 6: Coefficient Plots over Time (PF 2) (Proportionate Control)



Note: Panel A reports the coefficients for the Average Treatment Effects on the Treated (ATTs) over time using the Callaway and Sant'Anna (2021) model without probability weights. Panel B presents the same analysis with probability weights based on each firm's control weights, assuming proportionate control. Markups are derived from Production Function 2.

Figure 7: Proportion of Successful Matches



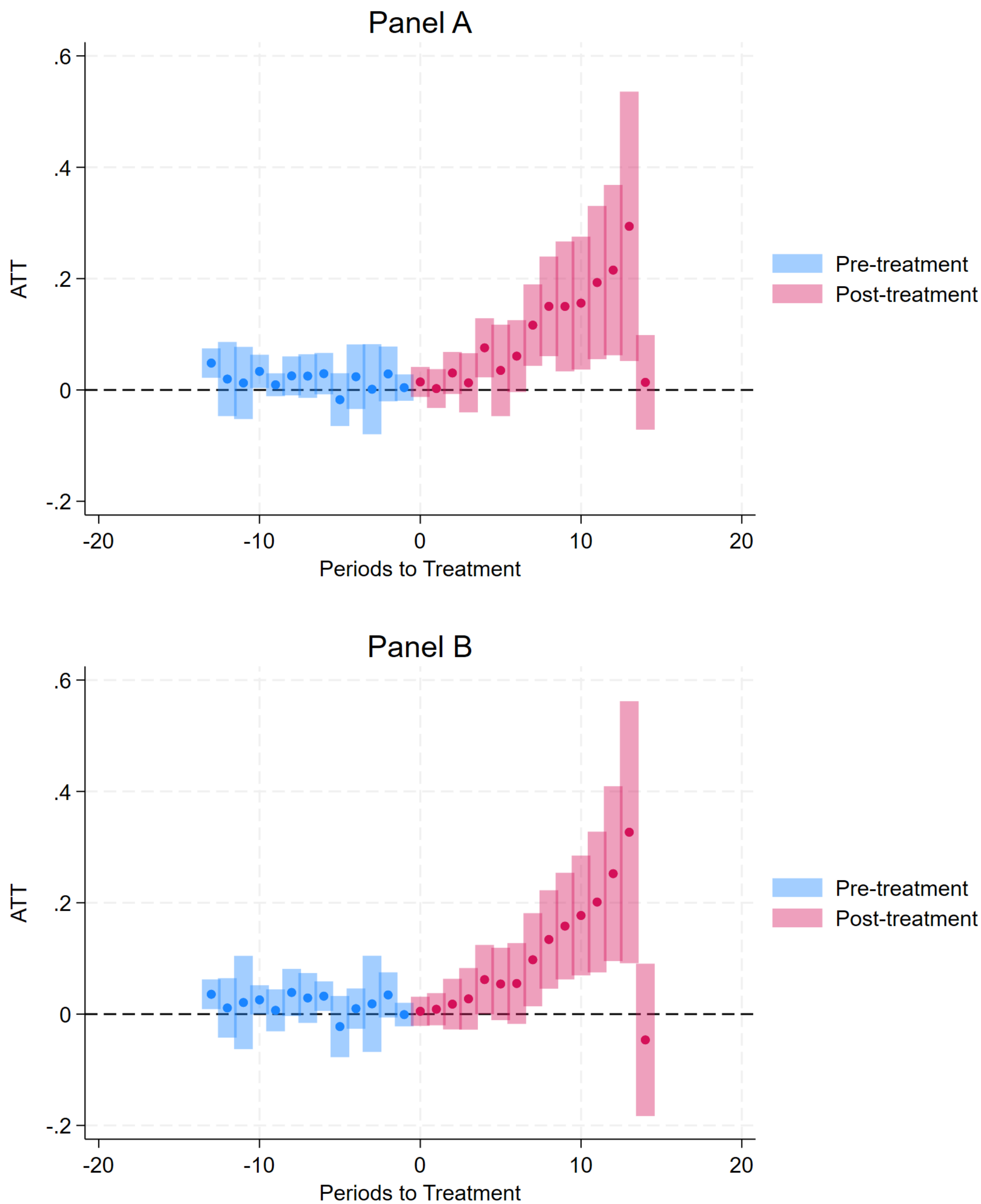
Note: In this Figure, grey bars illustrate the histogram of ownership values in the original dataset, while red bars illustrate the histogram of matched values after a process that combines fuzzy-matching and hand-matching techniques. The blue bars illustrate the histogram of unmatched values.

