Ownership and Productivity in Corporate America

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A thesis submitted for the degree of
Doctor of Philosophy

Trinity 2024

Based on a novel, comprehensive data set of U.S. corporations' ownership structures between 2000 and 2020, this thesis studies the incentives and effects of shareholder governance in U.S. corporations. Chapter 1 describes the data set construction and ownership structures of the largest U.S. firms. Different from previous work, our data set comprises all investors reporting common stock holdings to the Securities Exchange Commission. The analysis uncovers an unexpectedly high degree of heterogeneity in ownership structures and portfolio incentives. The fraction of control held by universally or within-industry diversified investors, who theoretically benefit from joint firm value maximization, increases substantially between 2000-2020. Highly diversified hedge fund activists and consolidation among asset managers are driving the growth of universal and common ownership, while undiversified corporate insiders and non-financial blockholders reduce both. Chapter 2 expands the analysis of shareholder governance into the effects of common ownership on corporate productivity. In theory, ownership of competing firms can soften competition and lead to higher markups or cause weaker managerial incentives and thereby lower productivity. Using panel regressions and an event study, we find that increased common ownership incentives indeed lead to lower productivity via less performance-sensitive managerial pay. Chapter 3 provides unprecedented evidence of activists' diversified portfolio holdings and incentives. Analyses of abnormal returns suggest that activist holdings of targeted and competing firms jointly outperform target-only holdings. An event study indicates that a reduction in product differentiation between targets and activist owned competitors, alongside profitability and market share increases at these competitors could be the origin of financial excess returns. This dissertation contributes to the empirical evidence of corporations' ownership structures and governance outcomes, demonstrating the need to assess governance effects considering all shareholders and diverging portfolio incentives.

Supervisors This thesis was supervised by Martin Schmalz and Steve Bond.

Total words This thesis contains approximately 79,000 words.

Statement of authorship The research contained in this thesis is exclusively carried out by me as a DPhil student at the University of Oxford between October 2020 and August 2024. No part of this thesis has been submitted for a degree at the University of Oxford or any other university. Chapter 1 and 2 are joint projects with Amir Amel-Zadeh and Martin Schmalz. Chapter 3 is entirely my own work.

Acknowledgment of funding I gratefully acknowledge funding from Saïd Business School Foundation. I am also thankful for generous financial support from Worcester College.

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To my family,
for always being there

Acknowledgments

This dissertation would not have been possible, and not nearly as enjoyable, but for the support and advice from a few people.

I am grateful to my advisors and co-authors, for their constructive criticism and advice over the past four years. Martin, your initial reaching out to me was instrumental to finding my way through the DPhil program. I hope that I managed to internalize some of your uniquely quick economic intuition and wide research interests. Your rigorous presentation training for the most renowned conferences and shared thoughts on life in academia, were certainly key to shaping my path post-DPhil and have provided me with presentation, discussion and strategic planning skills that I will continuously value. Steve, your feedback and detailed questioning of my methods not only helped me develop technical skills beyond anything I understood in MPhil coursework, it also taught me how to pose more rigorous and detail-oriented questions, which will be a useful skill in all future work. Amir, your willingness to discuss and comment on my work and writing at any point in this DPhil, has not only improved my writing style immensely, but also taught and carried me through the long submission and revision processes of academic papers.

I am grateful to my colleagues at the Business School and Economics Department in Oxford and Chicago. Your feedback on my working ideas and willingness to attend and comment on my presentations or read my work have been invaluable to me over the past four years. Without your support I would certainly not be where I am now. A special thank you to Luigi Zingales, Michael McMahon, Ken Okamura, Gregory Besharov, Oren Sussman, Anthony Limburg and Giulio Gottardo. The time I spent in conversation with you has benefited not only my dissertation, but also my personal development as a critical thinker, economist and teacher.

Most importantly, I am forever grateful to my family and friends. Your unwavering support and encouragement have made the past six challenging MPhil and DPhil years a brilliant and unforgettable experience. A time I would never want to miss in my life.

Abstract

Based on a novel, comprehensive data set of U.S. corporations' ownership structures between 2000 and 2020, this thesis studies the incentives and effects of shareholder governance in U.S. corporations. Chapter 1 describes the data set construction and ownership structures of the largest U.S. firms. Different from previous work, our data set comprises all investors reporting common stock holdings to the Securities Exchange Commission. The analysis uncovers an unexpectedly high degree of heterogeneity in ownership structures and portfolio incentives. The fraction of control held by universally or within-industry diversified investors, who theoretically benefit from joint firm value maximization, increases substantially between 2000-2020. Highly diversified hedge fund activists and consolidation among asset managers are driving the growth of universal and common ownership, while undiversified corporate insiders and non-financial blockholders reduce both. Chapter 2 expands the analysis of shareholder governance into the effects of common ownership on corporate productivity. In theory, ownership of competing firms can soften competition and lead to higher markups or cause weaker managerial incentives and thereby lower productivity. Using panel regressions and an event study, we find that increased common ownership incentives indeed lead to lower productivity via less performance-sensitive managerial pay. Chapter 3 provides unprecedented evidence of activists' diversified portfolio holdings and incentives. Analyses of abnormal returns suggest that activist holdings of targeted and competing firms jointly outperform target-only holdings. An event study indicates that a reduction in product differentiation between targets and activist owned competitors, alongside profitability and market share increases at these competitors could be the origin of financial excess returns. This dissertation contributes to the empirical evidence of corporations' ownership structures and governance outcomes, demonstrating the need to assess governance effects considering all shareholders and diverging portfolio incentives.

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Introduction

Research in corporate finance and more specifically in the sub-field corporate governance actively studies the links between human interactions and market forces and their impact on corporate performance, economic growth and welfare. One key interaction happens between the owners of a corporation and its managers, as the owners delegate control of their business and assets to specialized managers. Because owners earn a return on the business' asset value, while managers earn a pre-arranged wage, their incentives to maximize the business' value are not aligned, giving rise to the agency conflict. To protect the owners' financial interests and to alleviate the inherent monitoring issues a variety of mechanisms that align managers' incentives with those of owners have been studied theoretically and empirically.

Most theories of corporate governance assume that owners of a corporation are undiversified, meaning they are owners of exactly one corporation whose value and returns they seek to maximize. A corporate governance mechanism in this setting needs to incentivize the manager to maximize one firm's value, only. Reality diverges from this assumption. Free access to capital markets and the ability to own only small fractions of many publicly traded corporations, for example via index funds, imply that most owners of public corporations are highly diversified. These owners, who hold financial interests in many firms concurrently, benefit when those firms maximize their joint value and returns. However, if firms impose externalities on each other, for example through competitive links, maximizing one firm's value may come at a cost to another firm's value. In this setting it is unclear what the managers should be incentivized to do and what the effects of deviation from the own-firm-value maximization rule on firm performance are. This dissertation assesses the ownership of U.S. public corporations and portfolio structures of their shareholders, to determine the owners' prevailing interests and to analyze resulting managerial incentives, corporate performance and productivity outcomes.

To do so, I first establish a data set of common stock ownership structures of U.S. public firms in collaboration with my co-authors, that accounts for *all* owners of common stock. In contrast, virtually all existing broad-based empirical evidence on corporate ownership has been based on data of financial institutions' corporate holdings *only* (Thomson Reuters 13-F data). These financial institutional owners are highly diversified by the nature of their business and therefore benefit when the aggregate value of portfolio firms increases. Accounting only for these investors overestimates the owners' overall financial interests in joint firm value maximization. In addition, this research focuses on owners who often lack the incentive or the mandate to govern and discipline corporate managers actively. Our data set adds more dimensions to this analysis by identifying many influential and undiversified owners, such as families, founders, executives or non-financial investors, who typically have a stronger governance role and a concentrated financial interest in only one firm's value maximization. The resulting comprehensive ownership structures are more heterogeneous in investor types and portfolio incentives than existing research assumes. Comparable data sets have been used for single-industry studies or small hand-collected samples of firms, however, never at the scale we compiled. The data set comprises all measurable owners of corporate America, meaning all investors required to report their holdings of common stock to the Securities Exchange Commission (SEC). We scrape and parse all ownership reports available on the SEC's online database between 1999 and 2021. This includes financial institutional investment managers' holdings, reported on 13-F filings, blockholders' and hedge fund activists' holdings, reported on SC 13-D and SC 13-G filings, and corporate insiders' holdings, reported on Form 3, 4, and 5 filings. Separately, we manually assemble a list of all firms with multiple classes of common stocks outstanding and the differential voting rights attributed to each class. Adding this information to the ownership data, we can assign the correct number of votes to each shareholding, which can meaningfully differ from the number of shares held (e.g. Berkshire Hathaway Class B shares carry only 0.0001 votes per share whereas Class A shares carry 1 vote each). To combine ownership and control rights of the three different types of filers, we concatenate the data sets and remove duplicated ownership across or within file types, but aggregate ownership of investor groups if they file separate reports (such as BlackRock, BlackRock Germany and BlackRock Australia). More details on the data construction process are contained in the Appendix of Chapter 1.

The first chapter of this dissertation asks who America's largest corporations' most influential shareholders are and what their portfolio incentives are. It contributes novel insights to the research on shareholder structures (Azar & Vives, 2021; Schmalz, 2021), because many influential shareholders and their portfolio interests remain under-researched, while academic interest focuses on the concentration of assets among the "Big Three" institutional investment managers, BlackRock, Vanguard and StateStreet (Schmalz, 2021). Based on our comprehensive data set we find more heterogeneity among the largest shareholders of S&P 500 corporations between 2003 and 2020 than assumed. The Big Three and other large institutional investment managers hold substantial stakes in virtually all S&P 500 firms, with BlackRock and Vanguard, respectively, owning on average 6-8% of each firm. The average aggregate ownership of the Big Three alone accounts for 15-25% of all shares outstanding. With completely diversified holdings, giving rise to the label "universal owners", these investors have a financial incentive to help all firms maximize their returns, without imposing big negative externalities on each other. As previous analyses consider only these investors, incentives to internalize cross-firm externalities have often been inflated. Accounting for the whole ownership structure lowers the average level of incentives to internalize externalities, but also increases the heterogeneity of such incentives across firms. We identify another group of diversified investors who benefit from internalization, comprising strategic financial investors and hedge fund activists classified using data provided by Brav, Jiang, and Li (2022). These owners are selectively invested and engaged monitors of their portfolio firms. They have both the resources and the objective to affect corporate performance to derive a financial benefit. Given their ability to engage management and their selectively diversified portfolio holdings, these owners are more likely to impose managerial incentives to internalize portfolio firms' externalities on other portfolio firms. In contrast, corporate insiders and non-financial blockholders, who hold the largest ownership stakes in about 10% of the sample firms, are markedly less diversified and completely neglected in most existing work. Only 85% and 45% of insiders and non-financial blockholders, respectively, hold stakes in more than one firm in a given quarter, leading to a significant reduction in the average incentives to internalize externalities once they are taken into account. Following this first assessment of corporate ownership structures and investors' portfolio diversification, we study the drivers of cross-sectional and time-series variation in universal and common ownership. Universal ownership refers to the fraction of shares owned by investors diversified across almost all (95%) of the sample firms. Common ownership refers to the shares held by investors who own stakes in multiple firms competing in the same product markets. While universal owners in theory internalize any kind of spillover effects on every other firm, the externalities a common owner cares about are chiefly linked to competition and affect competitors, such as pricing, market power and cost-cutting. Universal and common ownership is measured by the average control-weighted cash flow right of investors in a firm a relative to their control-weighted cash flow right in a firm or competitor b. This measure is also referred to as profit weight, as it captures how much the owners of firm a care about firm b's profits relative to the profits of firm a (O'Brien & Salop, 2000). Common ownership only considers firm pairs competing in the same product market, while universal ownership considers any firm pair profit weight. Competitors are determined by common industry classifications or the Hoberg and Phillips, 2010 product similarity index. In panel regressions we find that insiders and non-financial blockholders unsurprisingly reduce both universal and common ownership, due to lower portfolio diversification. The Big Three, with sizable investments in every sample firm, increase universal ownership beyond what pure indexing implies, while their effect on common ownership over and above indexing is ambiguous, depending on the classification of competitors. The positive effect on universal ownership is likely driven by the consolidation of control across indexed and non-indexed sub-fund portfolios, leading to excessive levels of portfolio diversification relative to smaller institutional investment managers. An event study of the BlackRock-Barclays Global Investors acquisition further highlights that consolidation in the asset management industry increases both universal and common ownership significantly and persistently. Surprisingly, hedge fund activists also increase universal and common ownership on average and in contrast to the frequent implicit assumption that activists are only selectively diversified across a few targeted firms whose value they intend to maximize. Analyzing this group of investors in detail, we find that while the average activist increases universal and common ownership, "engaged" activists, referring to activists with an ongoing campaign in an industry, reduce universal and common ownership. This suggests that activists on the whole are more diversified than expected, however whilst running a campaign they are less diversified in this sector than the average institutional investor. Chapter 3 will analyze the question of activist ownership in greater detail. Overall, Chapter 1 provides comprehensive evidence that influential shareholders of the largest U.S. firms have more diverse portfolio interests than previously established. We find a surprising degree of diversified ownership among hedge fund activists, validating further research into activists' portfolio interests and how they impact corporate governance. We also document that the Big Three institutional investors contribute positively to universal ownership, over and above textbook-indexing implied levels, due to the centralization of control within fund families and due to consolidation in the asset management industry across fund families. This finding is interesting because it overturns previous results by Backus et al., 2021b and re-opens the discussion on the governance implications of control centralization and consolidation in the asset management industry. Future research into shareholder governance should take the overall ownership structure of corporations into account and distinguish between investors with different investment horizons, ability and portfolio incentives to engage management.

The second chapter delves deeper into the effects of owners' diversified portfolio interests on corporate performance, specifically focusing on the relationship between common ownership (portfolio holdings diversified across competing firms) and corporate productivity. Common owners in theory benefit when managers of their commonly owned, competing firms coordinate efforts to increase valuations of all firms, either by collaborating on process and product innovation to increase productivity and reduce costs (Anton et al., 2021), or by competing less fiercely and charging higher prices to increase profit margins (Rotemberg, 1984). A novel theoretical contribution by Anton et al., 2022, suggests that common ownership can also negatively impact productivity when common owners design managerial compensation packages to be less performance-sensitive. Less performance-sensitive pay makes managers more likely to "enjoy the quiet life" (Bertrand & Mullainathan, 2003), which may soften competition but can also reduce efficiency improvements. This theory predicts a link between more common ownership, less performance-sensitive pay and lower productivity. Chapter 2 asks whether empirically common ownership is associated with lower productivity and if managerial compensation is the linking element. Common ownership is measured following the existing literature and the first chapter as the average control-weighted cash flow stake in competitors relative to the base firm, also referred to as profit weight. Total factor productivity is estimated based on balance sheet data and the cost shares approach, following the applied microeconomics literature (De Loecker & Syverson, 2021). The use of input costs and output sales revenue instead of quantity data in a setting where markets are likely subject to market power implies that our productivity estimates confound actual quantity productivity with firm-specific markup variation. In order to address this weakness, we separately estimate the effect of common ownership on markups, to infer the qualitative relationship between common ownership and actual productivity. Panel regressions suggest a significant, negative and non-linear correlation. More common ownership has a substantial negative impact on the productivity of firms with initially low levels of common ownership, while firms with high initial common ownership observe an insignificant increase in their productivity. To establish causality, we follow the existing literature and deploy a difference-in-difference model using index additions of competitors as events that cause exogenous variation in ownership incentives. The addition of a firm to the index increases common ownership at index incumbent firms in the same industry (index incumbent competitors), while common ownership at non-competing index incumbents remains unaffected except for small index rebalancing effects. The average effect of index additions on incumbent competitors' productivity is insignificantly negative, because several shocks affect productivity in countervailing ways. For example, the index addition can reduce the cost of capital of the newly added firm (Afego, 2017), increasing its competitiveness and incentivizing index incumbents to increase their efficiency in order to remain competitive. This competition effect may offset changes in productivity caused by the increased common ownership. To focus on the effect of the change in common ownership, we test how a competitor's index addition alters managerial incentives and thereby affects the productivity of index incumbents. Combining an instrumental variables and a difference-in-difference model, we find that the reduction in the performance-sensitivity of managerial pay due to the increase in common ownership causes a significant reduction in the productivity of index incumbents. The negative impact of common ownership on productivity suggested by Anton et al., 2022 is therefore validated. To quantify the impact on total factor productivity and infer accurate policy recommendations, further analysis using actual (quantity) productivity measures is required, but our results offer the first robust directional insights.

The third chapter of this dissertation extends the analysis of hedge fund activists' stock ownership, portfolio incentives and governance implications. The key question answered is what hedge fund activist portfolios look like and whether activists internalize spillover effects of their campaigns on portfolio firms competing with the targeted firm. This adds an entirely novel perspective to the research on hedge fund activism, which neglected the portfolios and diversified incentives of activists to date (Brav, Jiang, & Li, 2022). Because of their ability to impact corporate governance and performance, the implications of diversified activist portfolio interests may be more relevant than of diversified index funds. Combining our ownership data set with a list of hedge fund activist campaigns to identify activists, target firms and campaign start dates, I establish the first comprehensive data set of hedge fund activists' quarterly portfolio holdings for 2000-2020. Despite limiting the analysis to single-strategy activists, I find a surprising level of diversification in hedge fund activists' portfolios at and around campaign start. More than a third of all activists concurrently hold the target firm and never-targeted competitors of the target at campaign start. Ownership of competitors is not passive at a constant level, but increases until campaign start and declines afterwards, analogous to activist holdings of the target firm. The first part of my analysis tests if diversified activists realize superior returns on their portfolio of targeted and competing firms, relative to target-only returns. Over a three year pre- and post-campaign start window, the buy-and-hold abnormal returns to the portfolio of targeted and competing firms are significantly positive and higher than the target-only returns of a given campaign. Based on corresponding calendar-time portfolios of targeted and competitor firms, I estimate portfolio alphas of a Fama-French 5 Factor model and find corroborating evidence that diversified portfolios outperform target-only holdings. The results suggest that excess returns are chiefly due to the competing firms providing a hedge against the target's deteriorating returns before campaign announcement, and slightly positive excess returns post-campaign start. Next I study economic spillover effects of campaigns on portfolio competitors that could rationalize the excess returns. I estimate a staggered difference-in-difference model using all campaigns with activist common ownership (of targets and competitors) between 2005 and 2016 as treatment events. Concerns regarding staggered treatment timing and two-way fixed effects are addressed with the corresponding econometric methods (stacked data and eventyear-by-firm or -year fixed effects, Baker et al., 2022). Control firms are competitors of the target, never owned by the activist and matched to both treated targets and treated activist owned competitors. I find that, in contrast to the controls, the similarity between targets' and activist owned competitors' products increases after the campaign start, implying lower product differentiation. This has a small negative impact on the targeted firm's productivity and sales share but benefits the activist owned competitors by markedly increasing their sales share, markups and profitability. Activist owned competitors significantly outperform non-activist owned competitors in response to the campaign, which explains their financial excess returns and implies that activists act on their diversified portfolio incentives. An analysis of announcement returns suggests the market is not aware of these incentives and spillover effects, as returns to commonly owned competitors do not react differently to the campaign announcement than other competitors' returns. Overall, Chapter 3 provides relevant evidence that activists are more diversified than previously expected and strategic about this diversification. Activist owned competitors benefit from positive spillovers derived from the activist campaign, contributing to the overall financial outperformance of the diversified activist's portfolio relative to the target-only returns. In light of these results, future research should assess the impact of activist campaigns on target firms, competitors and market structure taking into account the portfolio incentives of hedge fund activists. With more evidence on the competitive implications of diversified hedge fund activist campaigns, more oversight of activists' portfolio interests may need to be discussed.

The three key chapters of this dissertation identify heterogeneous levels portfolio diversification and incentives to internalize inter-firm spillover effects among hedge fund activists, large institutional investment managers and corporate insiders. Taking into account *all* owners of corporations reduces average incentives to internalize spillover effects relative to previous analysis. The diversified portfolio incentives of consolidated institutional investment managers and hedge fund activists are shown to have a negative impact on corporate productivity via managerial incentives and activist campaigns. In the latter case only targeted firms are negatively affected, while activist owned competitors increase their markups and profitability. Overall, these findings provide reason for concern about potential anti-competitive effects of the highly diversified portfolios of large and influential investors. However, different from existing work, my results suggest that an adequate policy response does not need to entail a blanket-ban on indexing or active governance. Instead, better regulatory oversight of consolidation in the asset management industry, hedge fund activist portfolio diversification and managerial incentive structures would address the concerns. Throughout this dissertation I demonstrate that accurate and comprehensive data on corporate ownership and investors' portfolio interests is a necessity to conduct unbiased empirical analysis in the field of corporate governance. To make such analysis feasible for other researchers, our data set on corporate ownership will become freely available for academic research with the conclusion of this dissertation.

Chapter 1

Mavericks, Universal, and Common Owners - The Largest Shareholders of U.S. Public Firms*

with **Amir Amel-Zadeh and Martin Schmalz**

Abstract We construct a novel dataset covering all types of known owners of the largest U.S. public firms. Ownership structures are more heterogeneous across firms – institutional investors are the largest owners less frequently and more firms are controlled by undiversified non-financial blockholders – than previously believed. Common ownership within industry is more pronounced than implied by indexing, overturning previous research. One reason is that activist shareholders often hold passive financial interests in product market rivals; another is mergers of asset managers. These findings inform with facts a thus far largely theoretical policy debate related to the changing nature of ownership of U.S. firms.

*We thank Matt Backus, Chris Conlon, and Michael Sinkinson for making code available, Patrick Bolton (discussant), Todd Gormley (discussant) and seminar audiences at the Federal Reserve Bank of New York and the Universities of Bonn, Groningen, Oxford, and Rotterdam, and the audience at MaCCI, CRESSE, NBER Summer Institute, EARIE, EWFS and the Royal Economic Society for valuable feedback. Vladimir Fedoseev and Hady Elkady provided outstanding research assistance. Amel-Zadeh acknowledges support from the Saïd Business School Foundation and Schmalz acknowledges support from Deutsche Forschungsgemeinschaft under Germany's Excellence Strategy – EXC 2126/1–390838866.

1.1 Introduction

A fast-growing academic literature and policy debate discusses the potential role of structural changes in U.S. corporate ownership structures for a wide range of outcomes, including corporate governance, product market competition, macroeconomic outcomes, and even climate change. For example, one literature suggests that so-called universal owners, thanks to ostensibly holding a 'stake in the overall economy', have both an incentive and the ability to induce portfolio firms to internalize ecological and social externalities (e.g., Hart & Zingales, 2017). The same authors, however, point out that universal investors often are also common owners of competitors, which may have the effect of lessening competition. The concern that first findings to that effect in specific industries (e.g., Azar et al., 2018) may have external validity has led some to suggest changes in antitrust enforcement that would likely cause economy-wide changes in corporate ownership structures (Posner et al., 2017). Meanwhile, others have observed that the rise of so-called 'passive' index ownership leads to disincentives to exert effective governance and monitoring, which some argue should be curbed by limiting voting rights of passive investors (Shapiro Lund, 2017).

Perhaps surprisingly given the advanced stage of this debate, there is not much of a factual basis. Little is actually known about the extent to which universal investors, common owners, or 'passive' funds have in fact become dominating shareholders of the largest U.S. firms, whether universal ownership is more widespread than common ownership, and whether institutional ownership has come to dominate ownership and control by insiders and non-financial blockholders. Neither is it known to what extent indexing drives universal and common ownership, or whether consolidation in asset management contributes positively as well. Prior claims to that effect in the literature are often based on the holdings of institutional shareholders (reported on SEC form 13-F) but omit the holdings of non-financial blockholders (think Elon Musk or Jeff Bezos), family offices, insiders, and activists. For example, Backus et al., 2021b, based on an analysis of 13-F records alone, claim that indexing explains the levels of "common ownership in America", whereas the holdings of the 'Big-3' asset managers contribute negatively.[2] Whether this claim is correct carries important

[2]Popular papers in the finance literature on related topics are likewise based on 13-F records alone (Gilje et al., 2020; Koch et al., 2021; Lewellen & Lowry, 2021).

policy implications. If indexing alone drove common ownership, this would suggest an incompatibility between cheap diversification and competition (as first suggested by Rotemberg, 1984. Perhaps not surprisingly, restricting textbook indexing – perhaps the most successful financial innovation of the 20th century – is not a popular idea among many audiences. If indexing alone drove common ownership, regulators would also be right to ignore the growing consolidation of asset management and associated increases in the concentration of corporate control. As we will show, however, these prior findings are qualitatively reversed when a more comprehensive and correct set of ownership records is consulted. Hence, this paper provides the factual basis for a new narrative on the drivers of universal and common ownership, including the role of concentrated asset management.

Let us illustrate with an example why the omission of investors other than 13-F filers could yield incorrect answers. Consider calculating a measure of common ownership that captures to which extent the most influential shareholders in one firm also have financial interests in the others between three of America's largest waste management firms, Republic Services, Waste Management, and Rollins (as of Q4 2020/Q1 2021) .[3]

Republic Srv	%	File		**Waste Mgmt**	%	File		**Rollins**	%	File
Cascade Inv	34.1	13-D		Vanguard	8.3	13-F		LOR Inc	45.1	13-D
BlackRock	6.3	13-F		BlackRock	7.2	13-F		Vanguard	5.5	13-F
Vanguard	5.7	13-F		State Street	4.8	13-F		Stichting Pe.	3.7	13-F
State Street	3.3	13-F		Gates Found.	4.4	13-F		BlackRock	3.6	13-F
TRowe Price	3.2	13-F		Cascade Inv	3.9	13-G		State Street	2.2	13-F

Table 1.1: Top 5 owners in three largest U.S. waste management firms Q4 2020

Table 1.1 shows the top 5 owners of the three firms. While the 13-F filers Vanguard, BlackRock, State Street, and other asset managers indeed have holdings in all three firms, the largest and arguably most influential owner of Rollins is LOR Inc., the family office of Wayne Rollins Sr., whose ownership stake can only be identified from SC 13-D filings. LOR Inc. does not hold significant stakes in the other firms. On the other hand, the largest blockholder in Republic Services is Cascade Investment (Bill

[3]One such measure are "profit weights" widely used in the economics literature (Antón et al., 2016; Backus et al., 2021a, 2021b; López & Vives, 2019).

Gates' family office), which also holds a large stake in Waste Management. (This is in addition to an ownership stake that Bill Gates already holds in the firm through the Gates Foundation). These holdings would likewise be overlooked by consulting 13-F records alone. We conclude from this example that ignoring holdings that are disclosed on filings other than 13-Fs has the potential to mask the true variation across U.S. firms' ownership structures, and will lead to over-estimates of the extent of universal and common ownership between two firms in some cases, and under-estimates in others. Either way, an analysis of 13-F records alone does not provide a suitable basis to inform a debate on the changing nature of the ownership of U.S. firms.

We address the question to which extent the intuition from the above examples generalizes to America's largest publicly traded firms. In particular, we first ask: who are America's largest firms' largest shareholders, and what are these shareholders' portfolio interests? We then examine the implications for the ownership structures of America's largest firms and, in particular, estimate how much "universal ownership" across all firms, and how much "common ownership" across industry rivals there is. In doing so, we identify which role blockholders and insiders play in explaining the variation across firms and over time in universal and common ownership. Lastly, we investigate whether the consolidation of asset managers increases measures of universal and common ownership, or whether the increase of textbook "indexing" alone explains the changing patterns of corporate ownership in America.

To answer the question what the drivers of common ownership of competitors and of universal ownership are, we construct a uniquely comprehensive and freely accessible dataset of U.S. corporate ownership that includes ownership records beyond those collected from 13-F filings used in prior research.

Considering 13-F records alone would cause researchers to ignore Elon Musk and Jeff Bezos, and lead to the erroneous conclusion that there is a high and homogeneous level of overlapping ownership between Amazon and Tesla. However, in fact, the stark difference in ownership structures and the unusually *low* level of overlapping ownership between Amazon and Tesla is precisely due to the presence of these relatively undiversified blockholders and insiders, who we call Mavericks, at the top of the ownership roster. At the same time, researchers using 13-F filings alone would have failed to observe the overlapping ownership holding by Musk between Tesla and Twitter, before taking Twitter private. Hence, omitting ownership by non-financial blockholders and insiders can lead to erroneous conclusions when examining common and universal ownership in either direction. Which direction the bias goes on average is an empirical question.

Furthermore, not all institutional investors are passive owners. Perhaps surprisingly, even activist investors do not always hold only one position per industry. For example, well-known "activist" investor Bill Ackman's Pershing Square is among the largest shareholders of Burger King, Chipotle, and Domino's Pizza, contributing *positively* to the level of common ownership in that industry.[4]

This is important because using measures that mask the variation in overlapping ownership can lead to underestimating the effect of such ownership on a variety of outcomes; and to a failure to reject the null hypothesis of no overlapping-ownership effects, as well as other econometric biases.[5]

In this paper we identify the largest shareholders for all single-class S&P 500 firms, examine their portfolio holdings and assess the effect of including blockholders and insiders in measures of common and universal ownership. For this we scrape and parse all ownership records from the SEC's EDGAR system for the years 2003-2020 for all single-class S&P 500 firms, and merge the ownership information thus obtained to construct ownership records at the firm level. In particular, we merge information from 13-F filings by institutional investors with SC 13-D and SC 13-G filings by blockholders, as well as Form 3, 4, and 5 filings by corporate insiders, and clean the data for duplicates and a large number of other errors. We first document which investor type, whether insider, activist, non-financial blockholder, financial institution or "Big Three", is the largest shareholder of a firm, of how many firms and whether their dominance varies over time. We identify activists following Brav et al.

[4]Pershing Square files 13-D in some and 13-F in other cases, however; management of the target firms may nevertheless perceive a 13-F position by Pershing Square differently than a similarly large 13-F position by a typical "passive" investor. ValueAct's insufficiently disclosed acquisition of an "activist" position in competitors Baker Hughes and Halliburton is another prominent example of activist common ownership (link).

[5]This concern has been shown to be relevant in practice. Anton et al., 2022 find that estimates of common ownership on managerial incentives roughly double once blockholders are included in the calculation of common ownership.

(2008) to capture the investors likely to engage with their portfolio firms.

We then examine how diversified the portfolios of the different investor types are, whether they are "mavericks", hold concentrated or diversified portfolios. Based on that, we calculate measures of universal ownership called "profit weights" or "kappas", which measure the extent to which the largest shareholders of one firm have a financial interest in other firms, compared to their financial interest in the base firm.

We also calculate profit weights of within-industry firm pairs, thus measuring horizontal "common ownership." We are particularly interested in assessing whether and by how much profit weights are affected by the holdings of activists, non-financial blockholders and insiders.[6]

To more formally examine the determinants of universal and common ownership, we regress the measures of universal and common ownership on holdings by the different owner types as well as measures of textbook indexing from the literature. Finally, we assess how concentration in the asset management industry affects universal and common ownership measures when taking into account blockholders and insiders. For this, we calculate the increase of universal and common ownership implied by the BlackRock-Barclays Global Investors acquisition and test whether it predicts future levels of overlapping ownership.

Our key findings are as follows. First, ownership structures are more heterogeneous across firms than previously believed, based on studies examining only institutional investor portfolios. For example, between 10% and 20% of firms have a dominant activist, non-financial blockholder or insider among their largest shareholders. Second, whereas exceptions exist, non-financial blockholders' and insiders' portfolios tend to be much less diversified than institutional investors' portfolios. In fact, most of them are mavericks who hold only a single large stake in one firm. As a result, universal and common ownership levels are lower once we account for the holdings of blockholders and insiders. Third, in contrast to our expectations, we find that activists hold surprisingly diversified portfolios, frequently comprising multiple firms in the same

[6] Profit weights are a weighted sum of a given firm's shareholders' portfolio profits, where the weights are the shareholders' respective control shares in the firm. Profit weights capture the extent to which the most influential shareholders should like the firm to behave as if it put weight on other firms' profits in addition to its own profits.

industry, even though they often actively engage in only one. Due to their selective diversification, activists contribute positively to common ownership.

Using our more accurate and comprehensive dataset also changes the sign for existing findings in the literature, specifically the finding in Backus et al. (2021b) that the level of common ownership is explained by "indexing" strategies. Instead, we find that the holdings of the Big Three institutional asset managers increase both universal and common ownership over and above the level explained by textbook indexing. Moreover, throughout our sample period from 2003 to 2020 we find that common ownership levels are higher than universal ownership levels, implying that policy makers could reduce common ownership of industry rivals without reducing textbook indexing, which involves holding a widely diversified portfolio of all firms rather than concentrated holdings in one industry. Lastly, we find that consolidation through mergers in the asset management industry increases both common ownership and universal ownership persistently.

A policy-relevant take-away from our analysis is therefore that there need not be a trade-off between good governance aided by the presence of large blockholders and a reduction of common ownership of industry competitors. The latter was previously believed to be driven by large financial and non-financial investors, but we show that in practice non-financial blockholders tend to be mavericks instead.

The finding that some active shareholders choose to hold product market competitors carries another important policy implication: common ownership can be reduced without restricting textbook indexing. It can be reduced by preventing active common ownership links among industry competitors that are frequently formed by family offices, hedge funds, and conglomerates. Increases in common ownership can further be prevented by policing mergers of asset management firms, which do not create more textbook index funds, but which increase concentration of corporate control by centralizing voting and engagement across funds.

A takeaway for academic researchers is that non-financial blockholders and insiders play an important role in driving the level and variation of universal and common ownership among America's largest firms, and that omitting these investors can lead to qualitatively wrong conclusions about the level, causes and consequences of both universal ownership and common ownership. Using only institutional ownership from 13-F filings as the basis for research on overlapping ownership is therefore not an innocuous shortcut. Consequently, past findings in the literature based on institutional ownership alone should be interpreted with caution as they likely suffer from bias.

This paper contributes to the literature that examines the cross-sectional variation and trends in ownership structures of U.S. listed firms and its consequences (e.g., Azar & Vives, 2021; Backus et al., 2021b; Koch et al., 2021; Schmalz, 2021). Specifically, we provide evidence on the drivers of common and universal ownership in the cross-section and over time in the S&P 500. We do so by assembling a uniquely comprehensive and freely available data set of all types of owners of the largest publicly traded firms in America.[7] We thus enable better measurement of universal ownership, common ownership, and its drivers and show that ignoring blockholders and insiders in measures of common and universal ownership, as practiced in the literature thus far, can lead to significant bias and, in some instances, overturn prior results.

Our contribution most closely relates to Backus et al., 2021b (BCS), who offer the most recent evidence on common ownership among the largest U.S. publicly traded firms before this paper.[8] BCS also provide a great service to the profession – including but not limited to the literature on common ownership – by making the 13-F ownership data they assemble freely available. They thus helped the field overcome challenges related to 13-F data provided by Thomson Reuters through WRDS that had been popular in the literature thus far. We build on their contribution by constructing a data set along dimensions they acknowledge to be missing in their paper:

"*Occasionally, these controlling shareholders are inside or retail investors (e.g., the Walton family) ... it is possible to use data from SEC Forms 4, 5, 6, and 144 ... to construct industry holdings where available. Similarly, there is additional information on firm cross-holdings in 13-D and 13-G reports, which are more difficult to incorporate because they are not filed on a quarterly basis. These data are impractical to clean for analysis at the aggregate level. However, it is feasible and important to do so for case studies of particular industries as, e.g., Azar et al., 2018 do when*

[7]We make the data freely available for academic research on corporateownershipdata.com.

[8]Earlier papers documenting a secular increase in common ownership, also based solely on 13-F data, are reviewed in Schmalz, 2018.

they compute the profit weights for airlines and as Backus et al., 2021a do when they compute the profit weights for cereal." (Backus et al., 2021b, footnote 12).

We scrape, parse, and clean also the remaining SEC filings to understand the extent to which incorporating these filings changes the measurement of common and universal ownership and might affect conclusions drawn from prior studies.[9]

1.2 Data set construction

1.2.1 Ownership records on SEC filings

We scrape and parse the ownership records of S&P 500 firms as reported on filings required by the Securities Exchange Commission (SEC). In contrast to Backus et al., 2021b, who collect institutional ownership records from 13-F filings, we scrape not only filings by large institutional investors, but also filings by corporate insiders and blockholders, utilizing all ownership reports for investors in U.S. public corporations available on the SEC Edgar Archive. The fraction of stock ownership that remains not captured by any filing is attributable to retail investors.

Specifically, we parse six different SEC filings. Table 1.2 provides an overview of the key attributes of each filing type. More detail can be found in the data appendix. To summarize, 13-F filings are required on a quarterly basis from institutional investment managers with more than $100 million assets under management holding equity securities (and certain equity options and warrants) that trade on a U.S. exchange. A 13-F filing lists all securities owned by the institutional investor at the end of the quarter. Investors who acquire more than 5% of any equity security of a company are required to file a form SC 13-D within 10 days after the acquisition. If such blockholders acquire the equity securities *"not with the purpose nor the effect of changing*

[9] Aside from expanding the ownership dataset with the filings missing in BCS, we also improve the accuracy of existing sources of 13-F records. Due to differences in our parsing methodology, in 55% of filings the Central Index Key (*cik*) we extract is different from the *cik* BCS extract. We end up with 55% more *ciks* than BCS. For details, see Appendix 1.A. Other significant differences between the 13-F-only analysis presented in this paper and BCS' analysis are due to differences in how we consolidate asset managers' holdings (e.g. we consolidate holdings of BlackRock and BGI only at the time when the acquisition was consummated, as opposed to throughout the sample). A limitation of our analysis relative to BCS is that our data starts only in 2000. Hence, our data set only substitutes for theirs only for the past two decades. We detail these differences throughout the paper and the appendix.

or influencing the control of the issuer" (17 CFR §240.13d-1b.1.i), they are allowed to report any ownership change using the shorter form SC 13-G, which, for example, does not require the investor to disclose their intentions of acquiring the beneficial ownership.

Lastly, the SEC requires corporate insiders, such as officers and directors as well as beneficial owners of more than 10% of outstanding equity and several other groups of insiders to report transactions in company equity securities using Form 4. A person who becomes a reporting person under the Form 4 requirements will initially file a Form 3 report, indicating the person now classifies as a corporate insider. A Form 3 need not yet report any equity ownership. Subsequently, whenever insiders change their holdings of company equity, they are required to file a Form 4 within 2 days of the transaction. Within 45 days of the end of a company's fiscal year corporate insiders must report all transactions they did not previously report, on a Form 5. Corporate insiders who failed to file a Form 3 or Form 4 report for transactions in the previous fiscal year, are required to report these on the Form 5, too. Unlike 13-F, SC 13-D and SC 13-G filings, Forms 3, 4 and 5 not only report the overall number of shares owned by a corporate insider, but also other information related to an insider's transaction. Insider ownership is additionally classified into direct and indirect holdings, where the latter reflects that the insider holds shares through a trust or a family member.

Our data starts in 2003 Q3 as SEC regulations only required Forms 3, 4 and 5 electronically from 2003 (13-F, SC 13-D and SC 13-G reports are available electronically from 1998/99). Due to the limited number of insider reports filed before June 2003, we focus our analysis exclusively on the period from July 2003 until December 2019.

1.2.2 Building a comprehensive ownership data set

Our data set of U.S. firms' ownership combines disclosed shareholdings of S&P 500 firms from 13-F, SC 13-D and SC 13-G filings as well as from Forms 3, 4 and 5. One important intermediate step in collating the ownership from 13-F filings is to consolidate separately filed 13-F reports of incorporated funds of large institutional

Form type	Owner	Filed electronically	Frequency
13-F	Institutional investors with >$100 million in AUM	since 1999	quarterly, within 45 days of each quarter end
13-D	Investors acquiring >5% of an equity share class	since 1998	within 10 days of crossing the 5% threshold and for any acquisition/disposition of 1% or more thereafter
13-G	Investors acquiring >5% of an equity share class that are (a) exempt (b) qualified institutional (c) passive investors	since 1998	(a) within 45 days of the end of the calendar year (b) as of the end of the calendar year or month (if >10%) (c) within 45 days of the end of the calendar year or month (if >10%)
3	insiders and shareholders owning >10% of an equity share class	since 2003	within 10 days of becoming insider
4	insiders and shareholders owning >10% of an equity share class	since 2003	within 2 days of transaction
5	insiders and shareholders owning >10% of an equity share class	since 2003	only if failed to file Form 4 within 45 days of fiscal year end

Table 1.2: Short summary of SEC filing requirements

investment managers. We detail in Appendix 1.A.3 how our approach differs from the methodology in Backus et al. (2021b). Once completed, the parsed data provides the Central Index Key identifying the filing owner (*ownercik*), the *cusip* number identifying each security owned, a description of the security (e.g. "call option", "common stock"), the quantity of shares owned and the market value of the owner's holdings.

For blockholder (13DG) and corporate insider (Form 345) filings we develop two novel parsing methods coded in Python. The SC 13-D and SC 13-G filings report the *cik* of the main filing owner, the *cusip* of the security owned, a description of the security, and the amount of shares owned and voted on directly or in a shared facility. One difficulty arising in 13DG parsing (see Appendix 1.A.4 for more details) is that one report can be filed by multiple reporting owners. For example, when the Walton siblings report their holdings in Walmart, this 13-G will be filed jointly by Robson, John and Helen Walton, as well as the Walton Family Trust. Each sibling owns and votes some stocks directly, but they share the voting power of stocks held in the Family Trust. Hence, the number of securities owned with shared voting rights is reported several times. We deal with this duplication by first parsing each reporting investors' individual direct and shared securities ownership. In the Walmart case, this will produce four observations, one for each sibling and one for the trust. Ultimately, we keep the largest aggregate amount of shares reported by any one reporting person and discard all other reported shares. This yields a conservative estimate of the stock ownership allocated to the main filing owner.

The Form 3, 4 and 5 filings report detailed information about each transaction made by corporate insiders in their company's equity (and derivative) securities. For each transaction the security, the number of shares transacted, the ex-post number of shares owned and the nature of ownership (direct or indirect via a trust or spouse) by the insider is reported as an individual entry. To capture the insider's aggregate ownership after the transaction, we extract the title of the security and the residual number of shares owned for each transaction and then discard all entries, except for the last one for each nature of ownership. For example, if Bill Gates reports two transactions on a Form 4, one reporting on shares he owns directly, the other on shares he owns indirectly via the Bill & Melinda Gates Foundation, then we keep the ex-post number of shares owned for both entries and add them up, to reflect the aggregate number of shares owned by Gates after the transactions.

A further complication arises because corporate insider ownership reports differ from 13-F and 13DG reports in that they do not identify each security by a *cusip*. Instead, equity securities and derivatives are reported in separate tables and the filer provides a non-standardized, textual description of the security transacted, such as "call option", "common stock", "equity", featuring various typos and ambiguities. While the *cusip* and security title reported in 13-F, SC 13-D and SC 13-G reports allows us to differentiate between common stock and other securities relatively easily, this is not always the case for the free text description in insider filings. To retain only holdings of common stock in our data set, we deploy an extensive text cleaning, filtering and interpretation routine to the security description.[10] This routine is described in more detail in Appendix 1.A.5. Following BCS, we only keep common stock holdings. We then merge the security description with the company's trading *cusip* identifier for the given quarter. The resulting output includes the filing owner's *cik*, the owned security's *cusip*, a cleaned security description and the number of shares owned.

After cleaning and identifying holdings from all filing types (large institutional, insider and blockholder ownership), we need to fill gaps between reporting quarters. While 13-F reports are filed quarterly, blockholder and insider reports are required only when transactions in the underlying security are made. To fill the gaps in blockholder and insider ownership between transactions, we forward fill the holdings reported by a given owner in a given security until the next reported ownership for this owner-security combination. The rationale is that ownership stakes should not change in the meantime without a report being filed. This interpolation will create duplicates that are removed in the next step. If at the end of our sample (1 January 2020), the most recent filing reported a non-zero ownership stake, we forward-fill this ownership stake until the end, for a maximum of six quarters.

The final step requires aggregating the holdings of each owner in each company across the different file types, facing two more challenges. First, stock holdings for a

[10]While Form 4 filings separately report transactions in derivative and non-derivative securities, the type of non-derivative security is generally only described in a text comment or footnote.

given owner, security and point in time can be filed in multiple types of reports. For example, the SC 13-G filed jointly by the Walton Family Trust and the Walton siblings will duplicate shares that are reported by the Walton siblings in their individual Form 4 filings. To avoid double-counting, we first remove different types of ownership reports filed by the same *ownercik* in the same quarter. Because in some cases the *ownercik* will not be the same across different filing types (in the Walton example the SC 13-G is filed by the Walton Family Trust and the Form 4 is filed by the individual sibling, where each party has its own *ownercik*) we then remove stock holdings of exactly equal size across different file types for the same firm in the same quarter. We then spot check whether the resulting ownership structures are economically sensible and cross-check our results against various commercial data bases for consistency.

The completed data sample contains ownership structures of 742 firms and slightly less than 500 firms each quarter.

1.3 Results

1.3.1 America's largest shareholders and their portfolio interests

Categorizing U.S. corporate ownership

Using our novel data set of stock holdings we capture the ownership of 70-90% of outstanding equity of our sample of S&P 500 firms. To evaluate who the largest shareholders are and what their portfolio incentives look like, we differentiate between five categories of investors: the Big Three, asset managers, activists, insiders, and blockholders.

First, we identify the Big Three asset managers, comprising BlackRock, Vanguard, and StateStreet, and all their consolidated sub-entities summarized as the **Big Three**. We further classify 350 investors as **activists** using the list of investors with active engagements between 2000-2016 compiled by Brav et al., 2008 and Brav et al., 2010.[11]

[11] The activist investors identified in Brav et al., 2008, 2010 file reports SC 13-D/G and 13-F. That is, they might have blockholdings in firms with the intend to engage and others where they do not, at least explicitly, signal an intention to engage. We therefore also identify for some of our subsequent analyses engaged activists (i.e., activist SC 13-D filers) separately.

Of the remaining investors, corporate **insiders** are those investors who file a Form 3/4/5 report but do not file a 13-F report. This assumes that asset managers who file 13-Fs together with Form 3/4/5 are likely to report a 10% ownership stake or report on behalf of an associated individual, and are therefore not themselves a director or executive. Other 13-F filers not classified as Big Three, activists or insiders are classified as **asset managers**.

All remaining investors, who either file SC 13-D and SC 13-G reports but are not listed as activists in the Brav et al., 2008 data, or who file Forms 3/4/5 together with 13-Fs, often because they hold ownership positions in excess of 10%, are classified as non-financial and other **blockholders**. These categories allow us to identify individual investors and their investment motivations better than categorizing them purely based on reported filing type (i.e., 13-F, 13-D/G or Form 3/4/5 filers). This is because some owners report their ownership holdings on multiple filing types. For example, Carl Icahn predominantly files 13-F reports and a few SC 13-D or Form 3/4/5 insider reports. Using only one file type would not identify him as an activist investor.

Table 1.3 shows correlations of average ownership holdings and common ownership measures across firm-quarters. Kappa and cosine similarity are highly positively correlated as expected and on average, indexing, Big Three and retail ownership are positively correlated with the two common ownership measures, while activist, engaged activist, insider and asset manager ownership are negatively correlated with common ownership. Aggregate holdings of activists and of the Big Three are positively correlated, while all other investors' holdings are negatively correlated with and possibly crowded out by the Big Three. Activist holdings are also slightly positively correlated with other asset managers' and non-financial blockholders' ownership stakes, while they are negatively correlated with insiders. This may suggest a complementarity between large institutional ownership stakes and activist engagements, while insider and activist ownership may have substituting effects in firm governance. Asset manager holdings are negatively associated with all other ownership categories. Insiders' ownership stakes are negatively correlated with other ownership stakes except for non-financial blockholders with whom they are positively correlated. The latter may be driven by ambivalent categorizations of a few insiders as non-financial blockholders, such as in the case of the Walton Family Trust in Walmart. Overall, the correlations between our different investor categories are reasonable and largely consistent with previous research into the ownership structures of large public corporations (Hadlock & Schwartz-Ziv, 2019).

The cross-section of U.S. public firm ownership

Figure 1.1 plots the cross-section of firms' ownership structures on 1 January 2020, with each firm represented on the horizontal axis and ownership captured by a vertical bar. The bar height reflects the share of equity for which we can identify the owner, and the colored parts of each bar depict the aggregate amount of equity owned by each type of investor. The largest aggregate stake in most firms is held by asset managers (excl. the Big Three), amounting to 30-50% of common stock across firms. This share was even larger at the beginning of our sample (see Figure A.1), but has declined due to the growth of Big Three ownership. In 2020 the Big Three hold between 15-25% of equity of all S&P 500 firms. Together, asset managers and the Big Three constitute between 60-80% of the equity ownership of most S&P 500 firms. Their ownership stakes, as well as those of some (but not all) non-financial blockholders and activists, are available via 13-F filings. Thus, using Thomson Reuters or other ownership data that relies solely on 13-Fs is a good approach when interested in the investors owning the largest fraction of equities. However, using only data from 13-Fs misses important insiders and blockholders, who are responsible for most variation in the cross-section of ownership structures (see Figure A.2).

Activists are present in almost all sample firms owning between 1-10% of equity. Since activists like Value Act or Pershing Square can utilize a small ownership stake with great effect on a firm's policies and performance, their stakes are important to consider in corporate governance analysis. Ownership stakes of corporate insiders and non-financial blockholders are very small or non-existent in most S&P 500 firms. In the few firms where they do exist, however, their ownership reaches 10-50% of common stock. Moreover, individual blockholders are by definition owners with stakes > 5% of equity suggesting that the number of investors who, in aggregate, own 10-50% is likely small (see Figure A.3). Thus, a large part of the cross-sectional variation in ownership structures comes from insiders and non-financial blockholders, who, together with their different incentives and varying levels of diversification, have been largely ignored in previous studies of corporate owners. In the time series the average and aggregate ownership stakes of insiders and non-financial blockholders are also persistent, while the holdings of asset managers and activists increase over time (see Figure A.4).

Before we evaluate the portfolio interests of our investor categories, we identify who the individual, largest shareholders of our sample firms are. The largest investors will be the most influential for corporate voting outcomes. Especially, if they are insiders or activists, they will be able to influence corporate strategies materially to align with their own interests. Consistent with our findings on aggregate ownership structures, asset managers, including the Big Three, are the largest individual owners of almost 90% of S&P 500 firms in our sample (see Figure 1.2). Over time, asset managers other than the Big Three are replaced by the Big Three as the dominant shareholders. After the global financial crisis of 08-09, BlackRock, Vanguard and State Street grow markedly to become the dominant shareholders of most firms. Each of the Big Three owns on average 4-9% of the common stock of the largest U.S. firms in 2020 (Figure A.5), which makes one of them the largest owner in almost 75% of our sample firms, and Vanguard on its own the dominant shareholder of more than 60% of firms (Figure A.6). About 10% of sample firms, however, are persistently dominated by an insider, activist or non-financial blockholder between 2003-2020. Among these, insiders dominate more firms than blockholders or activists. We therefore have a non-negligible number of firms for which an engaged owner dominates corporate votes and decisions. The question is, what are their financial interests?

U.S. firm owners' portfolio interests

To identify the likely financial interests of our owner categories, we distinguish them by how diversified their portfolio holdings are.[12] The first category (by diversification) are what we refer to as **mavericks**. These are investors who hold the equity of only one firm at a given point in time. Mavericks have no obvious financial interest in other

[12] As we cannot measure all portfolio holdings of individual investors, such as personal investments in bonds, ETFs, pension funds or retail holdings in equities, we likely under-estimate the extent to which this investor group is diversified.

firms. All other investors who hold equity in more than one firm at a given point in time and therefore have a financial interest in the performance of multiple firms are referred to as **diversified** owners. Among diversified owners we distinguish between two types: **diversified universal** and **diversified common owners**. Diversified universal owners hold shares in almost all firms in our sample at a given point in time (specifically owning shares in more than 95% of the sample firms). With a financial interest in all firms, these universal owners are believed to have incentives to encourage their portfolio firms to reduce negative ecological and social externalities (Hart & Zingales, 2017). In contrast, common owners are diversified across multiple, but not all firms. Importantly, they own shares in multiple firms within the same industry (primarily identified by SIC-4 digit codes) but can also own firms across industries.[13] Common but non-universal ownership may give rise to the potential anti-competitive effects discussed in the literature on common ownership (Schmalz, 2021).

Averaging across all owners of a certain type (activists, insiders etc.) and across all quarters in our data, we measure what proportion of each owner type has maverick, diversified, universal and common owner characteristics. Figure 1.3 shows the results and reveals two dominant groups of owner-type-diversification combinations. Asset managers, the Big Three and activists are mostly diversified owners, while corporate insiders and non-financial blockholders are mostly mavericks.

All asset managers, including the Big Three, are diversified and most own multiple firms within and across industries (diversified common and universal owners). Whereas the Big Three are universal owners in every quarter, only half of the remaining asset managers hold stakes in all sample firms. Consequently, the Big Three contribute to overlapping ownership across all firms (universal ownership), while other asset managers contribute potentially more to within-industry than across-industry overlapping ownership (common ownership).

In contrast, 85% of insiders and 45% of non-financial blockholders are undiversified mavericks, who reduce overlapping ownership. The remaining 15% of insiders are

[13]For robustness we also use Hoberg and Phillips, 2016 TNIC-3 product market competition indicators.

diversified, but not within industries, while the remaining half of non-financial blockholders is split between diversified non-common owners (diversified only across industries) and common owners (diversified across and within industry). Hence, insiders do not contribute to within-industry common ownership at all, but some non-financial blockholders do potentially contribute to it.

Most surprising is the diversification of activists. Less than 10% of them hold shares in only one firm or are perfectly diversified across industries in a given quarter. All other activists are diversified also within industries or are universal investors. This finding contrasts with our ex-ante belief that activists are highly concentrated investors with a few stakes spread across industries. They turn out to own all S&P 500 firms in 10% of our sample and otherwise own multiple firms in a given industry, contributing to overlapping ownership within industries and across all firms. Over time more activists become universal owners, implying more contribution to across industry common ownership (Figure A.7). The diversification of the other types of owners does not vary over time.

So far we have established that asset managers and the Big Three are the largest individual and aggregate owners of most S&P 500 firms, while corporate insiders, activists and non-financial blockholders dominate about 10% of firms. In most cases, the largest ownership stake is therefore owned by highly diversified, universal and common owners who contribute to overlapping ownership across firms, within and across industries. Only 10% of firms are dominated by a maverick or diversified non-common investors who either reduce overlapping ownership or contribute primarily to cross-industry overlapping ownership. In contrast to our ex-ante beliefs activists are present with relatively small stakes in all firms and mostly increase overlapping ownership, across *and* within industries.

1.3.2 Universal and common ownership in U.S. public firms

Profit weights

To investigate the level and variation of universal and common ownership across firms we calculate the Edgeworth coefficient of effective sympathy between two firm's ownership structures. This coefficient, also referred to as "kappa" or "profit weight", measures to which extent the most influential shareholders in firm a are invested and therefore have a financial interest in firm b.

Following Grossman and Hart, 1979 and Rotemberg, 1984 we derive the Edgeworth coefficient of sympathy from a firm's objective function maximizing shareholder value in the presence of overlapping ownership. Shareholder s' cash flow rights are identified by the fraction of outstanding equity they own (β_s). Their voting rights (γ_s) are a function of the respective ownership stake in a given firm. Backus et al., 2021b clarify the assumptions under which the objective function Q_a of firm a as a function of its shareholders' portfolios x can be re-written as the sum of own firm profits and weighted other firms' profits. The latter weights are the Edgeworth sympathy coefficients, or profit weights, labeled κ_{ab}.

As our measure of universal ownership we calculate profit weights for each firm-pair (within and across industries) whereas to measure common ownership we restrict profit weights to firm-pairs consisting of industry competitors only (identified by SIC 4-digit codes or Hoberg and Phillips, 2016 TNIC-3 product market competitor codes).

$$Q_a(x_a, x_{-a}) \approx \pi_a + \sum_{b \neq a} \underbrace{\left(\frac{\sum_s \gamma_{as}\beta_{bs}}{\sum_s \gamma_{as}\beta_{as}} \right)}_{\kappa_{ab}} \pi_b \tag{1.1}$$

Following most of the literature we assume proportional control, hence one share owned conveys one vote and $\beta_{bs} = \gamma_{bs}$ in the above equation. For robustness we also analyze common and universal ownership with alternative control assumptions. This is discussed in the robustness section 1.3.3.[14]

Trends in universal and common ownership

Averaging across all firm-pairs (within industry for common ownership) for each quarter, we find that common ownership is about 10% higher than universal ownership

[14] We further use alternatives to profit weights as measure of overlapping ownership. One alternative measure developed in the literature is the so called "GGL" measure (Gilje et al., 2020). We analyze trends in common and universal ownership as well as how different investor types contribute to this attentive common ownership measure (See Figure A.17). Our main results remain qualitatively similar using this measure. Because profit weights κ_{ab} are micro-founded in the theory of the firm, we focus our analysis on this measure.