Table 8: Panel Event Study: Index Entries in the S&P 500 (Reconstituted Control Weights)

	(1) PF1 Treatment (Reconstituted Weights)	(2) PF2 Treatment (Reconstituted Weights)
Average Treatment Effect on Treated (C&S)	0.0687216***	0.0684839***
	(0.002)	(0.002)

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. This table reports ATTs re-weighted with a generalized propensity score in line with Callaway and Sant'Anna (2021). Columns (2) and (4) incorporate probability weights based on each firm's control weights (defined in Section 4). Firm-fund-controls (including overhead) are included and are lagged prior to treatment as per Antón et al. (2023). Standard errors are clustered at the firm-level.

Figure 8: Coefficient Plots over Time (PF 1 and 2) (Reconstituted Weights)



Note: Panels A and B use the Callaway and Sant'Anna (2021) model to display the coefficients for the Average Treatment Effects on the Treated (ATTs) over time, incorporating probability weights based on each firm's control weights (defined in Section 4). In Panel A, markups are derived from Production Function 1, while in Panel B, they are derived from Production Function 2.

Table 9: Markups on Industry Profit Weights (Variations of FEs and SEs)

	PF1 Markups		PF2 Markups		
	(1)	(2)	(3)	(4)	(5)
Kappa (Industry)	0.137	0.118	0.124	0.107	0.233
	(0.018)**	(0.044)**	(0.015)**	(0.031)**	(0.000)***
	[0.034]**	[0.032]**	[0.030]**	[0.019]**	[0.001]***
Overhead	0.051	0.011			
	(0.317)	(0.822)			
Constant	0.514*	0.217	0.249	0.125	0.109
	(0.066)	(0.450)	(0.331)	(0.619)	(0.561)
Observations	3999	3877	5046	4999	5095
Firm FE	Yes	Yes	Yes	Yes	No
Industry FE	No	No	No	No	Yes
Industry-Year FE	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.843	0.916	0.839	0.913	0.647
F Statistic	4.715	2.540	6.945	3.273	9.328

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. All profit weights and firm-fund-controls are lagged by one period. Standard errors in curly parentheses are clustered at the firm-level, while standard errors in square parentheses are double clustered at the firm-year-level.

Table 10: Markups on Industry Profit Weights (Propensity Score Matching)

	PF1 Markups				PF2 Markups		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Kappa (Industry)	0.149**	0.164**	0.326***	0.137*	0.128*	0.304***	0.116*
	(0.028)	(0.032)	(0.000)	(0.063)	(0.069)	(0.000)	(0.083)
Overhead		0.031	0.125***	-0.030			
		(0.565)	(0.008)	(0.593)			
Constant	0.561**	0.733**	0.696**	0.205	0.427	0.035	0.207
	(0.049)	(0.019)	(0.019)	(0.545)	(0.164)	(0.890)	(0.498)
Observations	5046	3999	4047	3877	5046	5095	4999
Firm FE	Yes	Yes	No	Yes	Yes	No	Yes
Industry FE	No	No	Yes	No	No	Yes	No
Industry-Year FE	No	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	No	Yes	Yes	No
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Sq	0.857	0.852	0.591	0.914	0.849	0.628	0.913
F Statistic	5.095	4.974	8.138	2.409	5.263	9.162	2.469

Note: *** p≤0.01, ** p≤0.05, * p≤0.10. P-values are reported in parentheses. All profit weights and firm-fund-controls are lagged by one period. Standard errors are clustered at the firm-level. All Regressions are weighted with IPTWs, determined in accordance with PSM scores.