(Figure 1.4). More intuitively, the average profit weight attributed to industry competitors is 10% higher than the average profit-weight attributed to any S&P 500 firm. Both common and universal ownership measures have increased markedly over our sample period, from an average weight of 0.42 to 0.69 for a generic firm and an average weight of 0.47 to 0.75 attributed to an industry competitor. The difference between average universal and common ownership profit weights remains largely constant between 2003 and 2020, suggesting that overlapping ownership within industries has not been increasing more than overlapping ownership across industries. However, examining only average profit weights over time ignores possible trends in the underlying variation and distribution of profit weights across firm-pairs. The difference in average universal and common ownership profit weights could for example be driven by the tails of the distribution or by outliers. Looking at the distribution of firm-pair profit weights for all firms versus for industry competitors in Figure A.10b demonstrates that this is not the case. Instead, the distribution of common ownership profit weights is shifted to the right with respect to the universal ownership profit weight distribution.

Following Backus et al., 2021b we also evaluate the prevalence of profit weights larger than one for universal and common ownership. A profit weight larger than 1 means firm a shareholders care more about firm b profits than about firm a profits, implying an incentive to tunnel profits from one firm to the other. As evident in Figure A.11, across all firm-pairs such tunneling incentives exist in about 2% of cases in 2003, rising to 7% in 2020. Only considering within-industry firm-pairs, such incentives rise from 3% of cases to 6% of cases.

Who contributes to universal and common ownership?

From our previous discussion of the largest shareholders and their portfolio diversification, we know that the Big Three, asset managers and activists will likely contribute positively to overlapping ownership, while corporate insiders and non-financial blockholders limit its extent. The previous literature, however has argued that the Big Three do not contribute to overlapping ownership once we account for the increase in investor indexing (Backus et al., 2021b). As Table 1.3 shows, the measure of indexing suggested by Backus et al., 2021b is strongly positively correlated with the Big

Three share holdings and once both are included in a regression of profit weights on indexing and Big Three ownership, their study does not find a significant relationship between Big Three ownership and overlapping ownership.[15] We revisit this analysis below based on our refined scraping and cleaning of shareholding records and come to a different conclusion.

While asset managers, among them the Big Three, have frequently been associated with widespread overlapping ownership in the literature, the relationship between overlapping ownership and activists, insiders or non-financial blockholders has not been examined thus far. Below we therefore investigate to what extent the different owners contribute to universal and common ownership, when controlling for indexing and the overall shareholder structure.

This type of analysis requires complete ownership data. Thomson Reuters 13-F data used in prior studies or the data set provided by Backus et al., 2021b only comprise ownership holdings for large financial institutions or asset managers collected from 13-F filings, but ignore the systematically less diversified insiders and non-financial blockholders. Comparing our average and cross-sectional profit weights based on complete ownership data with those calculated using only 13-F institutional ownership reports, we find that such incomplete data over-estimates both universal and common ownership profit weights across the entire sample (Figures A.12a, A.13a).

We next analyze the contribution of the Big Three, activists, insiders and non-financial blockholders to universal and common ownership more formally in a linear regression setting. To do so, we regress firm-pair profit weights on the aggregate holdings of each owner type in the base firm (i.e., we regress κ_{ab} on aggregate Big Three, activist, insider, non-financial blockholdings in firm a), controlling for investor indexing using the measure suggested by Backus et al., 2021b, market capitalization, operating profits and retail share of ownership. To control for persistent differences in the ownership structures of firms a and b and for period-specific economic conditions, we include firm-pair and quarter-year fixed effects. In this analysis we also distinguish

[15] The indexing measure in Backus et al., 2021b measures the extent to which the investors in each firm hold portfolios similar to a "market portfolio" based on cash flow share weights (see Section III.C. in their paper).

the group of activist investors by whether they have an active campaign (i.e., file a SC 13-D) in the particular year-quarter, who we label *Engaged Activists*.

Table 1.4 shows the regression results for universal ownership in Panel A and for common ownership in Panel B using SIC-4 (columns (1)-(3)) and TNIC-3 (columns (4)-(6)) industry definitions to measure common ownership. For ease of comparison, we reproduce the main results in Backus et al., 2021b, which are based on univeresal firm-pairs and their 13-F ownership dataset, in Column (4) in Panel A.

The Table 1.4 Panel A reveals that insiders and non-financial blockholders contribute significantly negatively to universal ownership. This is consistent with the evidence presented above of their primarily undiversified maverick portfolio structure. On the other hand, the Big Three contribute significantly positively to universal ownership, even after controlling for investor indexing. These findings contrast with the results in Backus et al., 2021b, and our replication of their tests presented in column (4) of Panel A. BCS find a negative correlation between the Big Three holdings and universal profit weights once indexing is taken into account. Further investigating the source of the difference in results reveals that this is not due to the added blockholder and insider filings, but instead is driven by our more accurate parsing of share ownership reported on 13-F filings. This suggests that the impact of the Big Three across-industry overlapping ownership is not purely driven by investor indexing. Consolidation of ownership and voting decisions across funds within the same fund family may be a potential driver.

The results for common ownership in Table 1.4 Panel B are largely consistent with the findings for universal ownership when TNIC-3 industry definitions are used to measure common ownership within industries. Using SIC-4 industry classifications, the association of Big Three holdings with common ownership turns negative after controlling for indexing. This sign reversal is likely due to the higher granularity of industry classifications when using SIC-4 digit industries, rather than TNIC-3 pairs which compare to SIC-3 digit industries. Higher granularity implies fewer within-industry firm-pair profit weights (95066 instead of 282179). Among these firm-pairs, the Big Three must be less diversified than an indexed investor thus contributing less to common ownership between firms that compete closely.

Activists generally also contribute significantly positively to both universal and common ownership, once we control for investor indexing which negatively confounds the relationship between activists and overlapping ownership if not controlled for (see correlations in Table 1.3). Given their diversification across and within industries, activists contribute to more overlapping ownership and thus their ownership is positively associated with profit weights. In contrast, investors who are engaged in activism campaigns in a given firm, the 'engaged activists', do not seem to simultaneously engage in activism with another firm (either in the same industry or across all firms). Hence, ongoing activism campaigns contribute *negatively* to profit weights. These results suggest that activists usually run active campaigns in only one company in a given industry, while at the same time holding non-activist stakes in other firms within the same industry and across industries. Future research may be necessary to assess whether activists are concentrated in specific industries and what implications this has for firm performance and market competition.

Comparing the coefficients on investor holdings in the common versus the universal ownership regressions, insiders reduce common ownership more than universal ownership, while the coefficients are almost the same for non-financial blockholders. This supports our previous analysis of the size and diversification of investor types: few insiders are diversified and none are common owners, suggesting some contribute to universal profit weights but none to common profit weights. An equal proportion of non-financial blockholders is diversified across and within industries, yielding an equal effect on both profit weights.

Activists contribute more to universal than to common ownership, while the opposite holds for the Big Three. (Non-engaged) Activists are mostly diversified across- and within-industries, and individually hold larger stakes than asset managers (the omitted category in the regression), hence they contribute positively to both universal and common ownership. The Big Three, who are mostly universal owners, also contribute positively to both universal and common (using TNIC-3 industry classifications) profit weights. However, the regression results suggest that the Big Three are more diversified or hold larger positions among industry competitors, leading to a larger coefficient for common than for universal profit weights.[16]

The results in this section are relevant for academia and policy makers, as they inform the debate on drivers of overlapping within- and across-industry corporate ownership. In contrast to Backus et al., 2021b we find that the Big Three asset managers contribute positively to both within TNIC-3 and across-industry common ownership over and above what is implied by investor indexing. Hence, the centralization of voting power and financial interests across various index funds at the family level seems to enhance overlapping ownership beyond what an index portfolio requires. Second, we show that (non-engaged) activists are highly diversified, within and across industries, and contribute positively to both within and across-industry overlapping ownership, whereas engaged activist hold more concentrated portfolios. Hence future research may be needed to investigate to what extent activists focus on specific industries, particularly with respect to their activism campaigns, and what outcomes are implied by such concentration.

Effect of asset manager consolidation

Another potential driver of universal and common ownership are mergers of asset managers, that consolidate holdings and voting power in one investor. In the literature such mergers are frequently used as instruments to investigate the effect of overlapping ownership on corporate outcomes (Lewellen & Lowry, 2021). To analyze the role of asset manager mergers in driving universal and common ownership we focus on the effects of BlackRock's acquisition of Barclays Global Investors (henceforth BLK and BGI, respectively) in 2009. We also refer to this event as merger, because their portfolios are merged following the acquisition. Both BLK and BGI were universal owners of the S&P 500 firms before the merger, hence the joint entity does not create new common or universal owners. Instead it enhances overlapping ownership via larger holdings by the joint entity and thereby increases implied kappas (Figure A.14a).

We compare the merger-implied change in profit weights to the actual change in profit weights post merger, to gauge if there is a persistent effect on overlapping

[16] We run a series of robustness tests (see also section 1.3.3) using different measures of industry membership and different fixed-effect structures. Our results remain qualitatively similar.

ownership (Figure 1.5). Implied profit weights are calculated based on the ownership structures in 2009 Q1 by adding up the stakes of BlackRock and BGI to form the hypothetically merged portfolio. The implied change is the difference between implied and pre-merger (2009 Q1) profit weights, the actual change is the difference between post-merger (2010 Q1) and pre-merger profit weights. The scatter plot does not show a clear positive association between the implied and actual change in profit weights. Neither can we see a clear positive sign in the distribution of actual profit weight changes as we can for implied changes (Figure A.14a).

To establish whether the merger leads to a persistent increase in universal and common ownership we regress the post-merger actual change in profit weights on the merger-implied profit weight changes for each firm-pair. The main specification uses the actual profit weight change between 2010 Q1 and baseline 2009 Q1 as endogenous variable. We also examine the immediate merger effects on profit weight changes by 2009 Q4 and the more persistent effects by 2011 Q1 and 2012 Q1. We include an intercept to control for time fixed effects (as we are looking only at one quarter in each regression) and control for firm fixed effects, to eliminate any persistence in firm-specific stakes of BLK and BGI. The remaining variation in post-merger profit weight changes is driven solely by the cross-firm variation in BlackRock and BGI ownership stakes that are combined.

Our results in Table 1.5 suggest that implied profit weight changes are a statistically significant predictor of the post-merger profit weight changes in the immediate Q4 2009 quarter, but also for longer term changes until Q1 2012. This finding holds both for common ownership profit weights and universal ownership profit weights. Quantitatively the relationship between implied and post-merger profit weights is larger for industry competitors, suggesting that in our specific example, where both parties were universal owners already before the merger, the joint entity amplified common ownership more than universal ownership.

For robustness, we also investigate the discrete change in implied profit weights by regressing the post-merger profit weight changes on an indicator variable that is 1 for the top third of changes in implied profit weights due to the merger. Untabulated results reveal the treatment dummy is also significantly positively correlated with post-merger profit weight changes in all periods.

In addition to our previous findings, we show in this section that mergers among asset managers are another source of common and universal ownership growth. An alternative method to reduce overlapping ownership would therefore require restrictions on asset manager mergers. In our example the positive effect of asset manager mergers is due to an increase in the holdings of one already large, universal and common owner. In other mergers, the creation of new common or universal ownership may play an even more important role.

1.3.3 Robustness

In the preceding analysis we rely on the assumption of proportional control to calculate our measures of universal and common ownership. This assumption dominates the literature estimating profit weights and is founded theoretically by a the outcome of a standard voting model. To test whether our results are sensitive to this specific control assumption we re-calculate our profit weights once attributing more control to larger owners ($\gamma_{bs} = \beta_{bs}^2$) and once reducing the influence of larger owners ($\gamma_{bs} = \beta_{bs}^{0.5}$). Untabulated results and Figure A.16 reveal that the trends in universal and common ownership, as well as the relatively higher level of common compared to universal ownership are the same for both assumptions. The results of our regression analysis also hold.

Another key component of the analysis of common ownership, is the classification of industry competitors based on SIC 4-digit industry codes. These industry assignments are frequently imperfect or missing, hence we also conduct the complete analysis using the Hoberg and Phillips, 2016 TNIC-3 classification of product market competitors. The results on trends and levels of universal versus common ownership (Figure A.15) and the regression results for drivers of common ownership and merger effects (Tables 1.4, A.1) are unchanged by this choice.

1.4 Conclusions

We demonstrate that the size and portfolio diversification of 13-F filing institutional investment managers and activists on the one hand and those of non-financial blockholders and insiders on the other hand are systematically different. Because blockholders and insiders are the largest shareholders of 10-20% of S&P 500 firms, omitting such owners will lead researchers to mismeasure the variation in ownership structure and likely lead to bias in analyses of the effect of corporate ownership structures on various corporate outcomes. Adding these less diversified owners to the regularly analyzed sample of 13-F institutional ownership reduces estimates of common, within-industries ownership and of universal ownership consistently. Based on a complete data set of corporate ownership we find more heterogeneous ownership structures and investigate the drivers of universal and common ownership. We find that common ownership within industries is higher than universal ownership throughout our sample, suggesting that it is possible to reduce common ownership without reducing index investing, which is positively correlated with both. Instead, family offices as well as active mutual funds and hedge funds, including those commonly understood to be "activists", induce more common ownership among competitors and may be the lever to limit such within industry overlapping ownership.

Moreover, we find that the shareholdings of the "Big Three" institutional investors also contribute positively and statistically significantly to common and universal ownership over and above the effect of market-indexing, which is in contrast to previous findings in the literature. This implies that the consolidation of portfolios managed by sub-funds of the Big Three to the family level gives rise to aggregate ownership and voting power that increases common and universal ownership beyond the level necessary for index diversification. Relatedly, mergers in the asset management industry predict future increases in both common and universal ownership. These findings indicate that regulators can reduce common ownership of competitors without either sacrificing diversification or "universal ownership," but by addressing actively chosen common ownership positions and by scrutinizing consolidation in the asset management industry.

The data set we construct for the analyses in this study should also be interesting for research that can rely solely on filings by institutional investors (13-F filings), including the finance literature, because the data set we provide is more comprehensive. In particular, we parse 55% more *ownerciks* from the SEC filings than prior work.

Therefore, we propose that future research use the data set of ownership records used in the present paper, which we make freely available for academic use.

That said, this data set is unlikely to be free from errors, and new mistakes will be created as the data set gets updated. We invite all researchers to submit their proposed improvements and thus contribute to the continued maintenance of the first freely available and comprehensive ownership data set for U.S. firms.

One limitation of the part of our analysis measuring "universal" and "common" ownership is that we use only one measure proposed in the literature. Our conclusions do depend on the particular measure we used. Many other measures of common ownership have been proposed and can also be calculated, sometimes more accurately, using the data we construct.

A remaining limitation concerns the scope of our analysis, which is limited to the subset of S&P 500 firms that do not have dual-class shares or controlling owners. This limitation is particularly constraining when calculating within-industry measures of "common ownership", because not all rivals are S&P 500 firms in many cases. Including the firms with dual-class stock structures is likely to further increase the variation in ownership structures. Future research could expand the data set accordingly. We also do not observe all holdings by activists or insiders, but only those that are required to be reported to the SEC. More comprehensive reporting requirements would allow researchers to lift this limitation. If reporting dates were harmonized across institutions and insiders, the accuracy of the data could be further improved.

Another takeaway for policymakers is the necessity of a *comprehensive* set of ownership records to accurately assess the extent of common and universal ownership in their jurisdictions. Furthermore, understanding the respective drivers is essential for policymakers deliberating on potential measures to limit common ownership without preventing investor diversification. Basing such understanding on institutional investors' filings alone can lead to wrong conclusions. For example, our research based on more accurate institutional ownership data and controlling for insider and blockholder ownership does not support the finding that the sizable holdings of the "Big Three" institutional investors do not contribute to universal and common ownership over and above investor indexing. Investigating the effects of increasing ownership holdings of the Big Three further appears a fruitful avenue for future research. Relatedly, assessing the likely effect of consolidation in the asset management industry on universal and common ownership cannot accurately be performed based on 13-F ownership alone. We thus hope that by providing a more comprehensive ownership data set not only enables more high-quality research, but also enables competition authorities to measure the level of universal and common ownership more accurately, and to assess the likely effect of proposed policies – or the likely effect of not enacting any.

1.5 Figures & Tables

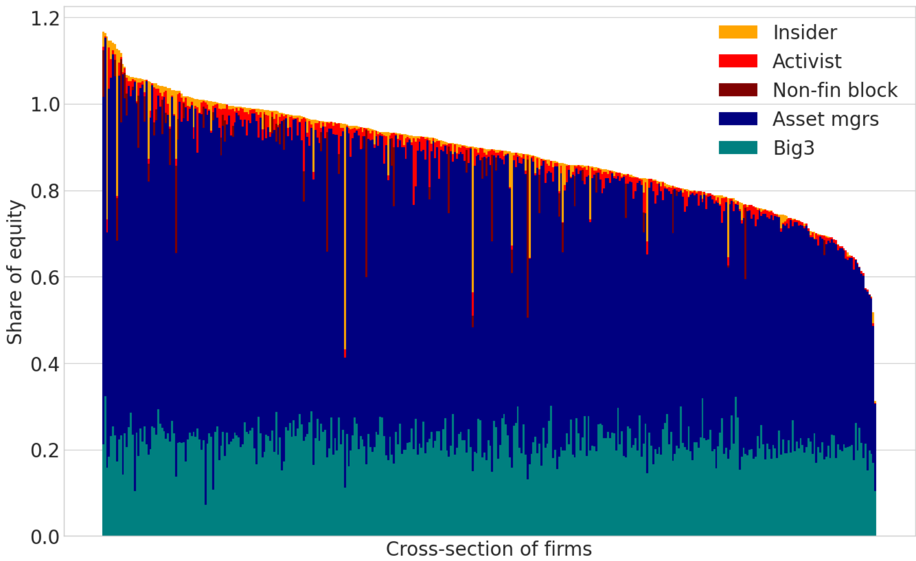


Figure 1.1: Ownership structures by filer type, 1 January 2020

Note: This figure depicts the captured ownership for each firm at the end of Q4 2019, differentiating ownership by how active the filer likely is. Each bar represents one firm. The bar height measures how much of the firm's stock ownership we capture. The red proportion of each bar represents the aggregate ownership of such investors identified by Brav et al., 2008 as "activists". The yellow proportion is the ownership of corporate insiders (filing Form 3/4/5 reports), who are not classified as "activists" by Brav et al. The navy part measures the share of equity owned by 13-F filings investors, who are neither activists, nor insiders, not BlackRock, Vanguard and State Street, as the "Big Three" ownership stakes in each firm are depicted in turquoise. The maroon part of each bar measures the remaining ownership captured by non-activist, non-insider, non-financial blockholders (SC 13-G filers). Bars exceeding a height of 1 are due to institutional investors short-selling common stock to each other, obliging both parties to report ownership of the underlying securities.

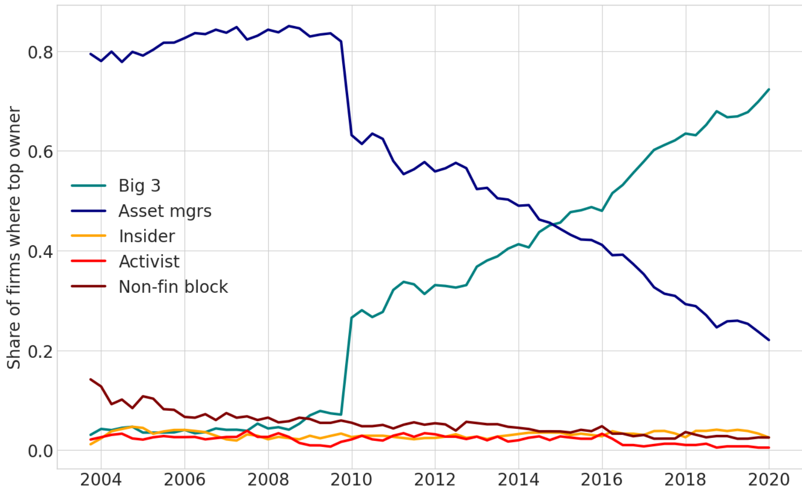


Figure 1.2: Top owner position by type of filer

Note: This figure depicts the quarterly share of firms in our sample for which an activist (Brav et al., 2008), an insider (Form 3, 4, 5 filers), a non-financial blockholder (non-activist, non-insider, non-asset manager), an asset manager (13-F filers, excl Big Three) or one of the Big Three (BlackRock, Vanguard, State Street) reports the largest ownership stake.

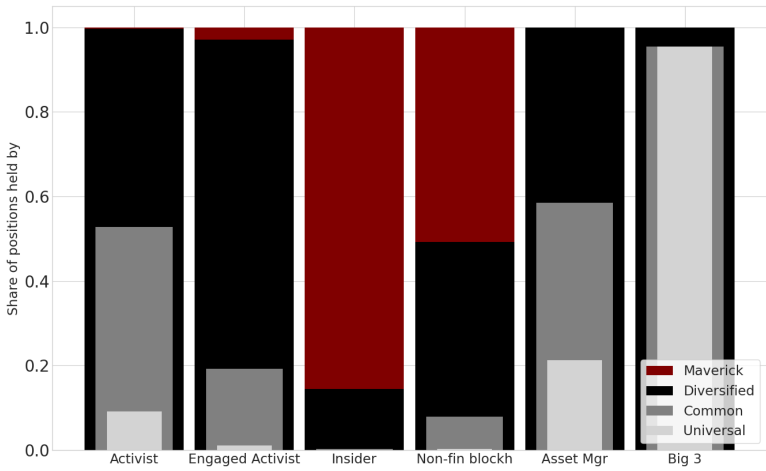


Figure 1.3: Diversification of certain investor groups

Note: This figure depicts which share of activist, engaged activist, insider, asset manager, Big Three and non-financial blocks' holdings is held by an undiversified maverick owner, by a diversified owner (non-universal and non-common, i.e. only diversified across industries only), a common owner (holds multiple firms in one industry and across industries at the same time) and a universal owner (holds more than 95% of the firms in the sample at the same time, making him both a diversified and a common owner).

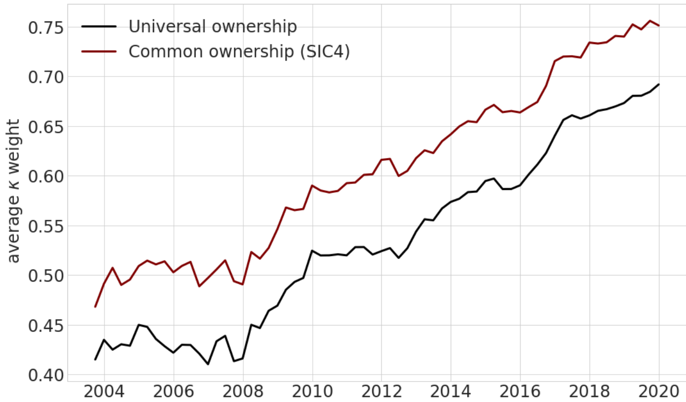


Figure 1.4: Average universal and common ownership profit weights

Note: This figure depicts the average universal ownership profit weights over time in blue and the average common ownership profit weights in dark red. The average common ownership profit weight is calculated using only profit weights of firm-pairs where both firms are in the same SIC-4 industry. Profit weights are averaged each quarter across firms weighting all firms equally.

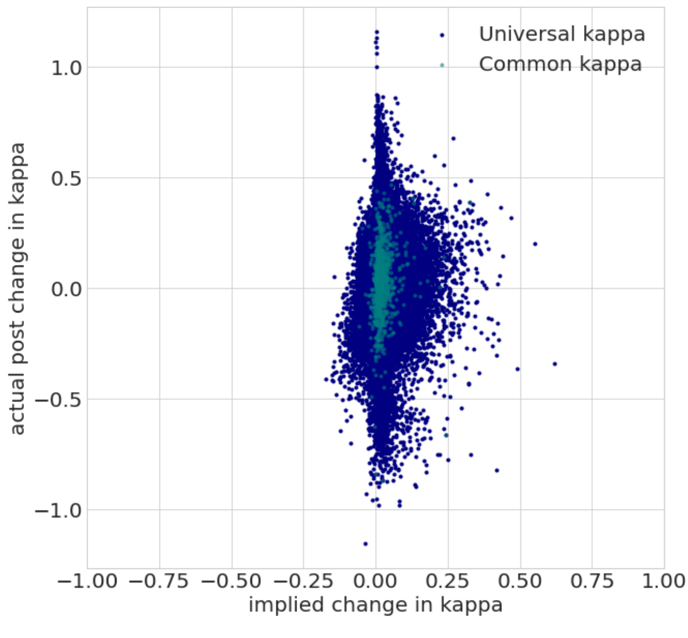


Figure 1.5: Change in profit weights implied and actual post merger

Note: This figure depicts the changes in profit weights implied by the merger of BlackRock and BGI versus the changes in actual post merger profit weights in absolute units. The "implied" firm-pair profit weight change is calculated as the difference between counterfactual profit weights with BlackRock & BGI holdings in 2009 Q1 added up vs the correct profit weights in 2009 Q1. Actual profit weight changes are the difference between profit weights in 2010 Q1 vs 2009 Q1.

	Kappa	Cosine sim	Indexing	Retail	Big3	Activist	Engaged activist	Insider	Asset manager	Non-fin blockholder
kappa	1.000									
Cosine	0.752	1.0								
Indexing	0.611	0.564	1.0							
Retail%	0.482	0.194	0.45	1.0						
Big Three	0.322	0.464	0.595	-0.089	1.0					
Activist	-0.206	-0.138	-0.303	-0.324	0.001	1.0				
Eng Activist	-0.114	-0.097	-0.195	-0.097	-0.021	0.717	1.0			
Insider	-0.226	-0.181	-0.369	-0.156	-0.094	-0.01	-0.002	1.0		
Asset Mgr	-0.441	-0.223	-0.409	-0.868	-0.174	0.105	-0.058	-0.094	1.0	
Non-fin Block	-0.312	-0.249	-0.427	-0.252	-0.204	0.056	0.012	0.092	0.03	1.0

Table 1.3: Correlations between owner types and common ownership.

Note: This table presents correlations of average holdings of corporate insiders (filing Form 3, 4, 5 reports), activists (Brav et al., 2008), non-financial blockholders (non-insider, non-asset manager, non-activists), the Big Three asset managers (BlackRock, Vanguard and State Street), and other asset managers (non-insider, non-activists, non-blockholder, non Big Three asset managers), a measure of investor indexing (Backus et al., 2021b), and the retail share of ownership (defined as 1 minus the sum of all the other captured ownership fractions).