Table 11: 2SLS Instrumental Variable Regressions

	PF1 Markups				PF2 Markups			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Index Entrant	0.013**		0.012**		0.013**		0.012**	
	(0.013)		(0.018)		(0.013)		(0.018)	
Kappa (Industry)		2.601**		1.427		4.192**		2.590*
		(0.044)		(0.118)		(0.027)		(0.056)
Observations	5128	5128	5081	5081	5128	5128	5081	5081
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F Statistic	6.150	4.772	5.616	4.020	6.150	3.701	5.616	2.867

Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$. P-values are reported in parentheses. First-stage regression results are presented in columns with odd numbers, focusing on industry profit-weights as the dependent variable. Conversely, second-stage regression results appear in columns with even numbers, with the dependent variable being markups, derived from either "Production Function 1" or "Production Function 2". All firm-fund-controls are lagged by one period. Standard errors are clustered at the firm-level.

Table A1: List of Variables

Variable	Definition
Firm-Fund Controls	
Firm Size	Logarithm of the firm's total assets
Return on Assets (RoA)	Net income scaled by total assets
Leverage Ratio	Total debt scaled by total assets
Tangibility	Property, plant and equipment scaled by total assets
Tobin's Q	Market capitalization of equity plus total debt, divided by total assets
Big Three Ownership	% of firm equity owned by Vanguard, Blackrock, and State Street
Form 3/4/5 Ownership	% of firm equity owned by insiders
13D Ownership	% of firm equity owned by 13D blockholders
13G Ownership	% of firm equity owned by 13G blockholders
Retail Ownership	% of firm equity owned by non-institutional investors
Additional Controls	
Overhead	Logarithm of the firm's selling, general, and administrative expenses

Unless stated otherwise, all specifications that incorporate firm-fund controls do not include Overhead. 13F Ownership is omitted from the set of firm-fund controls due to its collinearity with 13D, 13G, Retail, and Form 3/4/5 Ownership at the fund level. 13F data arises from obligations under Form 13F, where the SEC requires all institutional investment managers with at least $100 mil USD in AUM to disclose their equity holdings. 13D data arises from investor obligations under Form 13D, where the SEC requires a person or group acquiring more than 5% of a voting class of a company's equity shares to disclose their purchase. 13G data arises from investor obligations under Form 13G, where the SEC permits a person or group under 13D obligations to file a 13G filing instead if they have no intention of influencing control over the issuer. Form 3/4/5 data arises from investor obligations under Form 3/4/5, where any "insider" or beneficial owner of greater than 10% of a company's equity holdings must file a Form 3 filing with the SEC. Forms 4 and 5 are variants of Form 3.

8 Online Appendix

8.1 Markup Estimation: Theoretical Basis

Consider a firm with the production function of the general form:

$$Y_{it} = F_{it}(V_{it}, K_{it}, \omega_{it})$$

where Y_{it} is the output for firm i at time t, V_{it} is a variable input (typically labor or intermediate inputs), K_{it} is a capital input, and ω_{it} is an idiosyncratic productivity parameter. As detailed earlier in Section 2.2, the variable input of choice in my estimations relates to the firm's cost of goods sold (COGS), which aggregates all costs directly linked to the production of the goods that the firm sells, including materials, labor costs, and other intermediate inputs.