Panel A: Universal Kappa

	Complete data			BCS results
	(1)	(2)	(3)	(4)
Insider	-0.549***	-0.288***	-0.289***	
	(0.001)	(0.001)	(0.001)	
Eng. Activist	-0.550***	-0.488***	-0.488***	
	(0.003)	(0.003)	(0.003)	
Activist	0.141***	0.450***	0.449***	
	(0.002)	(0.002)	(0.002)	
Non-fin blocks	-0.432***	-0.178***	-0.178***	
	(0.001)	(0.001)	(0.001)	
Indexing		1.157***	1.151***	1.110***
		(0.001)	(0.001)	(0.001)
Big3	0.975***		0.025***	-0.236***
	(0.002)		(0.003)	(0.002)
Retail share	0.566***	0.414***	0.416***	0.670***
log Market Cap	0.047***	0.036***	0.036***	0.071
Op. Margin	0.001***	-0.001***	-0.001***	-0.005***
R-squared	0.797	0.808	0.808	0.721
R-squared Adj.	0.198	0.239	0.239	
p(F-stat)	0.000	0.000	0.000	
Pair FE	✓	✓	✓	✓
Quarter-Year FE	✓	✓	✓	✓
N	12647495	12647495	12647495	

Panel B: Common Kappa

	SIC-4 industries			TNIC-3 industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Insider	-0.809***	-0.407***	-0.401***	-0.746***	-0.397***	-0.400***
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.010)
Eng. Activist	-0.673***	-0.550***	-0.560***	-0.890***	-0.786***	-0.788***
	(0.040)	(0.039)	(0.039)	(0.024)	(0.023)	(0.023)
Activist	-0.056**	0.299***	0.311***	0.186***	0.504***	0.503***
	(0.022)	(0.022)	(0.022)	(0.014)	(0.014)	(0.014)
Non-fin blocks	-0.498***	-0.154***	-0.146***	-0.492***	-0.132***	-0.136***
	(0.014)	(0.014)	(0.014)	(0.008)	(0.008)	(0.008)
Indexing		1.281***	1.341***		1.363***	1.339***
		(0.015)	(0.016)		(0.008)	(0.010)
Big Three	0.945***		-0.272***	1.432***		0.097***
	(0.031)		(0.033)	(0.017)		(0.019)
Retail share	0.608***	0.456***	0.441***	0.632***	0.439***	0.445***
log Market Cap	0.054***	0.042***	0.041***	0.052***	0.037***	0.037***
Op. Margin	0.003*	0.001	0.002	0.009***	0.004***	0.004***
R-squared	0.780	0.794	0.794	0.813	0.825	0.825
R-squared Adj.	0.246	0.295	0.296	0.214	0.264	0.265
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000
Pair FE	✓	✓	✓	✓	✓	✓
Quarter-Year FE	✓	✓	✓	✓	✓	✓
N	95066	95066	95066	282179	282179	282179

Table 1.4: Drivers of universal and common kappas

Note: This table presents results of a regression of profit weights on aggregate holdings of corporate insiders (filing Form 3, 4, 5 reports), of engaged activists (investors that are currently running an activist campaign in underlying firm (Brav et al., 2008)), of activists (investors who at any point in our sample run an activist campaign in any sample firm (Brav et al., 2008), of non-financial blockholders (non-insider, non-asset manager, non-activists), of the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), the retail share of ownership (defined as 1 minus captured ownership fraction), and log market capitalization. Panel A, Columns (1)-(3) consider all firm-pair profit weights and thus represent an analysis of our "universal" ownership measure. Column (4) provides results for an analogous regression performed in Backus et al 2021 on 13-F institutional ownership data only. Panel B shows regression results when only considering firm-pairs in the same industry using SIC-4 (Columns (1)-(3)) and TNIC-3 (Columns (4)-(6)) industry groupings, interpreted as a measure of "common" ownership. We residualize and adjust the R-squared for quarter-year and firm-pair fixed effects (because κ_{ij} effect differs from κ_{ji}). One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

Panel A: Universal Kappa				
	Actual Change κ			
	2009Q4	2010Q1	2011Q1	2012Q1
Implied $\Delta\kappa$	0.649***	0.492***	0.463***	0.551***
	(0.009)	(0.010)	(0.012)	(0.013)
R-squared	0.984	0.991	0.995	0.995
R-squared Adj.	0.036	0.017	0.011	0.012
p(F-stat)	0.000	0.000	0.000	0.000
Firm FE	✓	✓	✓	✓
N	136653	136653	136653	136653
Panel B: Common Kappa				
	Actual Change κ			
	2009Q4	2010Q1	2011Q1	2012Q1
Implied $\Delta\kappa$	1.214***	0.853***	0.730***	1.170***
	(0.107)	(0.118)	(0.150)	(0.152)
R-squared	1.019	0.994	0.995	1.005
R-squared Adj.	0.109	0.047	0.021	0.053
p(F-stat)	0.000	0.073	0.000	0.000
Firm FE	✓	✓	✓	✓
N	1039	1039	1039	1039

Table 1.5: Merger contribution to universal and common kappa changes

Note: This table presents results for a firm-pair level regression of actual changes in profit weights due to the BlackRock-BGI merger on implied changes in profit weights. Actual changes are the difference between profit weights calculated for post-merger periods (2009Q4, 2010Q1, 2011Q1, 2012Q1) and profit weights calculated for the pre-merger period 2009Q1. Implied changes are the difference between counterfactual profit weights calculated based on 2009Q1 data when consolidating the BlackRock and BGI ownership stakes and the profit weights calculated on baseline 2009Q1 data. Panel A considers all firm-pairs in our sample, and therefore refers to "universal" profit weights. Panel B is restricted to firm pairs that are part of the same industry and therefore refers to our measure of "common" ownership profit weights. We control for firm-fixed effects and a constant controls for quarter-specific fixed effects. One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

Appendices of Chapter 1

Appendix 1.A Data construction

1.A.1 Overview

This data set is compiled to serve as more complete source of corporate ownership data than what is currently available and used in the academic literature. The data construction process is described in detail in the following sections. We utilize all ownership reports required by the Securities Exchange Commission (SEC) from investors in U.S. firms' securities. This comprises institutional investment managers' 13F-HR filings (henceforth *13F*), blockholders' SC 13-D and SC 13-G filings (collectively referred to as *13DG*), and corporate insiders' Form 3, 4 and 5 filings (collectively referred to as *F345*).

The ownership sample for this paper has been restricted to publicly traded U.S. firms, that are part of the S&P 500 index and have single class stock structures. This restriction was necessary to make our analysis comparable to existing work by Backus et al (2021) and others. Nevertheless we describe the complete data cleaning, aggregation and consolidation process in this section since Chapters 2 and 3 build on the entire data set.

First, we download all 13F, 13DG and F345 filings from EDGAR, the SEC's online archive and *parse* each report. Using file type specific Python code, we automatically extract the identifying information on the report date date, the owner, the owned security and the number of shares held from every filing. Each file type is processed with a separate script, because their formats vary significantly and present numerous challenges. Second we *identify* the owned securities using the unique *permco* identifier for each firm provided by CRSP and a class identifier to differentiate multiple classes of common stock. Once uniquely identified, we reduce the data set to the desired sample dimensions. In Chapter 1 we keep only common stock holdings for S&P 500 firms with single class stock structures between Q4 2003 and Q4 2020. For Chapter 2 we use ownership data for all firms with productivity estimates, while in Chapter 3 we restrict the data set to the holdings of all owners identified as hedge fund activists.

As some reports are filed less frequently than once a quarter, while others are revised multiple times within one quarter, we have to adjust the data. Individual holdings are *interpolated* between filings across quarters and only a single holding for each owner-corporation-class-quarter is kept per file type.

After parsing, identifying and interpolating the ownership report on different file types separately, we *merge* these three source of ownership data in the last step and *aggregate* to keep only a single holding for each owner-corporation-class-quarter. Doing so we have to account for duplicated and overlapping shareholdings, in order to not overstate the holdings of an individual owner. For each owner we keep all available information, such as the file types he reported ownership on and the other investors he co-filed ownership with, so as not to lose information about the intention and nature of each owner when dropping duplicates. Finally we aggregate ownership to the owner-corporation-quarter level by summing ownership of multiple class of common stock within the same corporation.

Variable description

The main variables in our data set are the *permco*, a five digit numeric code that uniquely identifies each firm; the *class id*, a numeric code that uniquely identifies each class of common stock held; the *ownercik* (central index key assigned by SEC) a multi-digit numeric code that identifies each owner; the *rdate*, the end date of the quarter for which we capture the ownership stake; the number of shares and the number of votes owned for the respective owner-corporation-quarter combination.

Additional variables occurring in our data construction are the *cik*, central index key of the subject company that is owned, and the historical *cusip*, an eight digit identifying code for each security. Neither variable is used in our data processing and analysis as they change over time and do not uniquely identify a security in the data.

Every report states its type, such as “SC 13-G” for a 13G report, or “13F-HR” for a 13F, or “3/A” for an amendment to an earlier Form 3 report. We call this *file type*, and use it to identify whether the owner is an institutional investment manager, a corporate insider, or another type of institutional investor.

We also use four different dates when compiling the ownership data, to differentiate between different events and file types. We capture the date when an ownership report is actually filed with the SEC as "filing date", *fdate*, and the date of the transaction that necessitates a 13DG or F345 filing as "event date", *event_ date*. Our data set identifies ownership for all owner-security combinations at the end of each quarter, resulting in the end of quarter "reporting date", *rdate*. For owner-security combinations where we have to interpolate holdings between filings that are multiple quarters apart, we highlight the quarter in which the ownership was originally reported as "filing-reporting date", *filing_ rdate*.

Security identification data set

Ownership reports filed with the SEC use either a security's historical *cusip* or a combination of the company central index key (*cik*) and free text descriptions to identify each security. Because *cusip* and *cik* codes for individual securities and firms change over time (e.g. due to security re-issuance and stock splits, or due to company name changes and acquisitions) we need a more permanent and unique identifying key to use throughout our data set. The best available key, that can be linked with other data basis, is a combination of *permco*, the permanent company number assigned to each corporation by the Wharton Research Data Services platform CRSP, and a class identifier, distinguishing securities of multi-class stock firms.

We compile a data set, referred to as identification data set, that links a firm's *cik*, its securities' *cusip* and the free text class description to our unique *permco-class id* security key for each month and can be merged onto the ownership data set.

To generate the identification data, we download monthly data for 1995-12 to 2020-12 from CRSP and COMPUSTAT on all securities contained in these databases. This includes the securities' respective identifiers (*gvkey*, *ncusip*, *cusip*, *cik*, *permno*, *permco*), the number of shares outstanding, the share price, industry information, share class information, and company-level information (name, headquarters). For any given month there can be multiple *ncusips* or *cusips* linked to a unique *permno* security identifier and we keep all duplicates, as they may allow us to identify more ownership in the various reports.

We use information on the security's "share code", share price and number of shares outstanding provided by CRSP to drop non-common stock and non-traded securities from the identification data set.

In a separate pipeline we compile a data set of multi-class companies, to identify whether a firm has multiple classes of common stock outstanding. If all outstanding classes of common stock are actively traded, then CRSP and COMPUSTAT provide relatively reliable estimates of the respective number of shares outstanding and trading price. However, for many multi-class firms at least one class of common stock is not actively traded (e.g. Berkshire Hathaway Class B Common Stock, or Facebook Class B Common Stock). Such share classes are missing in commercial data sources and thus do not have an unique security identifier (*permno*). Consequently, the firm cannot easily be identified as "multi-class" based on CRSP and COMPUSTAT data alone. To address this shortcoming, we manually compile a quarterly data set of firms with multiple classes of common stock and indicators for trading status, voting rights and number of shares outstanding if not available on CRSP.

The multi-class data set identifies each security with our usual unique *permco-class id* key and can be easily merge onto the main identification data set.

1.A.2 Multi-class identification data

The starting point of our candidate list of multi-class stock companies is based on Jay Ritter's database of IPOs (Loughran and Ritter, 2004), and lists of dual class companies in Gao et al., 2014; Gompers et al., 2010, as well as the Council of Institutional Investors' annual list of dual class companies since 2016.

We also use the labels created in our processing of Form 3/4/5 insider reports to find candidate dual class companies. Specifically, we search Form 3/4/5 reports for securities of the same company (identified by CIK) but with different free text descriptions of common stock classes. All cases where descriptions comprise two different letters after the word "class" or "series" are flagged, and also cases where some Form 4 descriptions name a "common stock" while others report a "class (...) common stock" are flagged. The latter can be valid or due to a misfiling by the insider, thus we double check all candidate dual class companies manually.

To verify whether our candidate dual class companies actually have multi-class stock structures, we review their 10-K annual and 10-Q quarterly filings for the period 2000-2020, as well as the Def 14A Proxy statements. The number of shares outstanding for each available class of stock is reported quarterly, either on the first page of the 10-K or the 10-Q filing alongside details on the trading status of each security. The Proxy statements contain information on the voting rights of each class of common stock at annual frequency.

Based on this information we compile a quarterly database of whether each candidate company has a multi-class stock structure, the names assigned to each class, the number of shares outstanding for each class and the number of votes attributed to each class of common stock.

Many different combinations of classes are possible, and not all multi-stock structures exist at IPO of a firm or continuously throughout the observation period. Our sample of multi-class companies grows quickly in recent years, especially in the tech and AI sectors and among the largest US corporations (Alphabet, Facebook).

Most companies opt for two classes of stock, where one class has no voting rights and the other has one vote per share, or a dual structure where the first class has one vote per share and the other class has ten votes per share. However, there are many other combinations of voting rights, some as extreme as a difference of 1:10,000 votes per share. Some multi-class stock structures with differential voting power can shift control to small groups of shareholders, creating the need to include these companies with accurate control rights in an analysis of corporate governance.

To merge the multi-class stock information on our identification data set, we use the unique *permco-class id* key assigned to each security. While the identification data set reports stock information at the monthly frequency, multi-class stock information (shares outstanding) is only available at the quarterly level. We fill all relevant columns (votes per share, aggregate number of votes outstanding) for single class companies based on the one share - one vote principle and assign *class id* to all single class securities to avoid confusion. The result is a comprehensive security-level data set that allows us to identify all holdings reported via *cusips*, *ciks* and class descriptions and lets us calculate the fraction of cash flow and voting rights held by each reporting owned.

1.A.3 13F reports

A 13F-HR report is required by institutional investment management firms with more than $100 million assets under management at the end of each quarter. It comprises a file header that is standard to all file types and then lists all securities owned by the institutional investor on the last day of each quarter in a table like fashion, see Figure A.1. These reports are filed in plain text format until 2013, with multiple of layout variants and misstatements, that necessitate manual checks and a flexible parsing routine. From 2013 on, many filings are reported in XML format, which is similar in structure to plain text, but the information contained in the table is linked to XML tags making it easier to identify individual items in the table.

A *cusip* can appear in several rows of the table, reporting ownership of a given security in multiple bundles, for example because of filing sub-funds. In non-XML filings such bundles can be reported in sequential lines, omitting identifying information in the rows after the first one (see figure), requiring extrapolation of identifiers for consecutive rows.

Parsing

From the filing header, which is mostly standardized across all file types (see Figure A.1) we parse the *ownercik*, *fdate* and *rdate* of each report. This information is common to and therefore duplicated for all shareholdings reported in the following holdings table. For a comprehensive ownership data set, we have to capture the *cusip* key of each security owned and the number of shares owned for each row of the holdings table. The total number of shares owned is usually a combination of the shares at "sole", "shared" and "none" free disposal to the investor, reported in the final three columns of the holdings table. To ascertain that the number we are parsing as number of shares owned is correct and not the market value of shares, or another erroneous value, our code checks if the number of shares captured is the result of some combination of the sole, shared and none numbers at the end of the row. Earlier 13F reports may also include the price of securities, in that case we also check if the number of shares captured is equal to the number resulting from dividing the parsed market value of holdings by the reported security price.

In addition to misparsing the number of shares owned, several other parsing difficulties arise because the *ownercik*, filing and reporting date may be missing from the file header. Our code searches for date-like patterns and other mentions of "CIK" or "Central Index Key" in the report to fill these gaps. In the worst case we follow Backus et al., 2021b and parse the *ownercik* from the file title.

Identification & Aggregation

Once all rows with information about each *cusip* and the respective number of shares owned is parsed and the header information on *ownercik*, *rdate* and *fdate* is added, we merge this data frame with our identification data set to link each *cusip* with the respective *permno*, the unique security identifier from CRSP for all traded securities.

This step is often complicated because the *cusip* format can vary between 7, 8 or 9 digit codes, where in some cases the final digits are dropped and in other cases leading zeros are dropped. We account for all these possibilities when identifying the securities. Any *cusip* that cannot be linked with a *permno* in the end is dropped from our sample[17]. Finally we merge the security *permno* to our unique *permco-class id* key.

Since the security holdings table can report ownership in the same security over multiple rows, we aggregate (sum) the number of shares owned by *permco-class id* across multiple rows in one 13F report (filename).

At this point we can have multiple 13F reports for the same *ownercik-rdate* due to amendments. A 13F amendment (13F-HR/A) is filed when the investor restates some of his shareholdings because they were previously misreported. An amendment can, but does not have to include the entire ownership table again. It may also report only those ownership holdings that were previously erroneous. Therefore we cannot simply parse the last 13F filing in each quarter to capture the complete shareholdings of the investor. Instead we parse all 13F reports and amendments filed during the quarter and then keep the last entry for each individual security (*permco-class id*). This procedure is based on the comprehensively validated assumption that if an amendment reports shareholdings in a *cusip*, and this cusip was also reported with a different

[17]Securities of foreign issuers or such securities delisted at the end of a quarter or traded on very minor exchanges do not have a *permno* key and can therefore be dropped from our sample.

number of shares on a previous filing in that quarter, then these are not newly added shares owned, but only a restated number of shares owned. Thus we keep the latest reported number of shares owned for every *permco-class id-rdate-ownercik*, sorting on filing date. In quarters where a security is subject to a stock split this procedure is amended, because restatements and backward looking adjustments for stock-splits cannot be differentiated. In these cases we keep the first reported ownership stake and discard the amendments, manually adjusting the holdings for stock splits.

The resulting 13F ownership data contains unique holdings for each *permco-class id-rdate-ownercik* combination. Using the additional information from the identification data set, we drop ownership in securities that are not common stocks and stocks attributed to companies not incorporated in the US.

Finally, we compute the fraction of outstanding shares owned, referred to as *beta* for each *permco-class id-rdate-ownercik* by dividing number of shares owned by the number of shares outstanding reported in CRSP or manually compiled for untraded dual class stocks.

1.A.4 13D & 13G reports

An investor who acquires securities of a company and subsequently owns more than 5% of the outstanding securities of this class, or who despite selling some securities still owns more than 5% of all outstanding securities, has to disclose this ownership on a SC 13-D or SC 13-G report within 10 days of the transaction. SC 13-D and SC 13-G reports are very similar in structure and format. The only difference is that SC 13-D reports contain an additional item in which the investor explains his intentions leading to the purchase or sale of shares. In the following we describe the general procedure to capture ownership reported in SC 13-D and SC 13-G filings, jointly referred to as 13DG filings.

Each 13DG filing consists of a header and a table that provides information about the owner, the security, the number of shares owned in total, with sole or shared voting power and sole or shared dispositive power. Below this table is a text section, that repeats the main information summarized in the table with more detailed explanations in written form (see Figure A.3).

One special characteristic of 13DG filings is that they can be filed by groups of investors, where multiple investors share the voting and dispositive power of the transacted shares in some fashion. This happens for about 45% of all 13DG reports we download. In these cases the table reporting ownership is repeated for each co-filing investor, separately containing the specific number of shares owned and controlled by each owner.

Two issues prevent an accurate identification of the individual interests of each co-filing investors. First, only the main reporting owner is identified by an ownercik in the file header, while all other investors are included by name only, at the top of their respective ownership tables. Second, the allocation of cash flow and voting rights among co-filing investors is often highly in-transparent and can only be understood by reading the accompanying footnotes and text items. Because the number of total shares owned can vary across reporting owners, can be duplicated for each owner or can require aggregation across all co-filing ownes, it is difficult to identify the correct holding to allocate to the *permco-class id-rdate-ownercik* key.

Parsing

From the filing header we again parse the *ownercik* and *fdate* of the report, in addition to the *event_ date* on which the transaction took place. We parse the *cusip* and share class from the following section of the header and attribute these to each reporting owner captured in the following table(s). From each table we identify the reporting owner's name and the number of shares owned in total and with sole or shared voting or disposal power. Fortunately, in 76% of filings with multiple owners all investors report the same number of total shares owned. In these cases we capture the *ownercik*, the *cusip* and the total number of shares owned reported in the first table, dropping all subsequent tables.

In all other cases with multiple reporting owners we capture for each table the owner's name, the respective sole-voting, shared-voting, sole-dispositive, shared-dispositive and total number of shares reported. To capture the most conservative estimate of a filing's aggregate ownership, we use the single largest number of total owned shares reported across all tables. We do not attempt to combine sole and shared voting or disposable shares to an aggregate ownership measure, because the results are more error-prone than our current conservative method.

The main errors in parsing arise because of these co-filing investors and because the security-identifying *cusip* key is not reported in a standardized and well-identifiable location. We correct for the first error by manually checking all cases with excessive share ownership, found wherever the shares held exceed the number of shares outstanding. To locate the *cusip*, we search the whole filing for multiple custom patterns of letters and numbers that correspond to the generic *cusip* format (deduced from the CUSIP Global Services description).

Identification & Aggregation

For each filing, we attribute the correct quarterly *rdate* to the transaction *event_ date* and link the *cusip-rdate* pair to our unique *permco-class id* key. This yields a unique *permco-class id-rdate-ownercik* combination associated with the conservative estimate of total shares owned.

As there may have been multiple transactions in a given quarter we check for duplicates of the *permco-class id-rdate-ownercik* combination and keep only the latest filing based on the transaction's *event_ date*. In case of stock splits in a given quarter, we adjust for it if the *event_ date* is earlier than the split date. Because 13DG filings are available for most firms in digitized form on Edgar since Q4 1999 and were infrequently available before that time, we keep only the latest of all filings made before 1999-Q4 for each *permco-class id-ownercik*.

The resulting 13DG ownership data contains unique holdings for each *permco-class id-rdate-ownercik* combination, just as the final 13F ownership data. Using additional information from the identification data set we drop ownership of securities that are not common stocks and companies not incorporated in the US.

Finally, we compute the fraction of outstanding shares owned, referred to as *beta* for each *permco-class id-rdate-ownercik* by dividing the number of shares owned by the number of shares outstanding reported in CRSP.

1.A.5 Form 3, 4 & 5 reports

Company officers, directors, 10% owners and other insiders are required to file a Form 4 report within 48 hours of purchasing or selling shares in their company. Form 3 reports are filed when a person becomes a corporate insider (e.g. due to election to the board) or on the first occasion an insider trades in his company's stock. If an insider neglected his reporting requirements within the set timeline, he will file a Form 5 report at the later date, instead of the Form 4 report.

The structure of Form 3, 4 and 5 filings is the same: each has a file header with information about the filing *ownercik*, the subject company *cik* and the *filing date*, followed by two tables. The first table lists all transactions in non-derivative securities of the company, where each transaction is reported in a new row. The second table lists all transactions in derivative securities in separate rows. The rows are in chronological order with the first transaction at the top and the last one at the bottom. For each row we are interest in the free text description of the security being transacted the number of securities owned after the transaction and the nature of ownership (directly or indirectly, e.g. by trust or family) for each transaction which impacts the aggregation of shareholdings (see Figure A.2).

Parsing

Parsing the downloaded Forms 3, 4 and 5 presents more challenges than the other filing types, because the security owned is not specified exactly by a *cusip*, but by a broader free text description and the company *cik*. Another challenge is that some insider reports are filed by several owners jointly, similar to 13DG filings. Unlike the 13DG multi-owner reports, however, in F345 filings each reporting owner is identified by name and *ownercik* and they all jointly own the reported shares. The is no distinction of sole or shared voting or disposal powers.

We parse the filing date and all *ownercik*-owner name combinations from the document header. From the tables listing non-derivative and derivative transactions, we parse for each row the free-text description of the security, the number of shares owned after the transaction and the nature of ownership.

Because the number of transactions across all insider reports is exceedingly large, we reduce the parsed data set before moving to the identification and aggregation step. As we are only interested in the number of shares owned in a certain nature after the last transaction reported on a F345, we drop duplicates on free-text description-by-nature of ownership and keep only the last row for each *cik-security description-nature of ownership-rdate-ownercik*. We differentiate by nature of ownership, because these will ultimately need to be summed up.

Identification & Aggregation

To identify the securities owned by corporate insiders we want to merge the combination of *cik* and free text description reported in F345 to our identification data set. The difficulty lies in the nature of the free-text description, which varies in accuracy, spelling and informativeness. If the security is described as "Common stock" or even more accurately as "Common stock Class A" it is easy to link the *cik*-free text to a *permno* in our identification data. However, where the description is only a company name, or general terms such as "equity", or a combination of these, it is much harder to identify the type and class of security owned. Reports encompass common and preferred stock, debt, options and many any other securities.

To filter through more than 40,000 different security descriptions, we use spelling correction packages and manual rules. In a first step, we label securities based on the most informative keywords found in the description. For example if the word "common" appears, the indicator for common stock is flagged, while when the word "option" appears, the option indicator is flagged. The Python library *difflib* allows to account for spelling mistakes by searching for words that are very similar to our pre-specified keywords. Similarity is measured by the *(Levenshtein) edit distance*, a specific distance metric between two words, and the acceptable distance can be varied manually.

With this methodology we assign more than 30 binary labels for security types, such as common stock, preferred stock, restricted stock units, trusts, options, debt, depository receipts, deferred compensation and many more (full list of most frequent labels and their categorization as either common stock or not in Table A.1). In addition, whenever we identify the term “class” or “series” in the free text field, combined with a single letter, we take note of this in another column. The full list of labels and labeling code can be provided upon request.

To categorize the stock class of multi-class firms we use the label flags and the class names extracted from the free text security description. Matching this combination into categories, we hierarchically narrow the set of the unmatched classes. We start with “class .”, then “voting”/“non-voting”, and finally “common” to distinguish similar sounding classes such as “voting common” and “common”. Finally we add manual labels to special classes of common stock.

If the free text description offers too little information to infer the security type, for example when just the company name is reported or an unknown abbreviation is used, we make assumptions about the security type. One such assumption is that descriptions that only state the company name are likely to refer to the main common stock of the company. Another is that if the description is long, ambiguous or incomprehensible, it is likely not common stock and we classify it as such and drop it consequently. This is a conservative assumption, in order to prevent the inclusion false entries in our data set. All of our assumptions and rules are verified by manually accessing and reading actual filings and comparing parsed ownership to holding information captured by Capital IQ or Factset.

Based on the resulting labels, we determine which securities confer voting and cash flow rights and should be included in our ownership database. Entries such as common stock, common equity or class - common stock are kept. Most other labels like debt, swaps, options, preferred equity, phantom stock and warrants are dropped from our sample. Using the remaining ownership data and class labels, we merge in our identification data set on *cik-rdate-class id* and thereby gain the unique *permco-class id-rdate* key for each reported holding. The identification data set includes indicators for multi-class *permcos* and *class ids* for each common stock class. Common stock of single class firms has the *class id* -1, to not confuse it with dual class firms that have “common stock” as one outstanding class.

Next we identify the main owner in a filing with several reporting owners (*main_owner*). Based on all pairs of co-filing owners and the number of co-filed re-

Table A.1: Labels of Form 4-filed security types

label	**classification**	class	class_id
common stock	common stock like	common	-1
common stock	common stock like	common	0
class "a" stock	common stock like	class a	7
voting stock	common stock like	voting common	26
non-voting common	common stock like	non-voting common	22
trusts	common stock like	common	-1
preferred stock	not common stock	-	-
(restricted) stock unit	not common stock	-	-
stock options	not common stock	-	-
debt	not common stock	-	-
depositary receipts (ADR)	not common stock	-	-
depositary shares (ADS)	not common stock	-	-
deferred compensation	not common stock	-	-
non-qualified & qualified (...)	not common stock	-	-
"company name" trust	not common stock	-	-
closed & open-end fund	not common stock	-	-
restricted performance (derivative)	not common stock	-	-

ports we investigate centrality graphs of each co-filing owner in a network of co-filers using the *networkx* Python library. Each graph has owners as vertices, connected by an edge if they appear on filings together and the number of co-filings determines the edge weights). The *main_ owner* of each filing is the *ownercik* with the highest number of connected owners, with the least highly connected top neighbor and the highest number of ownership reports filed throughout the sample period. The logic behind choosing the least connected top neighbor is that we want to reduce the number of main owners in each sub-graph of connected owners. We keep all owners for now, but reduce the data set to the last filing per quarter for each *cik-rdate-ownercik-file type* (F345) and then limit the data further to the unique, latest *cik-rdate-ownercik* report, preferring Form 5 to Form 4 to Form 3 entries.

Analogous to the 13F and 13DG ownership data sets, the final F345 ownership data contains holdings for each *permco-class id-rdate-ownercik*. Different from other filings we do not have a unique holding per *permco-class id-rdate-ownercik*, yet, as multiple *ownercik* and different *natures* of ownership for a given security-owner combination still report on the same holding. Nevertheless we can impose sample restrictions in line with the 13F and 13DG data and drop ownership of securities that are not common stocks and companies not incorporated in the US.

1.A.6 Merging

The final step of merging the three ownership data sets from 13F, 13DG and Form 345 filings together presents many more challenges due to duplicated ownership reports. There can be duplicated reports for the same owner in different filing types (e.g. BlackRock has to file a 13-F report for its ownership stakes every quarter, but when it changes its position in a company where it owns more than 5% of outstanding equity it also has to file a SC 13-G report). At the same time there can be multiple owners reporting the same shareholdings on the same file type (e.g. when both Bill and Melinda Gates report on a Form 4 their respective direct holdings, but also their joint indirect holdings in a company, because they control the Gates Foundation, which holds a stake in a company). Lastly, there can also be multiple reports for the same shares by different owners and different file types (e.g. Warren Buffett files a Form 4 report for firms where he is on the board and owns shares directly and indirectly through Berkshire Hathaway, and at the same time Berkshire Hathaway reports these holdings on a 13-F filing).