$F(\cdot)$ is assumed to be continuous and twice differentiable with respect to all its components. Accordingly, cost minimization of inputs implies the Lagrangian function:

$$\mathcal{L}_{it} = J_{it}V_{it} + r_{it}K_{it} + \lambda_{it}(Y_{it} - F_{it}(V_{it}, K_{it}, \omega_{it}))$$

Where J_{it} and r_{it} are respective prices for the variable inputs V_{it} and K_{it}. Assuming a single-variable input production technology, the first-order condition with respect to the variable input V_{it} is:

$$\frac{\partial \mathcal{L}_{it}}{\partial V_{it}} = J_{it} - \lambda_{it}\frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}} = 0 \tag{6}$$

Since $\frac{\partial \mathcal{L}_{it}}{\partial Y_{it}} = \lambda_{it}$ represents the marginal cost of production for any given level of output Y_{it}, we can define the markup as the price-marginal cost ratio, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$. Rearranging equation (6) and multiplying both sides with $\frac{V_{it}}{Y_{it}}$, we have:

$$J_{it} = \lambda_{it}\frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}}$$

or,

$$\frac{V_{it}}{Y_{it}}J_{it} = \lambda_{it}\frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}}\frac{V_{it}}{Y_{it}}$$

or,

$$\frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}} \frac{V_{it}}{Y_{it}} = \frac{1}{\lambda_{it}} \frac{J_{it} V_{it}}{Y_{it}} \tag{7}$$

Substituting $\lambda_{it} = \frac{P_{it}}{\mu_{it}}$ and the output elasticity of the variable input $\theta^{v}_{it} = \frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}} \frac{V_{it}}{Y_{it}}$ into equation (7), we have:

$$\frac{\partial F_{it}(V_{it}, K_{it}, \omega_{it})}{\partial V_{it}} \frac{V_{it}}{Y_{it}} = \frac{\mu_{it}}{P_{it}} \frac{J_{it} V_{it}}{Y_{it}}$$

or,

$$\theta^{v}_{it} = \mu_{it} \cdot \frac{J_{it} V_{it}}{P_{it} Y_{it}}$$

or,

$$\mu_{it} = \frac{\theta^{v}_{it}}{\alpha_{it}} \tag{8}$$

where $\alpha_{it} = \frac{J_{it} V_{it}}{P_{it} Y_{it}}$ is the variable input share of total output in equation (8). Given that the dataset records total sales (SALE) as the observed product of output prices and quantities $P_{it}Y_{it}$, and the total cost of goods sold (COGS) is observed as the product of variable input prices and quantities $J_{it}V_{it}$, the variable α_{it} is observable. Hence, estimating θ^{v}_{it} would allow the recovery of firm-level markups as defined in equation (8).

8.2 Markup Estimation: Empirical Methodology

To estimate firm-level output elasticities θ^{v}_{it}, I follow the standard "control function" approach in Olley and Pakes (1996) and Ackerberg et al. (2015), assuming a Cobb-Douglas structure for the production function[53]:

$$y_{it} = \alpha + \mathbf{w}_{it} \boldsymbol{\beta} + \mathbf{x}_{it} \boldsymbol{\gamma} + \omega_{it} + \varepsilon_{it} \tag{9}$$

[53]This approach assumes that productivity is Hicks-Neutral (Raval (2023)).

where y_{it} is the total gross output (log SALE), $\mathbf{w}_{it}$ is a vector of log free-variables (log COGS in "Production Function 1"), and $\mathbf{x}_{it}$ is a vector of log state-variables (log PPEGT in "Production Function 1", log PPEGT and log SG&A in "Production Function 2") and controls (each firm's share of industry sales at the 4-digit SIC industry level). The random component ω_{it} is the unobservable productivity element, while ε_{it} is an idiosyncratic output shock assumed to be distributed as white noise. Following Olley and Pakes (1996), I assume that productivity evolves according to a first order Markov process:

$$\omega_{it} = E\left(\omega_{it}|\omega_{it-1}\right) + \xi_{it}$$

where ξ_{it} is a productivity shock assumed to be uncorrelated with ω_{it} and state variables $\mathbf{x}_{it}$.[54] In my implementation, I further assume an AR(1) process for productivity like Raval (2023) and Baqaee and Farhi (2020), such that:

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it} \tag{10}$$

Following Olley and Pakes (1996), firm investment levels (log CAPX) may be used as a proxy variable for ω_{it}. Given the assumptions that (1) the investment policy function $i_{it} = f(\mathbf{x}_{it,}\mathbf{w}_{it}, \omega_{it})$ is invertible in ω_{it}[55], (2) i_{it} is monotonically increasing in ω_{it}, (3) the state variables evolve according to the investment policy function i_{it}, and are determined prior to time t, and (4) the free variables $\mathbf{w}_{it}$ are chosen at time t when the firm realizes its productivity shocks, the policy function may be inverted (Ackerberg et al. (2015)), yielding a proxy for productivity:

$$\omega_{it} = f^{-1}(i_{it}, \mathbf{w}_{it}, \mathbf{x}_{it}) = h(i_{it}, \mathbf{w}_{it}, \mathbf{x}_{it}) \tag{11}$$

where $h(\cdot)$ is an unknown function of observable variables. Substituting expression (11) into specification (9), we obtain:

[54]The productivity shock is also assumed to be uncorrelated with the controls.

[55]In Olley and Pakes (1996), the investment policy function is assumed to be independent of the free variables $\mathbf{w}_{it}$ which are determined when the firm realizes its productivity shocks. This assumption allows one to skip the second stage in estimating the elasticity of output with regard to the variable input (De Loecker et al. (2020)). However, Ackerberg et al. (2015) suggest that this elasticity can be consistently estimated in the first stage only if the free variables $\mathbf{w}_{it}$ (i.e., capital/overhead) show variability independently of the proxy variable i_{it} (i.e., investment). Thus, I allow for investment to depend on $\mathbf{w}_{it}$ in my estimation methodology, mandating a two-stage approach.

$$y_{it} = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + h(i_{it}, \mathbf{w}_{it}, \mathbf{x}_{it}) + \varepsilon_{it}$$

or,

$$y_{it} = \boldsymbol{\Phi}_{it}(i_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}) + \varepsilon_{it} \tag{12}$$

where $\boldsymbol{\Phi}_{it}(i_{it}, \mathbf{x}_{it}, \mathbf{w}_{it}) = \alpha + \mathbf{w}_{it}\boldsymbol{\beta} + \mathbf{x}_{it}\boldsymbol{\gamma} + h(i_{it}, \mathbf{w}_{it}, \mathbf{x}_{it})$. As both the production function and productivity are functions of the inputs, they cannot be separated in a first stage regression. To estimate the parameters outlined in specification (12), I estimate $\boldsymbol{\Phi}_{it}$ non-parametrically by fitting a third-degree polynomial for $h(\cdot)$ (Baqaee and Farhi (2020)).[56] This process yields the fitted residuals $\hat{\varepsilon}_{it}$, along with the fitted parameters $\hat{\boldsymbol{\beta}}$, $\hat{\boldsymbol{\gamma}}$ and $\hat{\alpha}$. Utilizing these fitted values, I compute the productivity $\omega_{it} = y_{it} - \hat{\alpha} - \mathbf{w}_{it}\hat{\boldsymbol{\beta}} - \mathbf{x}_{it}\hat{\boldsymbol{\gamma}} - \hat{\varepsilon}_{it}$ as indicated in specification (9), as well as the productivity for a previous period, ω_{it-1}.

Turning to specification (10), I derive $\xi_{it}(\theta_t)$ by projecting the productivity ω_{it} onto its lag ω_{it-1}, where θ_t relates to the vector of output elasticities $\{\theta_t^v, \theta_t^k\}$. As noted by Raval (2023) and De Loecker et al. (2020), $\xi_{it}(\theta_t)$ is a function of output elasticities since it is determined by both current and lagged productivities ω_{it} and ω_{it-1}, which, in turn, are influenced by these elasticities. Furthermore, as $\xi_{it}(\theta_t)$ is independent of inputs chosen before time t, moments of $\xi_{it}(\theta_t)$ multiplied by inputs chosen before the productivity shock, such as $E(\xi_{it}(\theta_t)w_{it-1}^v)$ or $E(\xi_{it}(\theta_t)x_{it}^k)$[57], are sufficient to identify the coefficients of the production function (Raval (2023)). Accordingly, in a second-stage, I harness GMM in exploiting the moment conditions:

$$E\left(\xi_{it}(\theta_t)\begin{bmatrix} w_{it-1}^v \\ x_{it}^k \end{bmatrix}\right) = 0$$

to estimate the parameters θ_t^v and θ_t^k, corresponding to the output elasticities of the variable input (in specification 8) and capital input. In the context of "Production Function 2", an additional moment identifies the output elasticity of the overhead (SG&A) input, $E(\xi_{it}(\theta_t)x_{it}^o) = 0$[58].

Finally, I follow De Loecker and Warzynski (2012) and Ackerberg et al. (2015) in correcting the

[56]Note that non-parametric estimation frequently incorporates polynomial approximations to achieve a flexible modeling of data relationships without prescribing a specific functional form (Munkhammar et al. (2017)).

[57]Note that w_{it-1}^v relates to the element corresponding to the (sole) variable input in the vector of free variables $\mathbf{w}_{it}$, while x_{it}^k relates to the element corresponding to k_{it} in the vector of state variables $\mathbf{x}_{it}$.

[58]Note that x_{it}^o relates to the element corresponding to overhead in the vector of state variables $\mathbf{x}_{it}$.

value of sales in the input share of revenue for the measurement error estimated in the first stage. To that end, I modify specification 8 so that the estimated markups correspond to:

$$\hat{\mu}_{it} = \frac{\hat{\theta}^{v}_{it}}{\alpha_{it} \cdot \exp\left(\hat{\varepsilon}_{it}\right)}$$

where $\hat{\varepsilon}_{it}$ corresponds to the fitted residuals estimated in specification 12.

8.3 Computation of Common Ownership Weights

As detailed in Section 2.3, I follow Backus et al. (2021b) in their definition and computation of firm-level profit weights. This approach posits that an investor s holds a proportional claim, denoted by β_{fs}, to the profits π_f of firm f, where β_{fs} represents the ownership share of firm f by investor s. An investor is a common owner if $\beta_{fs} > 0$ for multiple firms. The profits of a common owner can thus be defined as the sum of its profits from its portfolio investments weighted by its cash flow rights:

$$v_s = \sum_{\forall g} \beta_{gs} \pi_g$$

In Rotemberg (1984)'s framework, a firm acts to maximize the profits of its shareholders s. However, because porfolios differ across shareholders, investors will disagree about the optimal strategy. To resolve this, Backus et al. (2021b) introduce a crucial assumption that managers in firm f will place a Pareto weight γ_{fs} on the portfolio profits of investor s and maximize the Pareto-weighted sum of their investors' profits. These "Pareto weights" may be interpreted as "control weights", reflecting the influence of each investor's profits in the firm's decision-making process.

Given the aforementioned assumptions, the objective function of the firm may be rewritten as a weighted portfolio of own-firm and rival profits, where firm f attempts to maximize the expression Q_f:

$$
\begin{aligned}
Q_f(x_f, x_{-f}) &= \sum_{\forall s} \gamma_{fs} \cdot v_s(x_f, x_{-f}) \\
&= \sum_{\forall s} \gamma_{fs} \cdot \left(\sum_{\forall g} \beta_{gs} \cdot \pi_g(x_f, x_{-f}) \right) \\
&= \sum_{\forall s} \gamma_{fs} \beta_{fs} \pi_f + \sum_{\forall s} \gamma_{fs} \sum_{\forall f \neq g} \beta_{gs} \pi_g
\end{aligned}
$$