In order to deal with filing groups of owners and families of funds consistently, we compile in a separate spreadsheet the owner names and *ownerciks* that we consider to be a group. For example, Edward Lampert, ESL Investment, and RBC Investments, are all attributed to Edward Lampert and his *ownercik*, as Lampert is the majority shareholder of ESL, which is majority shareholder of RBC Investments. Similarly all holdings associated with BlackRock (BlackRock SE, BlackRock Germany, BlackRock Australia and others) are consolidated in the main BlackRock parent. We identify more than 450 such owner groups and make them available upon request. However, we are certain that this list is not comprehensive, yet, and therefore take further automated steps and manual edits to remove the remaining cases.

To remove duplicates from filing groups or aggregate holdings correctly we first stack the three ownership data sets constructed in the previous steps, and make sure the source file type (13F, 13D, 13G, F345) for each row reporting *permco-class id-rdate-ownercik-shares* is known. At this point the 13F data provides actual ownership information for each quarter, while we have accurate 13DG and F345 ownership reports only in quarters where a relevant transaction occurred and interpolated data points for all quarters in between. In addition, we have multiple rows for each F345 report that is co-filed by multiple insiders and multiple rows for each individual insider if he reports ownership of varying nature (e.g. direct and indirect via trust).

Sorting the stacked data set for each *permco-class id-rdate-ownercik*, we reduce the data to a single filing, preferring to keep 13F filed ownership, then F345 filed and, only if neither 13F or F345 reports are available, keep 13DG filed ownership in this order. Whenever we keep the F345 filing, we keep the disaggregated version with indirect and direct holdings. We assign a unique priority rank to each owner based on their aggregate number of reporting quarters (*consistency*) and their median fraction of shares outstanding held across all firms (*relevance*), to prepare the next consolidation step.

The data still contains gaps, for example, if a fund files a 13-F report with all holdings in 2010-Q4, but then falls below the reporting requirements and stops filing 13-F reports, and the next filing in 2012-Q1 is a SC 13-G because a holding grew above 5%. To close these gaps, we forward fill each holding for the unique *permco-class id-rdate-ownercik* key until the next entry for this key. Due to the potential for silent interests of 13DG or F345 filers, we extrapolate such holdings for up to three years after the final filing, unless the same owner also reports on 13F filings, in which case we do not extrapolate his holdings.

With a consistent quarterly ownership data set we begin dropping and consolidating overlaps in shareholdings. Exact duplicates of reported shares and approximate duplicates for large holdings, if $\beta>10\%$ and the reported shares differ by less than 0.1%, are dropped. We keep owners co-filing in F345 and 13DG reports rather than owners without co-filings and then keep the owner with the highest priority rank. In several consecutive steps we aggregate share holdings of F345 owners first within different *natures* of ownership (indirect & indirect, direct & direct) then across *nature* of ownership (direct & indirect) and drop overlaps by co-filing status and priority rank after each aggregation step.

Finally we consolidate holdings of owners categorized manually into owner groups.

For groups with no 13-F filing owner we keep the shareholdings of the highest priority rank owner and attribute them to the *main_ owner*'s *ownercik* identified manually (e.g. Edward Lampert in the examples above). If one or multiple group members file 13-F reports, then only 13-F based shareholdings are kept, summed up and attributed to the manually identified *main_ owner* (e.g. BlackRock).

Manual corrections

We spot check the resulting ownership data and manually correct any evident errors. Such errors are identified from the captured "beta" (the fraction of outstanding equity owned) being obviously too large (>100% of equity owned) or unlikely (few institutional investment managers own more than 50% of equity). We find several 13F filers (institutional investors) that correctly file ownership in excess of 50% of equity, but for most cases this constitutes a parsing error on our side or a reporting error of the investor or CRSP misreports the number of shares outstanding. We manually correct misparsed ownership by checking the original filing or ownership data on Capital IQ.

To keep a consistent picture of all manual edits, we compile a spreadsheet that identifies all *permco-class id-rdate-ownercik* combinations that are corrected and the nature of the adjustments. The types of adjustments vary substantially. In most cases we manually correct the number of shares owned, but we also drop companies in first and final quarters, where acquisitions or spin-offs distort the ownership structures, we correct the number of shares outstanding when CRSP reports it incorrectly, and we also correct several remaining owner overlaps, that are firm-specific and therefore not incorporated in our excel file of owner groups.

1.A.7 Data comparison

We compare our S&P 500 ownership data set extensively to various other data sets, based on coverage (missing owners or firms), existence of clearly false stakes (in excess of 1 or 0.5 for institutions) and random examples of individual firm's ownership structures. Overall we find that our data is more comprehensive and accurate than Thomson Reuters' S34 data on institutional ownership, which captures *only* 13F ownership and has multiple parsing issues.

Our data is similarly comprehensive as Factset and Capital IQ. Both struggle with the duplicated ownership reports across owners and file types, as we do, implying that in each data set you will find several company-quarters where the sum of all captured ownership exceeds the number of shares outstanding.

Most closely related by construction is the data set compiled by Backus et al., 2021b, henceforth BCS. We initially adopted the BCS parsing routine for 13-F filings and then enhanced and complemented it, to encompass all ownership reports and allow for more flexible information acquisition. In the following we compare our results in more detail to theirs.

BCS data

BCS parse the *cik* of the filing entities from the filename under which a file is saved on the EDGAR database. In about 55% of the filings, however, the number combination in the filename is not the correct *cik* of the filing entity, but instead a *cik* of another entity assigned by SEC. Manually checking some of these *ciks* reveals that they are mostly associated with entities that are consolidated by the SEC, hence not causing significant errors in the ownership measurement. In some cases, however, we find such *ciks* are associated with companies unrelated to the filers. Hence, BCS attribute about 55% of the filings to the wrong institutional investor leading to significant errors. We fix this issue by parsing the *cik* of the filing entity directly from the header text of the 13-F report.

Multiple other parsing issues of the BCS code arise because the format and structure of 13-F filings changes over time. Before the introduction of XML filing formats in 2013, the reports were produced and stored in plain text. Reading these reports with an automated approach is very difficult as each document format and structure may differ slightly from the other.

First, some filings have the order of the "value" and "shares" columns reversed. BCS manually compile a list of filings where they found this to be the case, swap the columns for such filings, and implement additional checks to see if the parsed number of shares is sensible. To avoid relying on such a manual approach and to account for other possible variations in the columns of ownership reports, we utilize the fact that the total shares reported in an entry of a 13-F filing equal the sum of three numbers placed at the end of each row: the "sole", "shared" and "none" columns provide the number of shares for which voting power is sole, shared or not owned. Our approach is to find the number in each row that equals the sum of these three. If this approach fails, we use the BCS method.

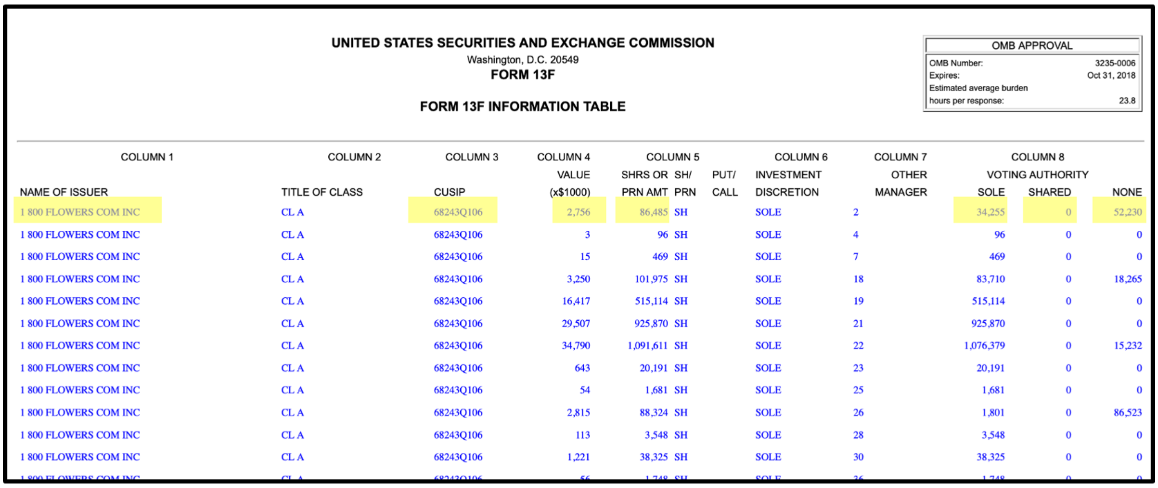
Second, earlier 13-F filings report some security holdings over multiple rows. BCS only parse the first row of such entries and skip the subsequent rows attributed to the same security. The neglected rows often contain very large ownership stakes, leading to significant errors in the data. We make sure that our code reads every line of the 13-F reported holdings and adds up those reporting on the same security.

Third, we improve on the consolidation of institutional ownership reports filed by previously separate asset managers that merged at some point. BCS also consolidate such merging entities, however they already consolidate holdings before the merger actually happened. Thereby corporate ownership by BlackRock is massively overstated in the quarters where it had not yet acquired Barclays Global Investors. We correct for this by consolidating holdings only after two institutional investors actually merged.

Fourth, we perform a more comprehensive identification of multi-class firms to attribute the correct number of votes to each class of common stock. We extend the list of multi-class companies to account for younger and very short-lived dual class firms. BCS drop a firm from the entire sample, if it has ever has a multi-class stock structure. In our single class data set we only drop multi-class firms in the quarters they had multiple classes of common stock outstanding.

Another small amendment of our code makes sure the reporting date of the filing (*rdate*) is parsed in cases when it is missing from the header. While BCS assign the filing date (*fdate*) to the reporting date in such cases, we check other parts in the filing text from which one can parse the reporting date.

Lastly, we amended the BCS code in order to create a complete database of corporate ownership for public US corporations. The original parsing code does not download and parse the 13-F filings completely, but instead parses only holdings for a pre-specified list of about 5000 securities. The list contains the unique *cusip* identifiers of the securities of S&P 500 firms. Securities of non-S&P 500 firms and even securities of S&P 500 firms that are not listed with the correct *cusip* are therefore missing. In order to create the exhaustive database we aim for, our code downloads all 13-F filings and parses all security holdings contained in the reports.



UNITED STATES SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549
FORM 13F

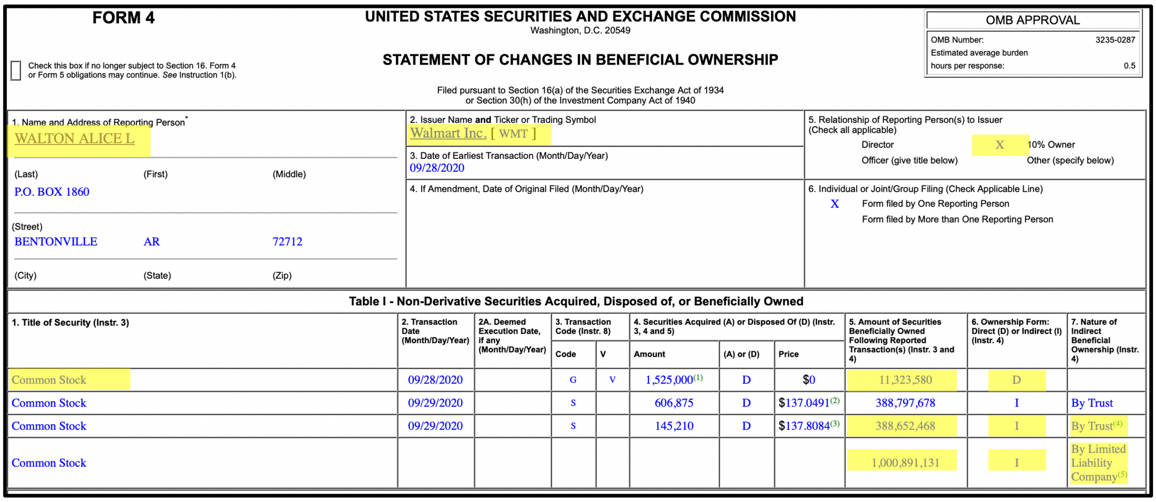
FORM 13F INFORMATION TABLE

OMB APPROVAL	
OMB Number:	3235-0006
Expires:	Oct 31, 2018
Estimated average burden hours per response:	23.8

COLUMN 1	COLUMN 2	COLUMN 3	COLUMN 4	COLUMN 5			COLUMN 6	COLUMN 7	COLUMN 8		
			VALUE	SHRS OR	SH/	PUT/	INVESTMENT	OTHER	VOTING AUTHORITY		
NAME OF ISSUER	TITLE OF CLASS	CUSIP	(x$1000)	PRN AMT	PRN	CALL	DISCRETION	MANAGER	SOLE	SHARED	NONE
1 800 FLOWERS COM INC	CL A	68243Q106	2,756	86,485	SH		SOLE	2	34,255	0	52,230
1 800 FLOWERS COM INC	CL A	68243Q106	3	96	SH		SOLE	4	96	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	15	469	SH		SOLE	7	469	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	3,250	101,975	SH		SOLE	18	83,710	0	18,265
1 800 FLOWERS COM INC	CL A	68243Q106	16,417	515,114	SH		SOLE	19	515,114	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	29,507	925,870	SH		SOLE	21	925,870	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	34,790	1,091,611	SH		SOLE	22	1,076,379	0	15,232
1 800 FLOWERS COM INC	CL A	68243Q106	643	20,191	SH		SOLE	23	20,191	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	54	1,681	SH		SOLE	25	1,681	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	2,815	88,324	SH		SOLE	26	1,801	0	86,523
1 800 FLOWERS COM INC	CL A	68243Q106	113	3,548	SH		SOLE	28	3,548	0	0
1 800 FLOWERS COM INC	CL A	68243Q106	1,221	38,325	SH		SOLE	30	38,325	0	0

Figure A.1: 13F filing example

Note: This figure depicts an excerpt of a holdings table reported on a 13-F filing. Highlighted in yellow are key information that our parsing routine extracts: company name, *cusip*, market value of shares owned, number of shares owned, sole, shared, and no voting authority shares. Information about the owner is contained in the generic file header, not displayed here.



FORM 4

UNITED STATES SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549

STATEMENT OF CHANGES IN BENEFICIAL OWNERSHIP

Filed pursuant to Section 16(a) of the Securities Exchange Act of 1934
or Section 30(h) of the Investment Company Act of 1940

OMB APPROVAL	
OMB Number:	3235-0287
Estimated average burden hours per response:	0.5

☐ Check this box if no longer subject to Section 16. Form 4 or Form 5 obligations may continue. *See* Instruction 1(b).

1. Name and Address of Reporting Person*
WALTON ALICE L
(Last) (First) (Middle)
P.O. BOX 1860
(Street)
BENTONVILLE AR 72712
(City) (State) (Zip)

2. Issuer Name **and** Ticker or Trading Symbol
Walmart Inc. [WMT]

3. Date of Earliest Transaction (Month/Day/Year)
09/28/2020

4. If Amendment, Date of Original Filed (Month/Day/Year)

5. Relationship of Reporting Person(s) to Issuer (Check all applicable)
Director — X 10% Owner
Officer (give title below) — Other (specify below)

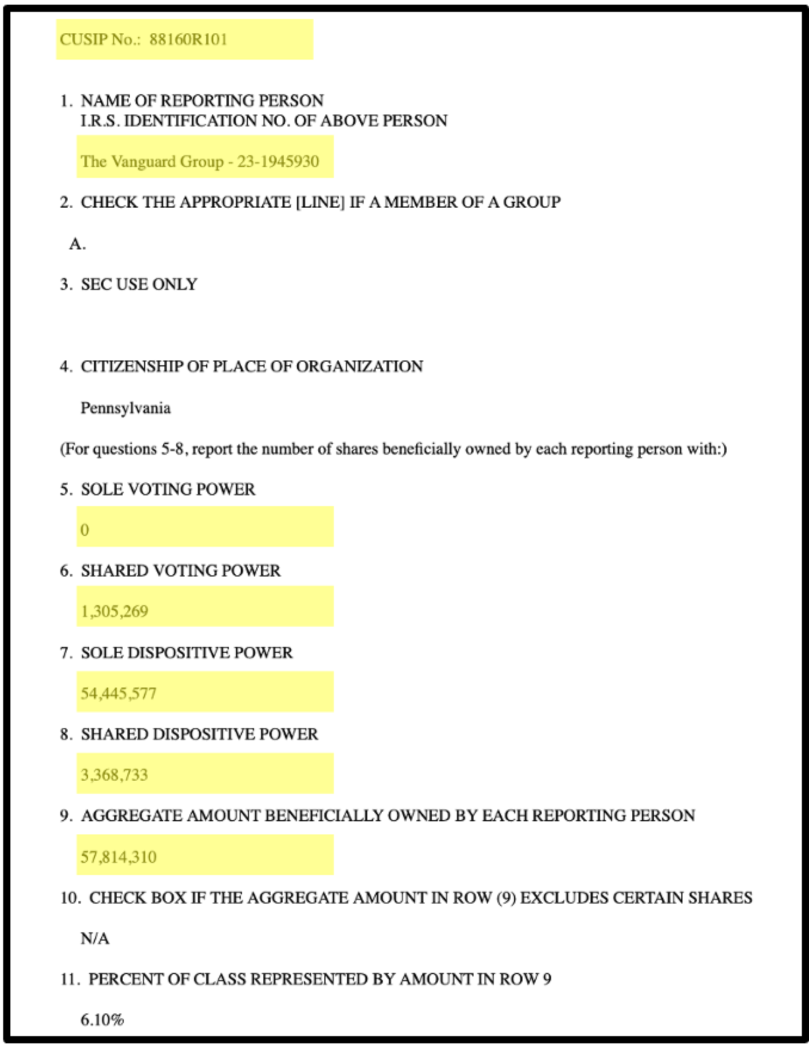
6. Individual or Joint/Group Filing (Check Applicable Line)
X Form filed by One Reporting Person
Form filed by More than One Reporting Person

Table I - Non-Derivative Securities Acquired, Disposed of, or Beneficially Owned

1. Title of Security (Instr. 3)	2. Transaction Date (Month/Day/Year)	2A. Deemed Execution Date, if any (Month/Day/Year)	3. Transaction Code (Instr. 8)		4. Securities Acquired (A) or Disposed Of (D) (Instr. 3, 4 and 5)			5. Amount of Securities Beneficially Owned Following Reported Transaction(s) (Instr. 3 and 4)	6. Ownership Form: Direct (D) or Indirect (I) (Instr. 4)	7. Nature of Indirect Beneficial Ownership (Instr. 4)
			Code	V	Amount	(A) or (D)	Price			
Common Stock	09/28/2020		G	V	1,525,000(1)	D	$0	11,323,580	D	
Common Stock	09/29/2020		S		606,875	D	$137.0491(2)	388,797,678	I	By Trust
Common Stock	09/29/2020		S		145,210	D	$137.8084(3)	388,652,468	I	By Trust(4)
Common Stock								1,000,891,131	I	By Limited Liability Company(5)

Figure A.2: F345 filing example

Note: This figure depicts an excerpt of a Form 4 filing, analogous to Form 3 and 5. Highlighted in yellow are key information that our parsing routine extracts: owner name, company name, free text security description, number of shares owned after each transaction, nature of ownership.



CUSIP No.: 88160R101

1. NAME OF REPORTING PERSON
I.R.S. IDENTIFICATION NO. OF ABOVE PERSON

The Vanguard Group - 23-1945930

2. CHECK THE APPROPRIATE [LINE] IF A MEMBER OF A GROUP

A.

3. SEC USE ONLY

4. CITIZENSHIP OF PLACE OF ORGANIZATION

Pennsylvania

(For questions 5-8, report the number of shares beneficially owned by each reporting person with:)

5. SOLE VOTING POWER

0

6. SHARED VOTING POWER

1,305,269

7. SOLE DISPOSITIVE POWER

54,445,577

8. SHARED DISPOSITIVE POWER

3,368,733

9. AGGREGATE AMOUNT BENEFICIALLY OWNED BY EACH REPORTING PERSON

57,814,310

10. CHECK BOX IF THE AGGREGATE AMOUNT IN ROW (9) EXCLUDES CERTAIN SHARES

N/A

11. PERCENT OF CLASS REPRESENTED BY AMOUNT IN ROW 9

6.10%

Figure A.3: 13DG filing example

Note: This figure depicts an excerpt of 13-D filing. Highlighted in yellow are key information that our parsing routine extracts: *cusip*, owner name, sole and shared voting and dispositive power shares held and aggregate shares held. If the filing is co-filed by multiple people such a table is replicated to each co-filing investor and parsed separately by our routine.

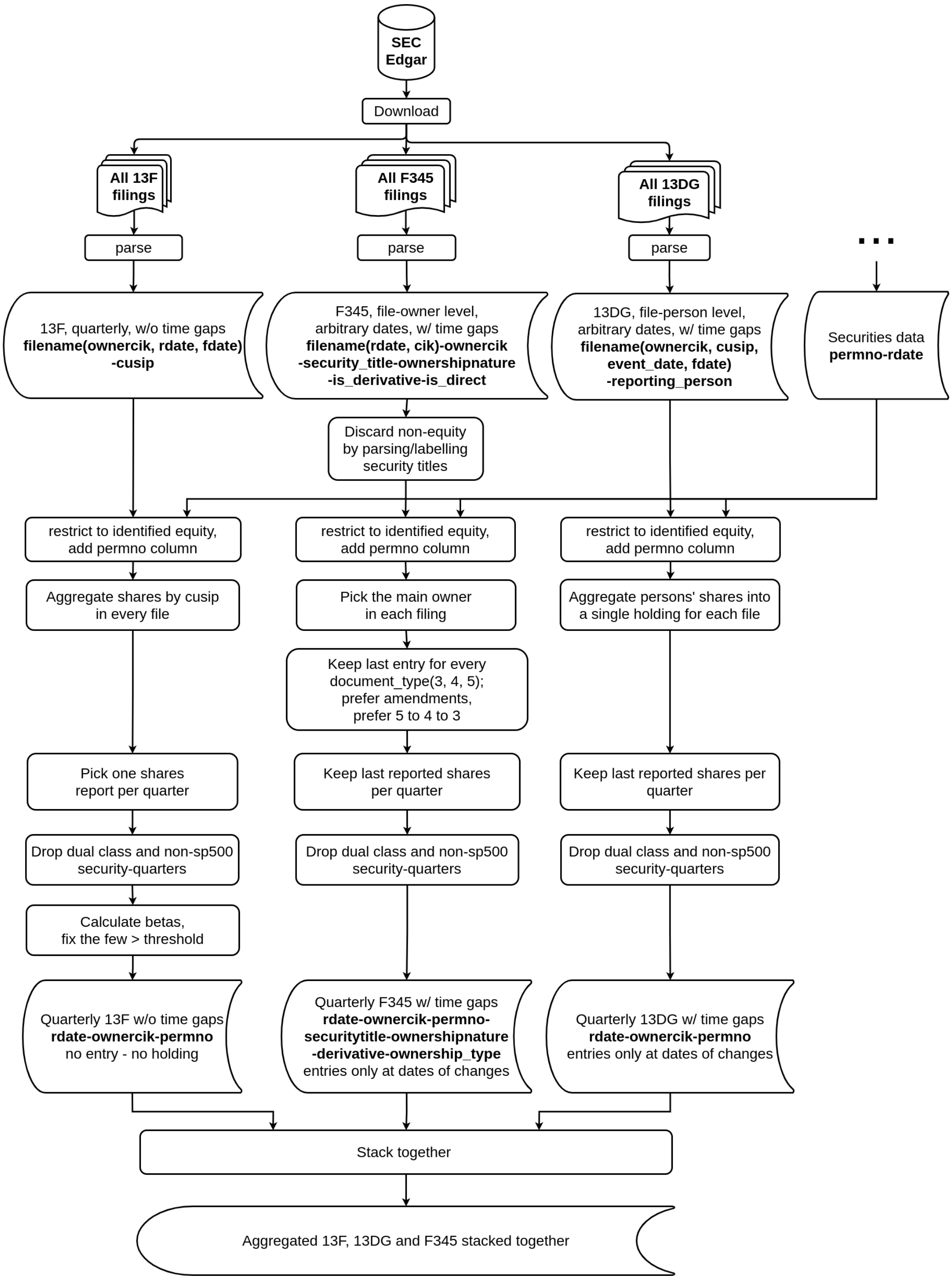


Figure A.4: Data aggregation process

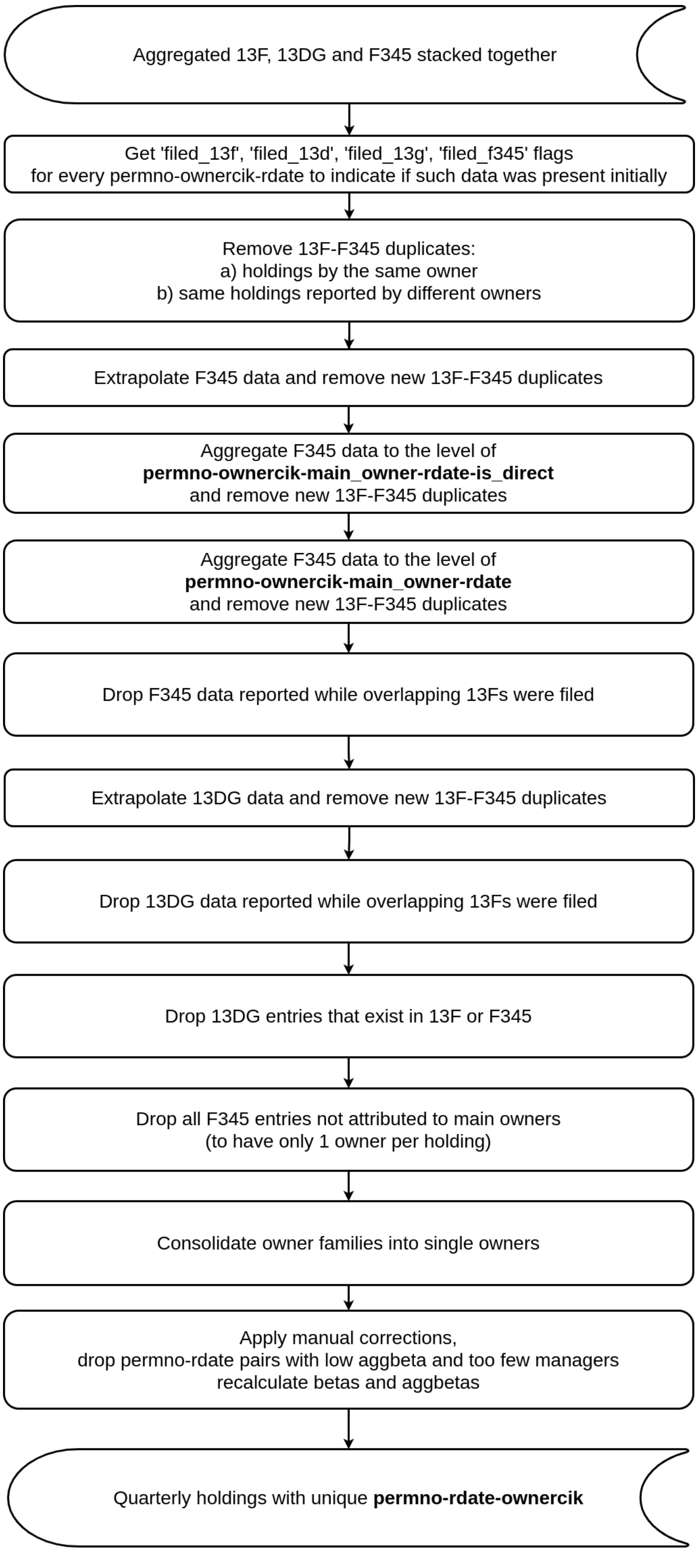


Figure A.5: Data merging process

Appendix 1.B Figures & Tables

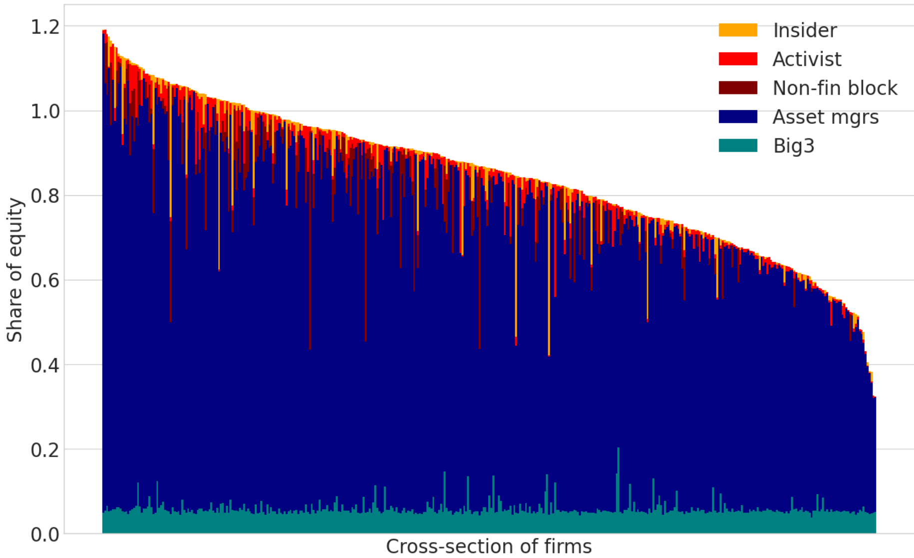


Figure A.1: Ownership structures by activism, 1 January 2005

Note: This figure depicts the captured ownership for each firm at the end of Q4 2004, differentiating ownership by how active the filer likely is. Each bar represents one firm. The bar height measures how much of the firm's stock ownership we capture. The red proportion of each bar represents the aggregate ownership of such investors identified by Brav et al., 2008 as "activists". The yellow proportion is the ownership of corporate insiders (filing Form 3/4/5 reports), who are not classified as "activists" by Brav et al. The navy part measures the share of equity owned by 13-F filings investors, who are neither activists, nor insiders, not BlackRock, Vanguard and State Street, as the "Big Three" ownership stakes in each firm are depicted in turquoise. The maroon part of each bar measures the remaining ownership captured by non-activist, non-insider, non-financial blockholders (SC 13-G filers). Bars exceeding a height of 1 are due to institutional investors short-selling common stock to each other, obliging both parties to report ownership of the underlying securities.