Normalizing the objective function Q_f by $\sum_{\forall s} \gamma_{fs} \beta_{fs}$, we can rewrite $Q_{fnorm} = \frac{Q_f(x_f, x_{-f})}{\sum_{\forall s} \gamma_{fs} \beta_{fs}}$ as:

$$
\begin{aligned}
Q_{fnorm} &= \pi_f + \sum_{\forall f \neq g} \left(\frac{\sum_{\forall s} \gamma_{fs} \beta_{gs}}{\sum_{\forall s} \gamma_{fs} \beta_{fs}} \right) \pi_g \\
&= \pi_f + \sum_{\forall f \neq g} \kappa_{fg}(\gamma_f, \beta) \cdot \pi_g
\end{aligned} \tag{13}
$$

so that κ_{ff} is normalized to 1 for all firms f. Accordingly, in firm f's maximization problem, the profit weight κ_{fg} may be interpreted as the value of a dollar of profits accruing to firm g, relative to a dollar of profits for firm f, or the "Edgeworth coefficient of effective sympathy" between firms f and g (Amel-Zadeh et al. (2022)).

By assuming a model of "proportional control" where $\gamma_{fs} = \beta_{fs}$, we can rewrite κ_{fg} in expression (13) so that:

$$
\begin{aligned}
\kappa_{fg}(\beta) &= \frac{\sum_{\forall s} \gamma_{fs} \beta_{gs}}{\sum_{\forall s} \gamma_{fs} \beta_{fs}} \\
&= \frac{\sum_{\forall s} \beta_{fs} \beta_{gs}}{\sum_{\forall s} \left(\beta_{fs} \right)^2}
\end{aligned}
$$

Letting $\boldsymbol{\beta}_f$ denote a vector over s, κ_{fg} may be rewritten as:

$$
\kappa_{fg}(\beta) = \frac{\boldsymbol{\beta}_f \cdot \boldsymbol{\beta}_g}{\boldsymbol{\beta}_f \cdot \boldsymbol{\beta}_f}
$$

or, by using the geometric definition of the inner product where $\boldsymbol{\beta}_f \cdot \boldsymbol{\beta}_g = \cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_g\right\|$:

$$\begin{aligned}
\kappa_{fg}(\beta) &= \frac{\cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_g\right\|}{\cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_f) \left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_f\right\|} \\
&= \cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \cdot \frac{\left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_g\right\|}{\left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_f\right\|} \\
&= \cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \frac{\left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_g\right\|}{\left\|\boldsymbol{\beta}_f\right\|^2}
\end{aligned}$$

where $\left\|\boldsymbol{\beta}_i\right\|$ represents the L_2 norm $\sqrt{\sum_i \beta_i^2}$. As Backus et al. note, κ_{fg} may be decomposed into two components:

$$\kappa_{fg}(\beta) = \cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \cdot \sqrt{\frac{IHHI_g}{IHHI_f}} \tag{14}$$

where $IHHI_f = \left\|\boldsymbol{\beta}_f\right\|^2$, representing the Herfindahl-Hirschman Index for the investors in firm f, while $IHHI_g = \left\|\boldsymbol{\beta}_f\right\| \left\|\boldsymbol{\beta}_g\right\|$. The first term in expression (14), $\cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g)$, represents the extent of "overlapping ownership" between firms f and g. As investor positions in firm f become more similar to firm g, the angle between these portfolios shrinks, and $\cos(\boldsymbol{\beta}_f, \boldsymbol{\beta}_g) \to 1$. The second term in expression (14), $\sqrt{\frac{IHHI_g}{IHHI_f}}$, represents "relative investor concentration", a term that depicts the "price" of investor control in firm f vis-a-vis firm g. Intuitively, holding all else equal, given that $IHHI_f$ is in the denominator, firms with concentrated investors will assign more importance to their own profits and less significance to competitor profits, resulting in a smaller value for κ_{fg}. On the other hand, with $IHHI_g$ in the numerator, investors with relatively more concentrated ownership in firm g will induce firm f to place greater emphasis on firm g's profits, leading to a larger value for κ_{fg}.