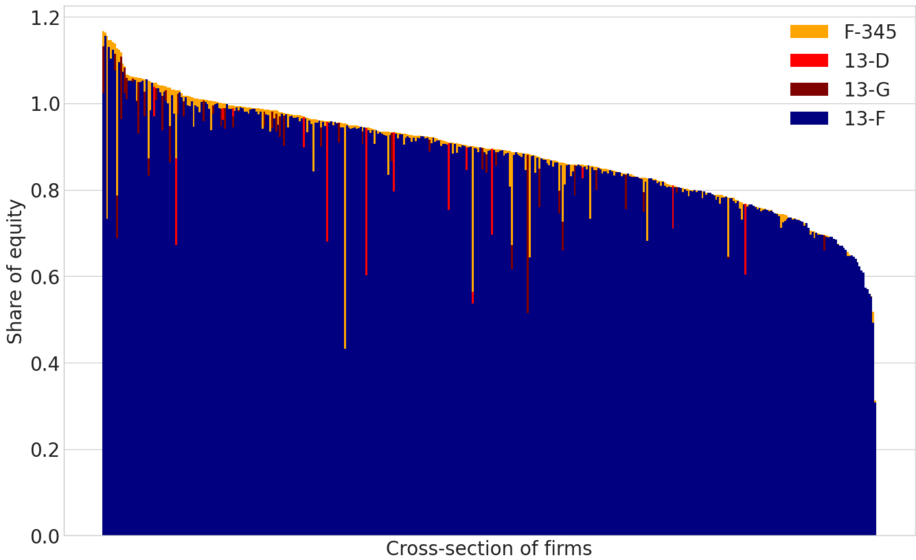


Figure A.2: Ownership structures by filer type, 1 January 2020

Note: This figure depicts the captured ownership for each firm at the end of Q4 2019, differentiating ownership by the filer reporting it. Each bar represents one firm. The bar height measures how much of the firm's stock ownership we capture. The proportion of each bar in blue represents the share of equity ownership identified by parsing 13-F filings. The red and maroon parts of each bar measure the additional ownership captured by parsing SC 13-D and SC 13-G filings, the orange part is captured by parsing Form 3, 4 and 5 filings. Bars exceeding a height of 1 are due to institutional investors short-selling common stock to each other, obliging both parties to report ownership of the underlying securities.

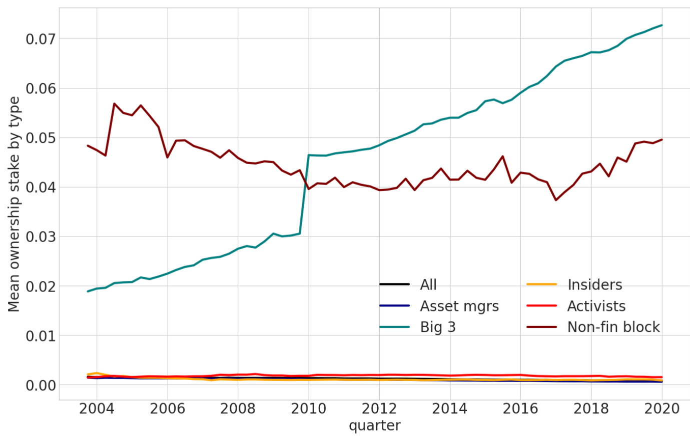


Figure A.3: Average individual ownership stake by filer type

Note: This figure depicts the average share of outstanding equity owned by an individual activist (Brav et al., 2008), insider (Form 3, 4, 5 filers), non-financial blockholder (non-activists, non-insiders, non-asset managers), asset manager (13-F filers, excl Big Three), one of the Big Three (BlackRock, Vanguard, StateStreet) and across all owners of an S&P 500 firm for each quarter.

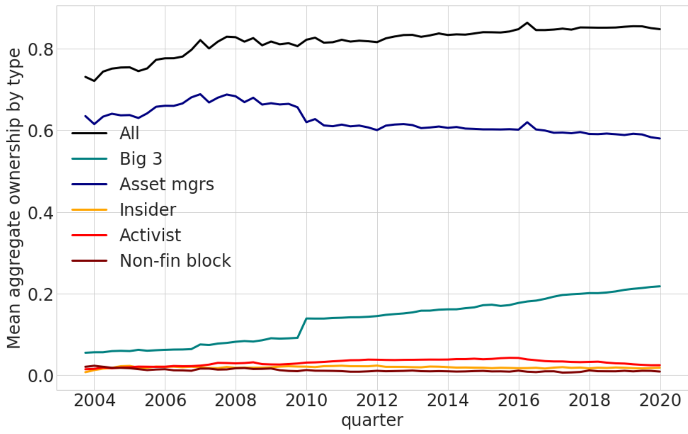


Figure A.4: Average aggregate ownership stake by filer type

Note: This figure depicts the aggregate share of outstanding equity owned by activists (Brav et al., 2008), insiders (Form 3, 4, 5 filers), non-financial blockholders (non-activists, non-insiders, non-asset managers), asset managers (13-F filers, excl Big Three), the Big Three (BlackRock, Vanguard, StateStreet) and across all owners of the average S&P 500 firm for each quarter.

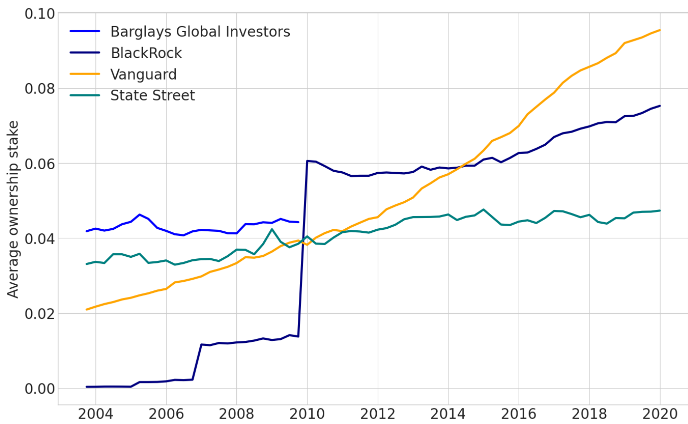


Figure A.5: Average ownership stake of Big Three & BGI

Note: This figure depicts the average share of outstanding equity of S&P 500 firms owned by Vanguard, BlackRock, State Street, and Barclays Global Investors (until the merger with BlackRock) each quarter.

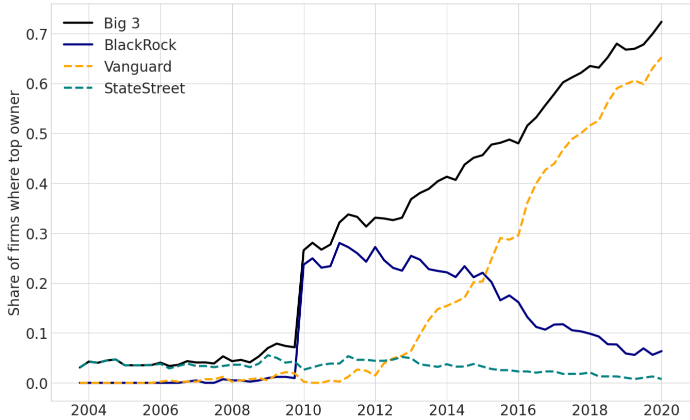


Figure A.6: Top owner position by Big Three

Note: This figure depicts the quarterly share of firms in our sample for which Vanguard, BlackRock, State Street, report the largest ownership stake, or one of the group does.

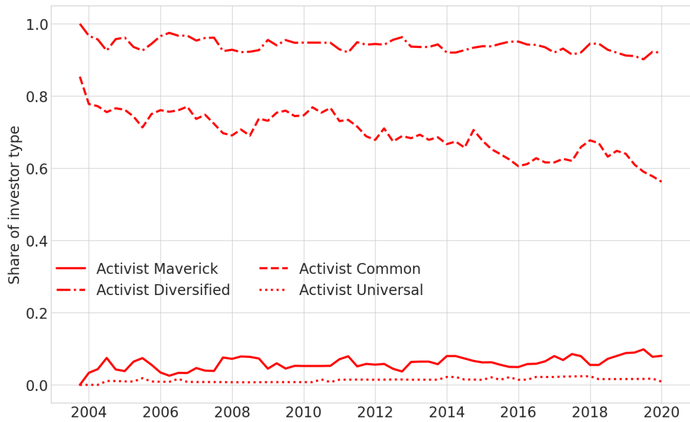


Figure A.7: Diversification of activist investors

Note: This figure depicts the quarterly share of activist investors that can be categorized as maverick owners, as diversified owners, as common owners or as universal owners. Maverick owners hold 1 security in a given quarter, diversified owners hold multiple firms per quarter but not within the same industry, common owners hold multiple firms competing in the same industry and across industries but less than 95% of all firms in the sample and universal owners hold more than 95% of all firms in the sample making them both diversified and common owners, too.

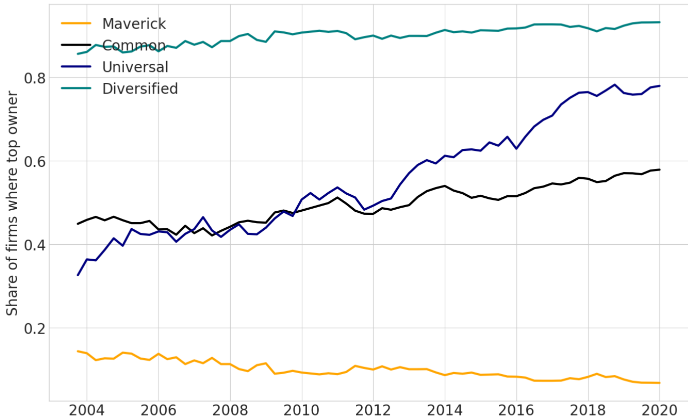
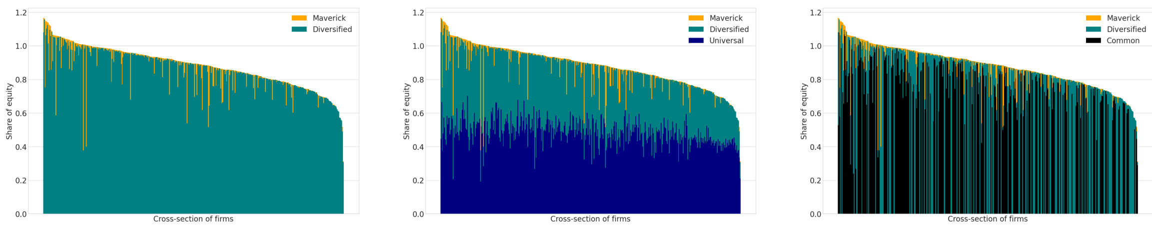


Figure A.8: Top owner position by diversification

Note: This figure depicts the quarterly share of firms in our sample for which a maverick owner, a diversified owner, a common owner or a universal owner reports the largest ownership stake. Maverick owners hold 1 security in a given quarter, diversified owners hold multiple firms per quarter but not within the same industry, common owners hold multiple firms competing in the same industry and across industries but less than 95% of all firms in the sample and universal owners hold more than 95% of all firms in the sample making them both diversified and common owners, too.



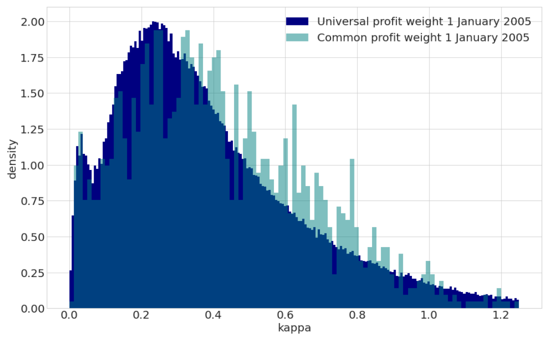
(a) Maverick & diversified ownership

(b) Maverick, diversified & universal ownership

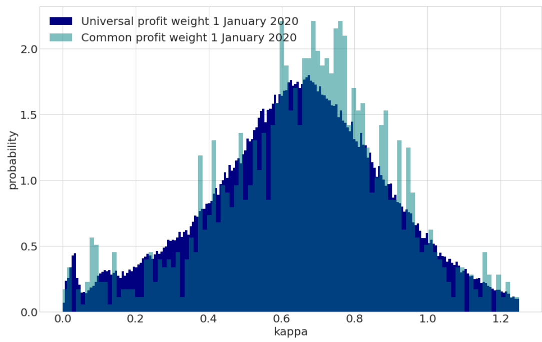
(c) Maverick, diversified & common ownership

Figure A.9: Ownership structures by diversification type, 1 January 2020

Note: These figures depict the captured ownership for each firm on 1 January 2020, differentiating ownership by the diversification of the investor. Each bar represents one firm. The bar height measures how much of the firm's stock ownership we capture. The proportion of each bar in turquoise represents the share of equity owned by diversified investors, who own shares in multiple companies but only across industries and in less than 95% of the sample firms. The blue proportion represents ownership by universal investors, where a universal investor owns more than 95% of the securities in our sample in the given period. The black part of each bar measures the holdings of common, but non-universal investors, who own shares in multiple firms in the same industry and across industries, but less than 95% of the sample. The orange part reports the holdings of undiversified shareholders, who own only shares in this company in the given quarter.



(a) 1 January 2005



(b) 1 January 2020

Figure A.10: Distribution of universal and common κ over time

Note: This figure depicts the distribution of universal and common ownership profit weights on 1 January 2005 and 1 January 2020. The distribution of universal kappas considers all firm-pairs. The distribution of common kappas considers only kappas for firm-pairs where both firms are in the same SIC 4 digit industry.

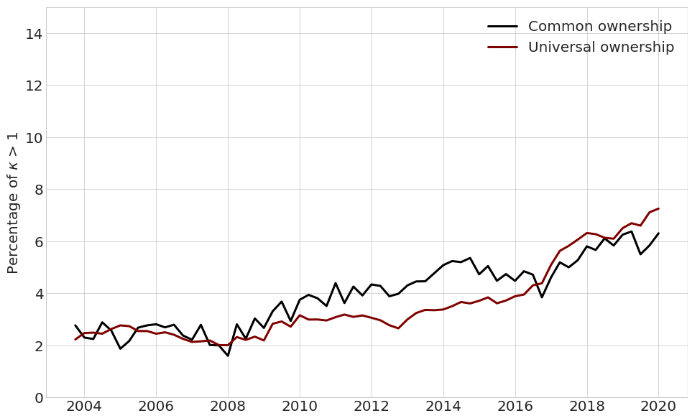
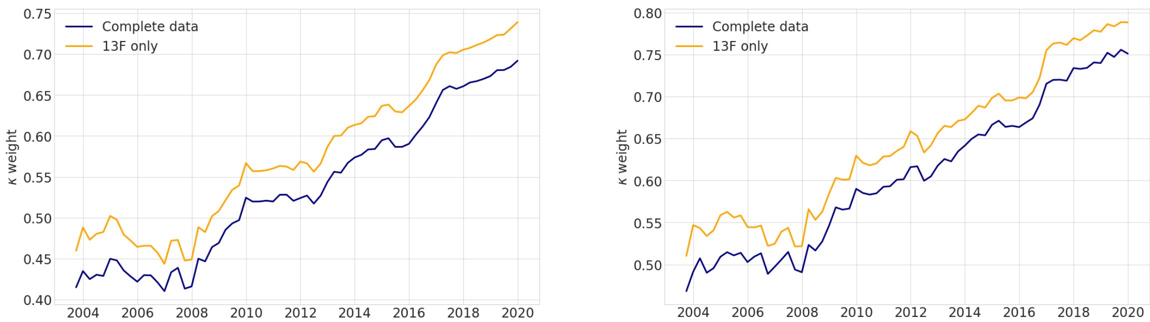


Figure A.11: Prevalence of tunneling incentives of universal and common owners

Note: This figure depicts the fraction of firm-pair profit weights that exceed 1 for universal ownership in black and for common ownership in dark red.

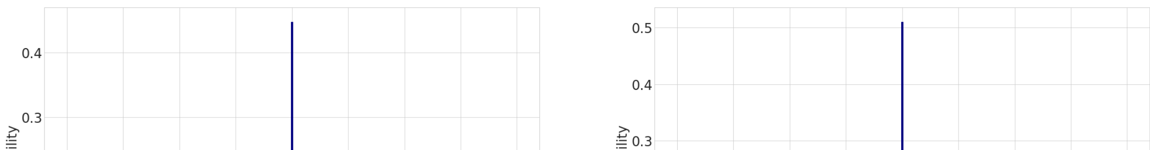


(a) Universal ownership

(b) Common ownership

Figure A.12: Average profit weight with complete & 13-F only data

Note: This figure depicts the average quarterly universal and common ownership profit weight calculated on the complete data set including 13DG and F345 filings (navy) and on 13F only data (orange). Average universal kappas consider all firm-pairs, average common kappas consider firm-pairs where both firms are in the same SIC-4 digit industry.

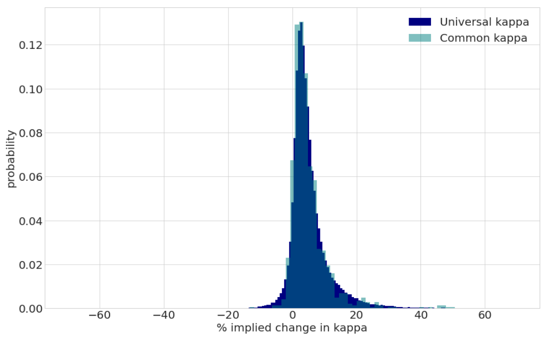


(a) Universal ownership

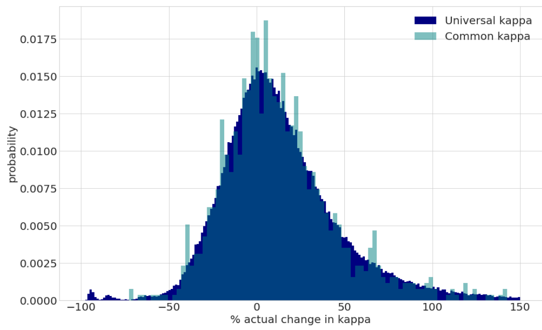
(b) Common ownership

Figure A.13: Distribution of changes in profit weights with complete data

Note: This figure depicts the distribution of percentage changes in universal and common ownership profit weights when adding corporate insiders and blockholders to the 13-F institutional ownership records and recalculating kappas on the complete data set. The distribution of change in universal kappas considers all quarters and all firm-pairs. The distribution of common kappas considers all quarters but only kappas for firm-pairs where both firms are in the same SIC 4 digit industry.



(a) Change in profit weights implied by merger



(b) Actual change in profit weights post merger

Figure A.14: Distribution of changes in profit weights due to BLK-BGI merger

Note: This figure depicts the distribution of percentage changes in ownership structure similarity implied by the merger of BlackRock and BGI on the left and the changes in actual post merger profit weights on the right. The "implied" firm-pair profit weight change is calculated as the difference between counterfactual profit weights with BlackRock & BGI holdings in 2009 Q1 added up vs the correct profit weights in 2009 Q1. Actual profit weight changes are the difference between profit weights in 2010 Q1 vs 2009 Q1.

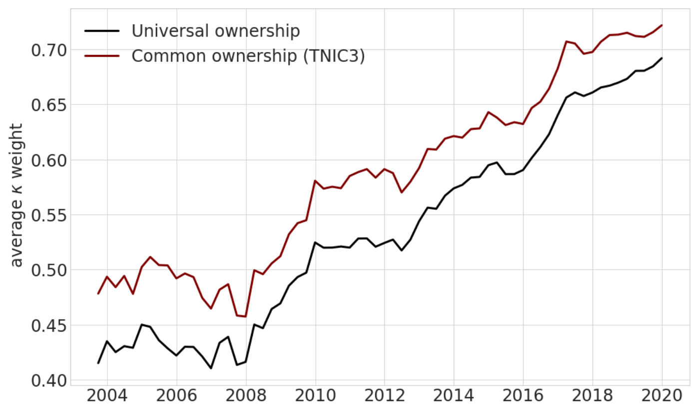


Figure A.15: Average universal and TNIC-3 common profit weights

Note: This figure depicts the average universal ownership profit weights over time in black and the average common ownership profit weights in dark red. The average common ownership profit weight is calculated using only profit weights of firm-pairs where both firms are in the same TNIC3 industry, as identified by Hoberg and Phillips, 2010. Profit weights are averaged each quarter across firms weighting all firms equally.

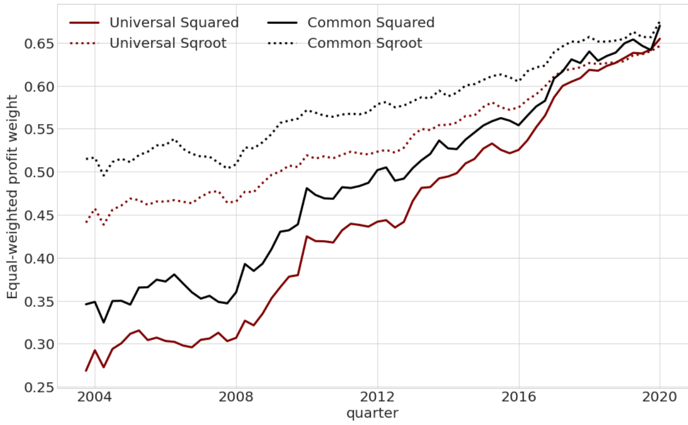


Figure A.16: Average universal and common κ varying control assumptions

Note: This figure depicts the profit weights under the assumption $\gamma_{bs} = \beta_{bs}^2$ in dark red and the profit weights under the assumption $\gamma_{bs} = \beta_{bs}^{0.5}$ in light red. Respectively, the unbroken line represents the average universal profit weights, while the dotted line represents average common ownership profit weights. The average common ownership profit weight is calculated using only profit weights of firm-pairs where both firms are in the same SIC-4 digit industry. Profit weights are averaged each quarter across firms weighting all firms equally.

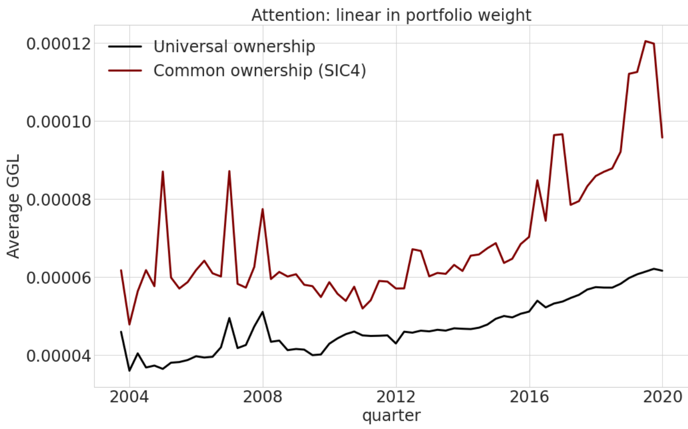


Figure A.17: Average universal and common ownership GGL weights

Note: This figure depicts the average universal ownership GGL weights (Gilje et al., 2020) over time in black and the average common ownership GGL weights in dark red. The GGL-attention proxy is linear in the weight of a certain firm in an investor's portfolio. The average common ownership profit weight is calculated using only GGL weights of firm-pairs where both firms are in the same SIC-4 industry. GGL weights are averaged each quarter across firms weighting all firms equally.

	Actual Change $\kappa_{common,post}$			
	2009Q4	2010Q1	2011Q1	2012Q1
Implied $\Delta\kappa_{com,imp}$	0.780***	0.548***	0.593***	0.700***
	(0.056)	(0.063)	(0.073)	(0.082)
R-squared	0.988	0.992	0.994	0.995
R-squared Adj.	0.053	0.021	0.018	0.020
p(F-stat)	0.000	0.000	0.000	0.000
Firm FE	✓	✓	✓	✓
N	3482	3482	3482	3482

Table A.1: Merger contribution to TNIC-3 common kappa changes

Note: This table presents results for a firm-pair level regression of actual changes in common profit weights due to the BlackRock-BGI merger on implied changes of profit weights only consider firm-pairs consisting of product market competitors as identified by Hoberg and Phillips, 2010. Actual changes are the difference between profit weights calculated for various post-merger periods (2009Q4, 2010Q1, 2011Q1, 2012Q1) and profit weights calculated for the pre-merger period 2009Q1. Implied changes are the difference between counterfactual profit weights calculated based on 2009Q1 data but when consolidating the BlackRock and BGI ownership stakes and the profit weights calculated on baseline 2009Q1 data. We control for firm and industry-fixed effects and a constant controls for quarter-specific fixed effects. One star denotes coefficients significant at the 10% level, two stars are significance at the 5% level, three stars are significance at the 1% level.

	2009Q4		2012Q1	
	$\kappa_{univ,post}$	$\kappa_{univ,post}$-13F	$\kappa_{univ,post}$	$\kappa_{univ,post}$-13F
Implied $\Delta\kappa_{univ,imp}$	0.649***	0.644***	0.793***	0.989***
	(0.009)	(0.007)	(0.013)	(0.010)
R-squared	0.984	0.972	0.995	0.999
R-squared Adj.	0.036	0.061	0.012	0.067
p(F-stat)	0.000	0.000	0.000	0.000
Firm FE	✓	✓	✓	✓
N	137849	137849	137849	137849

Table A.2: Merger contribution to universal kappa changes, complete & 13-F only data

Note: This table presents results for a firm-pair level regression of actual changes in universal profit weights due to the BlackRock-BGI merger on implied changes of profit weights, either using the complete ownership data set or only the subset captured with 13-F filings. Actual changes are the difference between profit weights calculated for various post-merger periods (2009Q4, 2010Q1, 2011Q1, 2012Q1) and profit weights calculated for the pre-merger period 2009Q1. Implied changes are the difference between counterfactual profit weights calculated based on 2009Q1 data but when consolidating the BlackRock and BGI ownership stakes and the profit weights calculated on baseline 2009Q1 data. We control for firm and industry-fixed effects and a constant controls for quarter-specific fixed effects. One star denotes coefficients significant at the 10% level, two stars are significance at the 5% level, three stars are significance at the 1% level.

	2009Q4		2012Q1	
	$\kappa_{com,post}$	$\kappa_{com,post}$-13F	$\kappa_{com,post}$	$\kappa_{com,post}$-13F
Implied $\Delta\kappa_{com,imp}$	1.214***	0.896***	1.170***	1.186***
	(0.107)	(0.072)	(0.152)	(0.100)
R-squared	1.019	0.987	1.005	1.012
R-squared Adj.	0.109	0.039	0.053	0.083
p(F-stat)	0.000	0.000	0.000	0.000
Firm FE	✓	✓	✓	✓
N	1039	1042	1039	1042

Table A.3: Merger contribution to SIC-4 common kappa changes, complete & 13-F only data

Note: This table presents results for a firm-pair level regression of actual changes in common profit weights due to the BlackRock-BGI merger on implied profit weight changes, using the complete ownership data set set or only the subset captured in 13-F filings. This regressions considers only firm-pairs consisting of product market competitors as identified by SIC-4 industry codes. Actual changes are the difference between profit weights calculated for various post-merger periods (2009Q4, 2010Q1, 2011Q1, 2012Q1) and profit weights calculated for the pre-merger period 2009Q1. Implied changes are the difference between counterfactual profit weights calculated based on 2009Q1 data but when consolidating the BlackRock and BGI ownership stakes and the profit weights calculated on baseline 2009Q1 data. We control for firm and industry-fixed effects and a constant controls for quarter-specific fixed effects. One star denotes coefficients significant at the 10% level, two stars are significance at the 5% level, three stars are significance at the 1% level.

	2009Q4		2012Q1	
	$\kappa_{com,post}$	$\kappa_{com,post}$-13F	$\kappa_{com,post}$	$\kappa_{com,post}$-13F
Implied $\Delta\kappa_{com,imp}$	0.780***	0.619***	0.700***	1.029***
	(0.040)	(0.072)	(0.082)	(0.058)
R-squared	0.988	0.985	0.995	1.002
R-squared Adj.	0.053	0.129	0.020	0.119
p(F-stat)	0.000	0.000	0.000	0.000
Firm FE	✓	✓	✓	✓
N	3482	3521	3482	3521

Table A.4: Merger contribution to TNIC-3 common kappa changes, complete & 13-F only data

Note: This table presents results for a firm-pair level regression of actual changes in common profit weights due to the BlackRock-BGI merger on implied profit weight changes, using the complete ownership data set set or only the subset captured in 13-F filings. This regressions considers only firm-pairs consisting of product market competitors as identified by Hoberg and Phillips, 2010. Actual changes are the difference between profit weights calculated for various post-merger periods (2009Q4, 2010Q1, 2011Q1, 2012Q1) and profit weights calculated for the pre-merger period 2009Q1. Implied changes are the difference between counterfactual profit weights calculated based on 2009Q1 data but when consolidating the BlackRock and BGI ownership stakes and the profit weights calculated on baseline 2009Q1 data. We control for firm and industry-fixed effects and a constant controls for quarter-specific fixed effects. One star denotes coefficients significant at the 10% level, two stars are significance at the 5% level, three stars are significance at the 1% level.

	(0) κ	(1) κ	(2) κ	(3) κ	(4) κ	(5) κ
Insider	-0.552***	-0.289***	-0.290***		-0.247***	
	(0.001)	(0.001)	(0.001)		(0.001)	
Activist	-0.077***	0.258***	0.257***	0.298***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Non-fin Block	-0.432***	-0.177***	-0.177***			
	(0.001)	(0.001)	(0.001)			
Big Three	0.980***		0.025***			0.016***
	(0.002)		(0.003)			(0.003)
Indexing		1.163***	1.157***	1.253***	1.157***	1.188***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Retail share	0.565***	0.412***	0.414***	0.428***	0.418***	0.423***
Firm age	0.001***	0.001***	0.001***	0.000***	0.001***	0.001***
log Market Cap	0.047***	0.036***	0.036***	0.034***	0.034***	0.033***
log Sales	0.009***	0.014***	0.014***	0.015***	0.014***	0.014***
Op. Margin	0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
R-squared	0.797	0.807	0.807	0.807	0.807	0.806
R-squared Adj.	0.196	0.238	0.238	0.235	0.234	0.232
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000
Pair FE	✓	✓	✓	✓	✓	✓
Quarter-Year FE	✓	✓	✓	✓	✓	✓
N	12647495	12647495	12647495	12647495	12647495	12647495

Table A.5: Drivers of universal kappa - all activists

Note: This table presents results of regressions of all firm-pair profit weights (our "universal" ownership measure) on aggregate holdings of corporate insiders (filing Form 3, 4, 5 reports), of activists (investors who at any point in our sample run an activist campaign in any sample firm, see Brav et al., 2008), of non-financial blockholders (non-insider, non-asset manager, non-activists), of the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), firm age, the retail share of ownership (defined as 1 minus captured ownership fraction), log market capitalization, log sales and operating margin. We residualize and adjust the R-squared for quarter-year and firm-pair fixed effects (because κ_{ij} effect differs from κ_{ji}). One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

	(0) κ	(1) κ	(2) κ	(3) κ	(4) κ	(5) κ
Insider	-0.553***	-0.314***	-0.315***		-0.247***	
	(0.001)	(0.001)	(0.001)		(0.001)	
Eng Activist	-0.406***	-0.051***	-0.052***	-0.008***		
	(0.002)	(0.002)	(0.002)	(0.002)		
Non fin block	-0.433***	-0.196***	-0.197***			
	(0.001)	(0.001)	(0.001)			
Big Three	0.964***		0.045***			0.016***
	(0.002)		(0.003)			(0.003)
Indexing		1.097***	1.087***	1.191***	1.157***	1.188***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Retail share	0.561***	0.406***	0.408***	0.422***	0.418***	0.423***
Firm age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Log Market Cap	0.046***	0.035***	0.035***	0.033***	0.034***	0.033***
Log sale	0.009***	0.013***	0.013***	0.014***	0.014***	0.014***
Op margin	0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
R-squared	0.797	0.807	0.807	0.806	0.807	0.806
R-squared Adj.	0.198	0.236	0.236	0.232	0.234	0.232
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000
Pair FE	✓	✓	✓	✓	✓	✓
Quarter-Year FE	✓	✓	✓	✓	✓	✓
N	12647495	12647495	12647495	12647495	12647495	12647495

Table A.6: Drivers of universal kappa - engaged activists

Note: This table presents results of a regression of profit weights on aggregate holdings of corporate insiders (filing Form 3, 4, 5 reports), of engaged activists (investors that are currently running an activist campaign in underlying firm, see Brav et al., 2008), of non-financial blockholders (non-insider, non-asset manager, non-activists), of the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), firm age, the retail share of ownership (defined as 1 minus captured ownership fraction), log market capitalization, log sales and operating margin. The first three columns consider all firm-pair profit weights and thus represent an analysis of our "universal" ownership measure. Column 3a provides results for an analogous regression performed in Backus et al 2021 on 13-F institutional ownership data only and serves to showcase how our improved parsing of Big Three holdings changes the coefficient sign. Columns 4-6 present regression results when only considering firm-pairs in the same industry, interpreted as a measure of "common" ownership. We residualize and adjust the R-squared for quarter-year and firm-pair fixed effects (because κ_{ij} effect differs from κ_{ji}). One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

	(0) κ	(1) κ	(2) κ	(3) κ	(4) κ	(5) κ	(6) κ	(7) κ
Insider	-0.237***	-0.322***	-0.291***	-0.333***	-0.275***	-0.358***	-0.378***	-0.289***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Activist	0.546***	0.525***	0.492***	0.588***	0.537***	0.539***	0.670***	0.449***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Eng Activist	-0.685***	-0.589***	-0.551***	-0.791***	-0.691***	-0.765***	-0.986***	-0.488***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Non-fin Block	-0.285***	-0.213***	-0.196***	-0.262***	-0.234***	-0.213***	-0.244***	-0.178***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Big Three	0.411***	0.107***	0.121***	0.323***	-0.459***	-0.565***	0.048***	0.025***
	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)
Indexing	1.186***	1.124***	1.136***	1.253***	1.315***	1.355***	1.343***	1.151***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Retail share	0.345***	0.383***	0.405***	0.360***	0.334***	0.350***	0.373***	0.416***
Firm age	-0.000***	0.005***	0.005***	-0.000***	-0.000***	-0.000***	-0.000***	0.001***
log Market cap	0.047***	0.022***	0.023***	0.047***	0.040***	0.043***	0.050***	0.036***
log Sales	0.004***	0.024***	0.021***	0.006***	0.004***	0.002***	0.002***	0.014***
Op. margin	0.010***	-0.001***	-0.001***	0.029***	0.007***	0.025***	0.036***	-0.001***
R-squared	0.467	0.560	0.806	0.493	0.477	0.503	0.531	0.808
R-squared Adj.	0.467	0.261	0.386	0.405	0.407	0.322	0.331	0.239
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm FE		✓						
Pair FE			✓					✓
Industry FE				✓		✓		
Quarter-Year FE					✓	✓		✓
Quarter-year#Industry FE							✓	
N	12647495	12647495	12647495	12647495	12647495	12647495	12647495	12647495

Table A.7: Drivers of universal kappa - vary fixed effects

Note: This table presents results of a regression of profit weights on aggregate holdings of insiders, activists, engaged activists, the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), the retail share of ownership (defined as 1 minus captured ownership fraction), log market capitalization, operating margin. We residualize and adjust the R-squared for the respective fixed effects. One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

	(0) κ	(1) κ	(2) κ	(3) κ	(4) κ	(5) κ	(6) κ	(7) κ
Insider	-0.527***	-0.459***	-0.460***	-0.549***	-0.543***	-0.559***	-0.687***	-0.401***
	(0.013)	(0.018)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
Activist	0.614***	0.441***	0.382***	0.559***	0.625***	0.523***	0.679***	0.311***
	(0.024)	(0.029)	(0.022)	(0.024)	(0.024)	(0.024)	(0.025)	(0.022)
Eng Activist	-0.821***	-0.664***	-0.679***	-0.757***	-0.860***	-0.761***	-1.034***	-0.560***
	(0.035)	(0.050)	(0.039)	(0.036)	(0.035)	(0.035)	(0.036)	(0.039)
Non-fin block	-0.334***	-0.222***	-0.220***	-0.319***	-0.236***	-0.207***	-0.254***	-0.146***
	(0.016)	(0.018)	(0.014)	(0.016)	(0.015)	(0.016)	(0.016)	(0.014)
Big Three	0.237***	0.081**	0.071***	0.277***	-0.634***	-0.692***	-0.875***	-0.272***
	(0.016)	(0.035)	(0.027)	(0.016)	(0.034)	(0.034)	(0.035)	(0.033)
Indexing	1.415***	1.278***	1.267***	1.332***	1.542***	1.441***	1.307***	1.341***
	(0.015)	(0.020)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Retail share	0.258***	0.370***	0.396***	0.353***	0.286***	0.398***	0.480***	0.441***
Firm age	0.000	0.005***	0.005***	-0.000	-0.000	-0.000***	-0.000***	-0.001
log Market cap	0.051***	0.010***	0.017***	0.046***	0.049***	0.050***	0.050***	0.041***
log Sales	0.009***	0.023***	0.018***	0.012***	0.004***	-0.002**	-0.002**	-0.000
Op. margin	-0.031***	-0.001	0.000	-0.003	-0.032***	-0.003	-0.004*	0.002
R-squared	0.477	0.606	0.788	0.511	0.493	0.530	0.568	0.794
R-squared Adj.	0.477	0.283	0.374	0.443	0.442	0.399	0.415	0.296
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm FE		✓						
Pair FE			✓					✓
Industry FE				✓		✓		
Quarter-Year FE					✓	✓		✓
Quarter-year#Industry FE							✓	
N	95066	95066	95066	95066	95066	95066	95066	95066

Table A.8: Drivers of SIC-4 common kappa - vary fixed effects

Note: This table presents results of a regression of profit weights of within SIC-4 industry competitors on aggregate holdings of insiders, activists, engaged activists, the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), the retail share of ownership (defined as 1 minus captured ownership fraction), log market capitalization, operating margin. We residualize and adjust the R-squared for the respective fixed effects. One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

	(0) κ	(1) κ	(2) κ	(3) κ	(4) κ	(5) κ	(6) κ	(7) κ
Insider	-0.424***	-0.432***	-0.412***	-0.511***	-0.461***	-0.537***	-0.549***	-0.400***
	(0.009)	(0.014)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Activist	0.684***	0.608***	0.562***	0.735***	0.683***	0.706***	0.847***	0.503***
	(0.015)	(0.018)	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)	(0.014)
Eng Activist	-0.783***	-0.864***	-0.876***	-0.960***	-0.819***	-0.965***	-1.138***	-0.788***
	(0.023)	(0.030)	(0.023)	(0.024)	(0.023)	(0.023)	(0.027)	(0.023)
Non-fin block	-0.497***	-0.165***	-0.179***	-0.390***	-0.441***	-0.311***	-0.374***	-0.136***
	(0.008)	(0.011)	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)	(0.008)
Big Three	0.264***	0.224***	0.198***	0.278***	-0.694***	-0.706***	-0.160***	0.097***
	(0.009)	(0.020)	(0.015)	(0.010)	(0.018)	(0.019)	(0.015)	(0.019)
Indexing	1.369***	1.271***	1.308***	1.394***	1.507***	1.516***	1.492***	1.339***
	(0.009)	(0.012)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)
Retail share	0.340***	0.412***	0.428***	0.392***	0.326***	0.385***	0.428***	0.445***
Firm age	0.000***	0.004***	0.004***	-0.000***	0.000***	-0.000***	-0.000***	0.001
log Market cap	0.052***	0.024***	0.024***	0.048***	0.045***	0.045***	0.054***	0.037***
log Sales	-0.001*	0.013***	0.006***	0.008***	-0.001**	0.003***	0.003***	-0.001
Op. margin	-0.012***	0.000	0.002	0.015***	-0.014***	0.011***	0.018***	0.004***
R-squared	0.501	0.616	0.823	0.535	0.512	0.546	0.581	0.825
R-squared Adj.	0.501	0.281	0.378	0.449	0.461	0.393	0.407	0.265
p(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Firm FE		✓						
Pair FE			✓					✓
Industry FE				✓		✓		
Quarter-Year FE					✓	✓		✓
Quarter-year#Industry FE							✓	
N	282179	282179	282179	282179	282179	282179	282179	282179

Table A.9: Drivers of TNIC-3 common kappa - vary fixed effects

Note: This table presents results of a regression of profit weights of within Hoberg and Phillips, 2010 TNIC-industry competitors on aggregate holdings of insiders, activists, engaged activists, the Big Three asset managers (BlackRock, Vanguard and State Street), a measure of investor indexing (Backus et al., 2021b), the retail share of ownership (defined as 1 minus captured ownership fraction), log market capitalization, operating margin. We residualize and adjust the R-squared for the respective fixed effects. One star denotes coefficients are significant at the 10% level, two stars significance at the 5% level, three stars significance at the 1% level.

Chapter 2

Common Ownership, Incentives & Productivity*

with **Amir Amel-Zadeh and Martin Schmalz**

Abstract We collect comprehensive ownership data for the universe of U.S. public firms to examine whether variation in ownership helps explain variation in productivity. We find that common ownership of product market rivals is negatively associated with total factor productivity in panel regressions, with larger effects on firms with lower initial levels of common ownership. Using index additions of competitors as shocks to common ownership, we find evidence of a causal relation between ownership and productivity. This is driven by a negative effect of common ownership on the performance-sensitivity of managerial compensation, which in turn causes lower productivity.

*We thank Vladimir Fedoseev for his excellent research assistance. We acknowledge funding support from Said Business School Oxford.

2.1 Introduction

Investors who own shares in multiple firms competing for the same product market have been termed "common owners". Common ownership has been on the rise, among other things due to consolidation in the asset management industry, due to the centralization of votes across funds within investment advisers, and due to deliberate decisions by active shareholders to concentrate their portfolio in product market rivals (Amel-Zadeh et al., 2022). The level of common ownership is now so large that it cannot be ignored for purposes of studying firm behavior: the largest three asset managers control about a quarter of votes of S&P 500 single-class firms, and an even greater fraction of votes actually voted.

In theory, such common ownership can soften incentives to compete, either because companies "looking out for their investors" maximize their most influential owners' aggregate portfolio returns (Rotemberg, 1984) or because common owners have reduced incentives to manage agency problems (Anton et al., 2022), thus enabling managers to lead a "quiet life" (Hicks, 1935). Both theories predict higher product prices due to common ownership, but for different reasons – and they make different predictions for effects on productivity. The former theory assumes that ownership does not affect costs and predicts that less vigorous competition leads to increased profit margins; the latter theory predicts that common ownership exacerbates agency problems, thus reduces productivity, and *thereby* raises product prices. Furthermore, theory also allows for the possibility that common ownership *increases* incentives for cost-reducing innovation (Anton et al., 2021; López & Vives, 2019). Extant literature, reviewed below, has examined effects of common ownership on product prices, R&D investments, and patenting, but not on productivity.

We investigate empirically whether and how common ownership affects firm-level productivity.

This appears an even more important question to address than whether common ownership affects product prices: the welfare effect of product price increases that come from a lessening of competition and higher margins due to a change in firms' objectives but have no effect on the supply curve, is limited to the usual deadweight loss. The welfare effect of a lessening of competition due to reduced productivity and an inward-shift in the supply curve can be orders of magnitude greater. For this reason alone, studying productivity effects appears of first-order importance. A second reason why distinguishing between the theories is important is because the results may give cues as to the optimal policy response: policy proposals that would weaken institutional investors' ability to shape firm objectives may *strengthen* competition in theories in the tradition of Rotemberg. The same policies may further *weaken* competition in theories in which mismanaged agency conflicts and reduced productivity are at the core of the problem.

To answer this question, we first construct a uniquely comprehensive data set of ownership and control structures of all public U.S. firms, which we plan to make freely available to researchers with the present publication. In contrast to thus far commonly-used data sources, our data set includes not only institutional investors' holdings, but also those of large individual shareholders and corporate insiders, which are often the most influential or even controlling shareholders of U.S. public firms. We calculate the extent to which the most influential shareholders in one firm hold financial stakes in product market rivals, and relate this measure of common ownership to measures of managerial incentives taken from Edmans and Gabaix, 2016 and estimates of total factor productivity derived from balance sheet data as per De Loecker and Syverson, 2021.

We first establish a link between common ownership and productivity in panel regressions. To address potential reverse causality concerns and the endogenous relationship of common ownership and productivity due to unobserved omitted variables, we include year-by-industry fixed effects.

Our panel results indicate that common ownership is related to reduced productivity. Controlling for managerial incentives does not affect the significance of these results, although it reduces the size of the coefficients at the margin. This finding is consistent with common ownership affecting productivity, at least in part indirectly, via the governance channel. Quantitatively, if common owners increase their holdings of a firm by 10%, productivity decreases by about 1%.

To test whether the panel correlations have a causal interpretation, we next limit the variation in ownership used for identification to variation caused by index additions of competitors (Anton et al., 2022; Boller and Scott-Morton, 2020). Such index additions do not directly affect the ownership of incumbents, but they introduce variation in the extent to which index incumbents' shareholders have financial interests in rivals. The direct effect of common ownership on productivity corresponds to the difference in treated and untreated firms' productivity after the index addition. To test for the indirect effect via managerial incentives, we use the shock to common ownership from index additions to instrument the proportionate change in incentives and estimate how the instrumented change in incentives affects productivity.

The addition of a firm to the S&P 500 index increases common ownership between the added firm and index incumbents in the same industry, while common ownership of index incumbent firms in other industries is mostly unaffected. Ongoing portfolio re-balancing likely mutes the overall increase in common ownership, especially over a longer time-horizon, but we find a significant temporary shock to common ownership of index incumbent competitors. Controlling for a multitude of firm and ownership attributes, the direct effect of common ownership on productivity is on average insignificantly negative. One possible interpretation of this finding is that there is no measurable direct causal effect of common ownership on productivity. Another possible interpretation is that index additions of competing firms affect productivity via various channels, not all linked to common ownership, and on average balancing each other out. For example, Afego, 2017 find that index additions experience a reduction in their cost of capital and thereby increase competitive pressures on index incumbents to raise their efficiency in turn. This positive effect of competition on productivity (Backus, 2020) may cancel out a concurrent negative effect of common ownership.

To remove confounding competition effects, as well as to test for a specific mechanism that links common ownership to productivity, we use the change in managerial incentives caused by a shock to common ownership. The first stage difference-in-difference model estimates a highly significant 13% reduction in managerial incentives of index incumbents in response to the index addition and consistent with the prior literature (Anton et al., 2022). Regressing productivity on the instrumented variation in managerial incentives, the effect on productivity is positive and statistically significant. We thus conclude that there may or may not be a direct effect of common ownership on productivity, but an indirect effect exists, as reduced managerial incentives due to a positive shock to common ownership lead to a reduction in annual productivity of about 1.65% for the four years post-treatment. Coincidentally, via the same mechanism, we find that markups decrease as common ownership increases.

Our results are most consistent with the theory that common ownership exacerbates agency problems, reduces the performance-sensitivity of managerial compensation, and subsequently leads to lower corporate productivity.

We contribute to the literature studying the effects of common ownership on corporate outcomes by analyzing the perhaps most important outcome variable, productivity, as well as the channel by which common ownership may have such an impact. Most closely related to our work is Anton et al., 2022, who develop a theoretical mechanism of how common ownership can affect productivity via managerial incentives. Their empirical exercise is focused on the relation between common ownership and managerial incentives, leaving the effect on productivity untested. Our analysis fills this gap and provides empirical evidence for the causal impact of common ownership on productivity through its negative effect on managerial incentives. Additionally, we show that the causal effect of common ownership on managerial incentives holds when accounting for corporate insider ownership and dual class stock structures, which were missing in the Anton et al. data.

To the best of our knowledge, this paper is the first to study the relationship between common ownership and productivity for a broad cross-section of U.S. firms. Bas et al., 2023 study the correlation of common ownership and productivity in a cross-country analysis. They do not test particular mechanisms against each other.

The prior empirical literature has studied the relationship between common ownership and competition-related outcomes, such as prices, innovation and R&D investments (Anton et al., 2021; Aslan, 2019; López & Vives, 2019)), and between common ownership and financial returns (Boller & Scott-Morton, 2020; Lewellen & Lowry, 2021), either for a broad cross-section of firms or a single industry (Azar et al., 2018; Backus et al., 2021a). A comprehensive review of these papers is provided by Schmalz, 2021.

Furthermore, we add a novel dimension to the older literature on the relationship between corporate ownership attributes, incentives and productivity. Existing work studies the effect of managerial, institutional and family ownership on incentives and productivity (Amit & Villalonga, 2020; Hartzell & Starks, 2003; Hill & Snell, 1989). In response to the well-established concerns about the endogeneity of ownership and productivity (Demsetz & Lehn, 1985), we adopt a methodology developed by Boller and Scott-Morton, 2020 that provides reasonably exogenous variation in common ownership.

We also contribute to the applied-microeconomics literature investigating the reasons for the cross-sectional and time-series variation in firm-level productivity. For a comprehensive summary of exiting work on the drivers of productivity dispersion we refer the reader to De Loecker and Syverson, 2021. Closely related to Backus, 2020, who argues that competition is a key driver of varying productivity, our findings suggest that differences in common ownership cause productivity dispersion mainly via managerial incentives. The link between managerial incentives and productivity was first proposed by Hicks, 1935 and empirically investigated by Bertrand and Mullainathan, 2003. The difference between Bertrand and Mullainathan, 2003 and our work is the cause of the variation in managerial incentives.

We do not directly address the question whether changes in ownership of U.S. corporations may help explain the declining trend in U.S. productivity (Sprague, 2021); our focus is instead on understanding the cross-sectional variation (Syverson, 2011).

Finally, we contribute to the literature and academic profession by making the underlying data set of corporate ownership structures for all publicly listed U.S. firms freely available to other researchers. We thereby hope to make research into corporate governance and shareholdings more accessible to researchers globally, and to improve the robustness of findings by providing a comprehensive and accurate ownership database.

2.2 Data & variable construction

The analysis in this paper is based on a novel data set of the complete institutional and insider ownership structure of U.S. publicly traded firms. Below we describe the data construction at a cursory level. For a detailed account of the cleaning, consolidation and correction routine we refer the reader to Appendix 1.A of Chapter 1. The total factor productivity estimates are derived from Compustat balance sheet data using the standard procedures employed in the applied microeconomics literature (De Loecker & Syverson, 2021). We focus our analysis on the estimates based on the cost shares approach. Findings for total factor productivity estimates based on the proxy (Ackerberg et al., 2015) and dynamic panel production function approach (Blundell & Bond, 2000) are provided in the robustness section. Finally, we follow Anton et al., 2022 and use estimates for CEO wealth-performance sensitivity derived and provided by Edmans and Gabaix, 2016 as proxy for managerial incentives.

2.2.1 Ownership data and measures

The ownership data underlying this project is unique in its comprehensiveness, accuracy and time-coverage. With an extensive, automated routine coded in Python we scrape, parse and consolidate all available ownership reports filed with the Securities Exchange Commission (SEC) since 1999. This combines the holdings of asset managers, blockholders and corporate insiders in one, accessible database for the first time. Since we are interested in both cash flow and control rights, we adjust the voting rights of shareholders in firms with multiple classes of common stock to reflect the actual number of votes held. The resulting data set comprises ownership and control structures of U.S. public firms with single and multiple stock classes between 2000 and 2020.

The types of ownership filings consolidated in our data set are 13-F reports of institutional asset managers, SC 13-D and SC 13-G reports submitted by blockholders with or without an intention to engage a given firm, and Form 3/4/5 reports by corporate insiders, such as C-Suite executives, board members or other employees with stock holdings in their own firms. We provide more detail on the filing requirements and formats in Amel-Zadeh et al., 2022 which employs the same data collection routine for the subset of single-class S&P500 firms. From each filing type we parse all relevant information to identify securities, holding sizes and owners. The filings differ substantially in the information contained and their formatting, thus we apply a filing-specific pipeline to the 13-F, the SC 13-D/G, and the Form 3/4/5 reports, respectively, in order to clean and capture the reported ownership. Each pipeline is extensively spot-checked, and captures more comprehensive and cleaner ownership data across a wider range of firms than the commonly used, publicly available ownership data sources (Backus et al., 2021b; Hadlock & Schwartz-Ziv, 2019).

Within each pipeline we separate firms with a single class of common stock outstanding from those with multiple classes of common stock, in order to attribute the correct number of votes to each share holding. For that purpose, a separate data set on publicly traded firms with multiple classes of common stock, their respective voting rights and number of shares outstanding of less commonly traded classes is compiled manually, extending and expanding on existing data by Gao et al., 2014 and Gompers et al., 2010. We merge the security level information on votes and shares outstanding to the ownership data based on security identifiers or extensively cleaned descriptions of security classes (see Chapter 1 Appendix).

The resulting three data sets for institutional ownership, blockholder ownership and insider ownership provide information on the shares and votes held at the security-owner-quarter level but with gaps. Blockholder and insider filings are required only when stock holdings change, implying that in quarters without trades we do not observe an ownership report. Before merging the data of the three investor types, we interpolate the holdings of blockholders and insiders to have consistent quarterly filings. This step relies on the assumption that investors file according to the requirements whenever they change their holdings and thus stakes do not change between two reports. An additional complication arises where blockholders or insiders file non-zero stock holdings in their final ownership report. The filing requirements imply that such investors have become silent holders of stock who continue to hold the same number of shares indefinitely. However, this may not be true in the long run as investors die or transfer their holdings without proper filing notice. To account for silent blockholders but limit indefinite ownership, we extrapolate final non-zero holdings of insiders and blockholders for twelve quarters.

Combining the ownership of different investor types can create a substantial amount of duplication at the security-owner group-quarter level. For example, as we observe 13-F and SC 13-G filings reporting the same number of shares owned in the same firm and in the same quarter but by different owners. This is the case because the institution holding the shares reports this ownership, but the controlling shareholder of the institution reports it as well. Warren Buffett for Berkshire Hathaway or Carl Icahn for Icahn Enterprises are cases observed in the data. Alternatively, duplication occurs across Form 4 and SC 13-G/D filings. For example, a family member can sit on a corporation's board and file an insider report on the controlling stake held in trust with the family trust, while the trust also reports these holdings, as is the case for the Walton family members and the Walton Family Trust in Walmart. We consolidate the holdings of such investor groups first using a manually compiled list of "investor groups", where the shares and votes owned are likely under the control of one individual or where we assume that the group will act as one entity in most voting choices. For example the different BlackRock entities filing separate 13-F reports are all aggregate to one BlackRock Family. Analogously, the different ownership stakes of the Walton siblings are mainly held in the Family Trust, such that we keep the Trust as the main owner. For controlling owners of asset managers, such as Warren Buffett for Berkshire Hathaway, we assume that the individual is in control of how the votes owned are cast and therefore attribute the ownership to the individual. In a second step to remove duplicate ownership we drop exact matches in share holdings of a certain size at the security-quarter level. Spot-checking some of these cases suggests we capture a non-negligible amount of duplicate filings not yet accounted for in our "investor group" data.

After cleaning and consolidating the complete data to a unique security-owner-quarter level, we attribute the correct number of votes to each holding and sum the stock and vote holdings across different stock classes. The result is a unique firm-owner-quarter data set of stock and vote ownership, that can be merged with firm-level information on incentives and productivity.

For this analysis, we focus our attention on companies for which the reported share holdings account for more than 30% of the outstanding shares, and do not exceed 150% of outstanding stock. Both restrictions seem necessary to ascertain that we remove firms with erroneous ownership data from our analysis and that we focus on firms for which we can identify a meaningful subset of owners. Aggregate reported ownership in excess of 100% of shares outstanding is a common feature even in the best commercial ownership databases, such as Capital IQ and Factset. It is driven by the extensive share lending of large asset managers and hedge funds. Where we capture less than 30% of aggregate ownership, this may be due to a limited float of common stock or widely dispersed ownership, especially prevalent in very small firms.

The resulting data set contains quarterly holdings of all investors required to report their investments to the SEC for most publicly traded companies from 2000-Q4 until 2019-Q4. The sample consists of more than 6000 firms in total, with a declining number of unique firms per quarter, starting at more than 4000 and ending closer to 2500. The total number of investors has been roughly constant at about 120,000 since 2004, when a change in S.E.C. regulation began mandating corporate insider reports. Before 2004 insiders of significant size were required to report as blockholders, hence the more meaningful subset of insiders is already contained in our earlier sample. Over time the number of blockholders and corporate insiders (i.e. filers of SC 13-D, SC 13-G or Form 3/4/5 reports) has been declining gradually, while the number of institutional investment managers required to file 13-F reports has been increasing.

Common ownership interests reflected in our ownership data are primarily measured by the so called "profit weights", following the literature beginning with Rotemberg, 1984 and Backus et al., 2021b and since then widely used in the relevant economics literature. The key underlying theory is based on a firm's objective to maximize shareholder value taking into account the portfolio interests of its diversified and undiversified shareholders. Backus et al., 2021b clarify the assumptions under which the objective function Q_f of firm f, a function of its shareholders' portfolios x, can be re-written as the sum of own firm profits and weighted competitors' profits. The weight on competitor g's profits is referred to as profit weight of fg, and corresponds to the sum of vote-weighted cash flow interests in firm g relative to the sum of vote-weighted cash flow interests in firm f across all shareholders of firm f. The profit weight is also referred to as "Edgeworth coefficient of effective sympathy" or "κ_{fg}" and is frequently used in the applied industrial organization and common ownership literature (Anton et al., 2022; Azar & Vives, 2019).

$$Q_{ft}(x_f, x_{-f}) \approx \pi_{ft} + \sum_{g \neq f} \underbrace{\left(\frac{\sum_i \gamma_{ift} \beta_{igt}}{\sum_i \gamma_{ift} \beta_{ift}} \right)}_{\kappa_{fgt}} \pi_{gt} \tag{2.1}$$

In the above equation β_{if} and γ_{if} are the fraction of shares of firm f and the fraction of votes of firm f owned by shareholder i, respectively. In our analysis the fraction of votes is the number of votes held according to the number and class of shares owned, divided by the total number of votes outstanding for the firm. For all single class firms we assume the one share-one vote proportional control structure.

The calculated common ownership profit weights are unique and directed at the firm-pair level. For each period t, firm f has a κ_{fg} for its competitor g and a different κ_{fh} for its competitor h, whilst firms g and h again have different profit weights for each other and firm f. To investigate the relationship between common ownership and productivity at the firm-year level we measure for each firm the equally-weighted average profit weight across all its competitors, κ_f. Competitors are firms in the same historical NAICS industry at the 3-digit level. This level of granularity is chosen to correspond to the level of production function estimates. Alternative weightings of profit weights based on market capitalization share and sales share are considered in our robustness analysis.

While profit weights are the key measure of common ownership used in this paper, two alternative measures are employed to ascertain the robustness of our results and to simplify interpretation. The first alternative measure is the cosine similarity of the vectors describing cash flow ownership in firms f and g. Under the assumption that cash flow and voting rights are the same ($\beta = \gamma$), Backus et al. show that profit weights can be decomposed into this similarity measure and a measure of relative investor concentration. In addition to being more-readily interpreted than profit weights, cosine similarities of cash flow ownership are an attractive measure as they provide an insight into whether similarity in cash flow interests is related to productivity outcomes, regardless of investor control.

$$\kappa_{fgt} = \underbrace{cos(\beta_{ft}, \beta_{gt})}_{cosine-similarity} * \sqrt{\frac{\sum_i \beta_{igt}^2}{\sum_i \beta_{ift}^2}} \tag{2.2}$$

A third measure of common ownership we employ is the aggregate fraction of votes held by "common owners" ($aggCO_f$). Common owners are defined as investors in firm f who concurrently hold shares in at least one competitor in the same NAICS-3 industry.

$$aggCO_{ft} = \sum_{i_{co} \in i} \gamma_{ift} \tag{2.3}$$

2.2.2 Productivity estimates

In this paper we consider total factor productivity residuals as the key measure of corporate productivity. Total factor productivity, henceforth TFP or Ω, measures the unexplained variation in output once a given number of inputs (materials M, overhead A and capital K) are combined using the firm-specific technology or production function $f(\cdot)$. Log normalized variables are denoted by lowercase letters. The following paragraphs describe our measures of inputs and outputs, and how we estimate the production function parameters.

$$Output = \Omega * f(M, A, K) \quad \Rightarrow \quad \omega = output - f(m, a, k) \tag{2.4}$$

For our estimation we use publicly available balance sheet data from Compustat for the universe of U.S. firms between 1995 and 2020. Data on sales revenue, cost of goods sold, property plant & equipment, administrative expenses and labor expenditures is cleaned as in De Loecker et al., 2020, removing missing values, trimming outliers at the 1st and 99th percentile, and deflating the values using average annual GDP deflator data provided by the Federal Reserve Economic Data center (FRED). To allow for variation in technology (TFP) when firms merge, acquire or divest a substantial amount of assets, we artificially split the firm into two entities before and after the acquisition/divestiture event. This only affects TFP estimates based on the dynamic panel and proxy approach. Finally, we drop firms that change historical NAICS-3 sectors more than four times in our sample period, firms that have negative net sales (sales minus cost of goods sold minus administrative expenses) for more than 50% of their existence in our data set, and remove financial firms as well as public utility firms due to fundamental differences in their production functions, accounting practices, and regulatory constraints.

Our main specification assumes output and revenue are generated with a Cobb-Douglas production function using three inputs: cost of goods sold m, administrative expenses a and capital expenditures k. We also consider TFP estimates based on a two input production function, which drops administrative expenses as input. The equation below describes the log-linearized Cobb-Douglas production with three inputs, where each input has a firm- and year-specific output elasticity α.

$$
\begin{aligned}
output_{ft} &= \omega_{ft} + \alpha^{m}_{ft} m_{ft} + \alpha^{a}_{ft} a_{ft} + \alpha^{k}_{ft} k_{ft} + \epsilon_{ft} \\
\omega_{ft} &= output_{ft} - \alpha^{m}_{ft} m_{ft} - \alpha^{a}_{ft} a_{ft} - \alpha^{k}_{ft} k_{ft} - \epsilon_{ft}
\end{aligned}
\tag{2.5}
$$

To estimate the TFP residual, ω_{ft}, of this production function, we follow the empirical industrial organization literature, and approximate the inputs' output elasticities using the factor cost shares approach. Factor elasticities are approximated by the cost share of a variable input (COGS and XSGA) in total costs, see 2.6. Imposing constant returns to scale we derive the factor elasticity of capital expenditures. The underlying assumption holds that firms are statically cost-minimizing, their technology has roughly constant returns to scale and materials and administrative expenses are flexibly adjustable inputs. A detailed discussion of the assumptions and applicability of this approach is provided in De Loecker and Syverson, 2021.

$$
\begin{gathered}
\hat{\alpha}^{m}_{ft} = \frac{COGS_{ft}}{TotalCost_{ft}} \qquad \hat{\alpha}^{a}_{ft} = \frac{XSGA_{ft}}{TotalCost_{ft}} \qquad \hat{\alpha}^{k}_{ft} = 1 - \hat{\alpha}^{m}_{ft} - \hat{\alpha}^{a}_{ft} \\
TotalCost_{ft} = COGS_{ft} + XSGA_{ft} + usercost_{ft} * PPENT_{ft}
\end{gathered}
\tag{2.6}
$$

Finally, we compute TFP estimates by subtracting the measures of output produced using the inputs and estimated factor shares from revenues.

$$
\tilde{\omega}_{ft} = revenue_{ft} - \hat{\alpha}^{m}_{ft} cogs_{ft} - \hat{\alpha}^{a}_{ft} xsga_{ft} - \hat{\alpha}^{k}_{ft} kexp_{ft} - \epsilon_{ft} \tag{2.7}
$$

A significant caveat to whichever estimation approach we use, is that all estimates rely on input cost and sales revenue data from Compustat, instead of using input and output quantities .

$$
\omega = output - f(m, a, k) \;\; \neq \;\; revenue - f(cogs, xsga, kexp) = \tilde{\omega} \tag{2.8}
$$

The estimated TFP residual, $\tilde{\omega}$, therefore does not measure productivity exactly, but conflates quantity and price variation (omitting subscripts for legibility). This is especially relevant in the presence of heterogeneous levels of market power causing firm-specific price markups. Estimating a negative effect of common ownership on $\tilde{\omega}$, henceforth revenue productivity, can imply a negative effect markups (μ) or on actual productivity (ω). Lacking a firm-specific price deflator, price variation due to quality differences or market power cannot be eliminated from our TFP residual and we cannot estimate the effect on actual productivity separately from revenue productivity.

$$\begin{aligned} revenue - f(cogs, xsga, kexp) &= (p + output) - f(p^m + m, p^a + a, p^k + k) \\ \tilde{\omega} &\approx prices + \omega \end{aligned} \tag{2.9}$$

However, we can estimate markups, μ, and separately investigate how common ownership affects them. Knowing how both revenue productivity and markups are affected, allows us to disentangle the effects on actual productivity and to make directional predictions.

Table 2.1 outlines what different combinations of effects on revenue productivity and markups imply for the relationship between common ownership and actual productivity. Since we cannot test for ω directly, we evaluate the effects of common ownership on $\tilde{\omega}$ and μ to infer a directional path for ω.

	Estimate 1	Estimate 2	Inference
common ownership	$\tilde{\omega}\downarrow$	markup $\uparrow$	$\omega \downarrow\downarrow$
	$\tilde{\omega}\downarrow$	markup $=$	$\omega \downarrow$
	$\tilde{\omega}\downarrow$	markup $\downarrow$	$\omega \downarrow$
	$\tilde{\omega}\downarrow$	markup $\downarrow$	$\omega =$
	$\tilde{\omega}\downarrow$	markup $\downarrow\downarrow$	$\omega \uparrow$

Table 2.1: Interaction: Markups, Revenue & Actual productivity

Following De Loecker et al., 2020, markups are estimated as the product of a variable input's factor elasticity, which we proxy with the cost share of cost of goods sold, and the inverse sales ratio of that input. The underlying assumptions are the same as above.

$$\mu_{ft} = \hat{\alpha}^m_{ft} * \frac{sales_{ft}}{cogs_{ft}} \tag{2.10}$$

Our main specification estimates firm-specific productivity and markups using firm-specific cost shares and inputs. Following previous work, we also use median factor elasticities across all firms within one industry in robustness test. These smoothed elasticities remove some unwanted idiosyncratic volatility in the cost shares, but also impose a common technology on all firms within an industry. For markups this methodology implies that the markup variation across firms is only driven by the inverse sales ratio of materials, which can easily be distorted by outliers and offers limited insights for the purpose of this analysis.

As robustness check we validate our analysis using TFP residuals estimated using the proxy and dynamic panel approach. A detailed discussion of the underlying assumptions, advantages and disadvantages of each approach is provided by De Loecker and Syverson, 2021. For the proxy approach we do not re-estimate the output elasticities of individual inputs but use the estimates derived and kindly made available by De Loecker et al., 2020. The production function estimation following the Blundell-Bond dynamic panel data approach (Blundell & Bond, 2000) is performed on our data at the sector level and on a rolling window of 5 years. The elasticity estimates of both approaches are unique at the sector-year level. Analogous to the cost shares approach we subtract the firm-specific input costs weighted by the estimated elasticities from sales to arrive at the TFP estimates.

Two remaining limitations of our TFP estimates are that we do not account for different technologies in multi-product firms, nor for selection bias introduced by firm survival over time. Lacking data on private firms we are not able to control for the selection bias inherent in this estimation. However, the factor elasticities are estimated at sufficiently broad industry categories, that production technologies are not targeted at individual product-levels, but rather at the "basket"-level of goods and services provided by a firm.

2.2.3 Sample Description

The key variables in our final data sample are firm-specific productivity estimates, henceforth TFP, and measures of common ownership at the firm-year frequency. Common ownership measures are based on ownership in the fourth quarter of every year. To test the mechanism via managerial incentives, we approximate the performance-sensitivity of managerial compensation with wealth-performance sensitivity estimates from Edmans and Gabaix, 2016, henceforth WPS. Merging the three different data sets implies a substantial loss of data, as productivity estimates are not available for all firm-years for which we would have ownership data, and the wealth-performance sensitivity estimates are available for even fewer firms. The resulting sample covers a total of 3,700 firms with an average of 1,600 firms per quarter, yielding 34,100 firm-year observations. All key variables have been extensively cleaned in the estimation process (see above paragraphs), hence we do not further curtail the sample at this point.

We add controls for ownership structure attributes and firm characteristics to this data sample. Categorizing shareholders into groups for corporate insiders, activists (Brav et al., 2008, 2010), the Big Three asset managers (Vanguard, BlackRock & StateStreet), undiversified or universal investors (owning >95% of all firms in a given year), we include the aggregate fraction of votes held by each group and a dummy for firms which have a controlling owner (>50% of votes held by one investor) as firm-level controls. The rationale is that the existence or non-existence of influential insiders or activists may influence corporate productivity and will not be fully captured by our common ownership measure. In terms of firm characteristics we control for market capitalization, market share by market capitalization (at the same industry level used to calculate profit weights), firm age (years since first listing) and an indicator for dual class and S&P 500 constituents. Summary statistics of all relevant variables are provided in Table 2.2.

2.3 Analysis & Results

The key question to be answered by the following analysis is whether common ownership affects firm productivity. This question is central to an ongoing debate among academics and policy-makers on whether common owners have anti-competitive effects. Theory predicts that common owners benefit if commonly owned firms charge higher prices and compete less aggressively. However, the mechanism how diversified shareholders convey this objective to delegated managers was unclear, until Anton et al., 2022 proposed a link between common owners and managerial incentives that can lead to softer competition. An essential feature of this mechanism, which was not considered in previous theories, is a concurrent negative effect on productivity. As common owners set less performance-sensitive compensation in order to lessen competition, managers are also less incentivized to continuously improve productivity, which may lead to stagnant or even reduced productivity.

Based on a similar data sample to ours, the authors find empirical evidence for a broad-based negative effect of common ownership on performance-sensitive compensation. Since they do not investigate the follow-on effects on corporate productivity and competition, it remains an open empirical question if the concurrent effect on productivity exists. Previous research into the link between common ownership, competition and productivity, has only been conducted at the industry-level and findings vary across industries. Using our data set covering most publicly traded firms in the U.S., we are able to evaluate the relationship between common ownership, incentives and productivity for a larger cross-section of the economy than previous studies.

Figure 2.1a and especially the cross-sectional patterns in our data provide a first glance at the relationship of interest. Scattering productivity estimates on common ownership profit weights for all firm-year observations, and estimating the linear effect of common ownership on productivity by common ownership quintile, we observe an interesting non-linear relationship. For the observations with low levels of common ownership the estimated effect seems negative, while it turns positive for observations with high levels of common owners. In the following we will test if this non-linear relationship remains significant when controlling for firm-, industry-, and time attributes.

In contrast to the cross-sectional evidence, time-series trends in Figure 2.1b do not depict a clear correlation. Over the past 20 years, common ownership among U.S. firms has increased markedly and steadily, while average productivity (and markup) estimates seem largely flat. If at all, one might conjecture a small positive correlation between the two variables over time. A pairwise correlation analysis presented in Table 2.3 supports this graphical trend. Across the whole data set and without controls, the correlation between common ownership and productivity is positive and statistically significant, although economically small. To remove confounding effects from this raw correlation coefficient and to establish a causal link, we first employ a panel analysis, regressing productivity on measures of common ownership, controlling for various ownership and firm attributes, industry-by-year fixed effects and clustering standard errors. As the panel regressions are still subject to concerns about reverse causality, we follow Boller and Scott-Morton, 2020 and use S&P 500 index additions as an exogenous shock to the common ownership of index incumbent competitors, employing a difference-in-difference model to test for its effect on productivity.

2.3.1 Panel regressions

Covering 20 years and about 3,700 firms across 90 industries, our data allows a detailed investigation of the relationship between common ownership and TFP using panel regressions. To control for potential bias introduced by unobserved industry or time-period characteristics that are correlated with both productivity estimates and measures of common ownership, we include industry-by-year fixed effects and cluster standard errors by year. The remaining variation in the variables of interest is across firms within industry-year.

Our main specification relates the firm-level log-normalized productivity estimate ($\tilde{\omega}_{ft}$) to the equally-weighted average profit weight (κ_{ft}) placed by firm f on its competitors, or alternative measures of common ownership. In addition to the industry-by-year fixed effects (α_{st}), we control for firm size (log market capitalization), firm age, firm market share (by market capitalization), leverage, dual class status, S&P 500 constituents and ownership structure characteristics, such as the aggregate fraction of vote ownership captured, the aggregate vote fraction held by corporate insiders, activists, engaged activists, universal owners, a dummy for controlled firms, and ownership concentration. As intuition suggests that low levels of common ownership will have little impact on corporate outcomes, whilst high common ownership may have more pronounced effects, we control for non-linearity in the relationship between outcomes and profit weights using a squared common ownership measure.

$$\begin{aligned} \tilde{\omega}_{ft} &= \beta_1 * \kappa_{ft} + \Phi * X_{ft} + \alpha_{st} + \varepsilon_{ft} \\ \tilde{\omega}_{ft} &= \beta_1 * \kappa_{ft} + \beta_2 * \kappa_{ft}^2 + \Phi * X_{ft} + \alpha_{st} + \varepsilon_{ft} \end{aligned} \tag{2.11}$$

Table 2.4 reports the findings for profit weights as key independent variable and measure of common ownership. The estimation results in Columns (1)-(2) suggest that profit weights have a significantly negative and non-linear impact on TFP. The level effect in Column (1) is negative and significant, but its magnitude more than doubles when controlling for the quadratic effect in Column (2). All control variables have the expected relationship with productivity. Large firms, more levered firms and S&P 500 constituents have significantly higher productivity, while older firms, and firms constituting a larger fraction of market capitalization have lower TFP. More ownership concentration, insider and general activist control negatively impact productivity and markups, while higher engaged activist control improves both.

To interpret the size of the estimated effects, Figure 2.2a plots the marginal effect of profit weights on productivity at different points of the common ownership distribution. For profit weights below 0.25, which holds for more than half of our sample, an increase in common ownership has a significant negative effect on productivity. An increase in profit weights by one standard deviation, corresponding to a doubling of κ for the average firm, reduces TFP by about 1.1% on average. For the least commonly owned firms this effect more than doubles. Predicted productivity outcomes based on common ownership levels are depicted in Figure B.5b. Across the whole distribution of profit weights the lowest predicted productivity levels are found in firms with intermediate levels of common ownership.

The non-linearity of the effects is relatively intuitive in an example: If a firm is initially not commonly owned, while its two competitors are already commonly owned then, according to theory, the two commonly owned competitors are already producing with lower efficiency and thus likely at lower markups due to the presence of a maverick competitor. When the common ownership of these two firms increases further, productivity and markups will not be markedly affected. However, when the maverick competitor becomes commonly owned, its productivity and markups will change markedly as they were initially higher that those of the competitors.

Our working hypothesis is that common ownership reduces productivity by lowering managerial incentives. We include managerial incentives approximated by manager's wealth-performance sensitivity (WPS) as a control variable in the regression, to ascertain that the relationship between productivity and common ownership remains significant once we account for this channel.

$$\tilde{\omega}_{ft} = \beta_1 * \kappa_{ft} + \beta_2 * \kappa_{ft}^2 + \beta_3 * wps_{ft} + \Phi * X_{ft} + \alpha_{st} + \varepsilon_{ft} \tag{2.12}$$

Results in Columns (3)-(4) of Table 2.4 are largely unchanged. The negative and non-linear effect of common ownership on productivity remains significant when holding WPS fixed, although the coefficient size decreases slightly.

Since our productivity estimates confound price and actual productivity effects, we run the same regression with markups as dependent variable, to discern the dynamics underlying our panel estimates. Table B.1 in the appendix provides the corresponding results and Figure B.5 showcases the main implications graphically. The relationship between common ownership and markups is also significantly negative and non-linear. The coefficient for markups is smaller, however, and once we control for managerial incentives the linear effect on markups turns insignificant. For higher levels of common ownership the predicted productivity estimates are substantially lower than predicted markups. These results suggest that part of the negative relationship between common ownership and productivity may be attributed to markup variation, but its size requires that actually productivity is also negatively affected.

The appendix provides further regression results showcasing how the non-linear effect of common ownership on productivity may be distributed across firms with different characteristics. Tables B.5, B.6 and B.7 in Columns (1)-(4) provide estimates of the linear and non-linear effect of common ownership on productivity for two sub-samples of the data. The first subset contains only firms of below median age, common owner vote holdings and market capitalization, while the second subset considers the above median firms. The firm age and aggregate common owner control does not alter the coefficients significantly, although the effect on productivity seems slightly more prevalent among young and high common ownership firms. Dividing the sample into below and above median size firms reveals an interesting twist, as the negative effect on productivity is concentrated among smaller firms, while the positive effect on markups is more pronounced for larger firms. This finding is consistent with larger firms commanding higher markups, while smaller, younger and increasingly commonly owned firms are hurt by lower productivity.

Profit weights are a theoretically sound measure of common ownership, however they are often difficult to interpret in practice. Therefore, we extend our analysis to two more readily interpreted measures: the cosine vector similarity between cash flow ownership of two firms and the aggregate fraction of votes held by common owners. The regression specification, fixed effects and controls are the same as before.

Using the similarity of cash flow ownership vectors, we find qualitatively and quantitatively highly similar results, see Table B.2 and Figure B.4. Ownership similarity reduces productivity significantly in a linear fashion. Controlling for non-linearity, the effect becomes quantitatively larger and remains significant. Overall the coefficients on ownership similarity are slightly larger than for profit weights and controlling for managerial incentives does not render any coefficients insignificant, although it reduces their absolute size marginally. The congruence of these results with the previous regressions using profit weights suggests that the similarity of cash flow ownership structures among competitors is a driving force between the correlation of common ownership and productivity. This finding substantiates a decomposition of common ownership by Backus et al., 2021b, showing that ownership similarity contributes more than three-quarters of the variation in common ownership profit weights, if one assumes the one share-one vote principle.

The link between productivity and the aggregate fraction of votes held by common owners behaves analogous to the findings for profit weights and ownership similarity (see Table B.3 and Figure B.3). If common owners increase their vote ownership by 10%, TFP is decreased by 1%, the effect is markedly larger for less commonly owned firms.

2.3.2 Diff-In-Diff analysis of index additions

The panel results gathered so far, associate various measures of common ownership with lower productivity. However, the fixed effects and controls employed do not allow us to infer a causal link. It may be that the least productive firms attract mostly activist investors, who have industry-specific expertise through ownership and campaigns at competitors. This story would imply reversed causality, where lower productivity causes higher common ownership. To test if causality runs from common ownership to productivity we need an exogenous shock to common ownership, that affects productivity only via its impact on common ownership incentives.

Following Boller and Scott-Morton, 2020, we use the addition of a firm to the S&P 500 index to shock the common ownership incentives of index incumbent competitors and estimate a difference-in-difference model for the productivity changes in treated versus untreated index incumbents. Intuitively, as a firm is added to the index, the competing index incumbent's ownership structure itself does not change. However the profit weight the incumbent places on the new index member increases, as index funds increase their exposure to the new index constituent. This increases the within-industry common ownership of index incumbent competitors, but should not affect common ownership of index incumbent firms in other industries.

Our complete ownership data at the quarterly level suggests that ownership by large institutional asset managers changes frequently, and sometimes markedly, in response to index reconstitution and other events. Thus the "shock" to the common ownership of index incumbent competitors versus non-competitors is likely only measurable in a relatively short event window. Once added to the index, firms mostly stay in the index for a longer time. Hence, the higher pair-wise level of common ownership should be persistent and we therefore try to identify the longer run impact on treated index incumbents. Table 2.5 provides the regressions results for changes in common ownership on a treatment dummy, that is 1 for index incumbent competitors and 0 for index firms in other industries, and various controls for firm and ownership characteristics measured the year before addition. Both profit weights and ownership similarity are significantly more positively affected for treated firms than for control firms, suggesting there is significant exogenous variation in common ownership in the short term. Over a longer time horizon the significance vanishes.

Industries are defined by historical NAICS-3 digit classifications and our event window covers 4 years before and after the index addition. Given our data set, the treatment events are restricted to happen between 2005-2015 to allow for 4 observation years before and after treatment. In this time period we have 140 index additions, where an index incumbent in the same NAICS-3 industry exists. Of those only 90 additions are "true additions", meaning the added firm was not a member of the S&P 400 Mid-Cap index previously (Boller & Scott-Morton, 2020). Firms which are in the S&P 500 at the time of the event, in the same historical NAICS-3 industry as the added firm, and do not get dropped from the S&P 500 in the following year are classified as "treated" firms. "Control" firms are members of the S&P 500 in the addition year, but in a NAICS-3 industry without an addition in that year, or the previous and following year. For our 90 true treatment events we end up with 260 treated and 220 control firms. In appendix Figure B.7 the number of treatment and control firms is plotted over time. Evidently not all treatment and control firms are in the sample for the whole event window.

Using a difference-in-difference model, we compare the change in productivity estimates of treated firms to control firms, before and after the addition event. The outcome variable is regressed on a *treated* dummy, which is 1 for treated and 0 for control firms, a *post* dummy, which is 1 for all firms in the year of treatment and subsequent years but 0 before, and the interaction of the treated and post dummies. The interaction is 1 for treated firms from the year of addition onward and otherwise 0. We include firm-specific controls such as market capitalization, firm age, dual class indicators, market share, and ownership structure controls for ownership concentration and aggregate vote ownership captured in total; of insiders; activists; and universal owners. All control variables are measured with a one year lag. Since the trends of these controls may be affected by the treatment, we interact the controls with the *post* dummy. To control for further unobserved variables, we add industry and year fixed effects and cluster standard errors by year and firm.

$$\tilde{\omega}_{ft} = Post_{ft} * Treat_{ft} + Post_{ft} + Treat_{ft} + \Phi_1 X_{ft} + \Phi_2 Post_{ft} * X_{ft} + \alpha_t + \alpha_s + \varepsilon_{ft} \tag{2.13}$$

Table 2.6 presents the regression results for this analysis and Figure 2.3 plots the average annual effect for treated firm productivity relative to untreated firms. The interacted *post#treat* coefficient suggests a negative but insignificant effect of index additions on treated index incumbents' TFP. Either the link between common ownership and TFP does not exist or it is obfuscated by other consequences of the index addition. For example, the cost of capital of firms added to an index has been shown to decline (Afego, 2017), which implies that incumbents have and incentive to increase their efficiency to remain competitive. This channel follows Backus, 2020, who proposes a link between productivity and competition. The competition incentive to increase productivity counterbalances the common ownership effect decreasing productivity, resulting in an overall insignificant effect. To distinguish between these channels, we examine managerial incentives as the linking element between common ownership and productivity in the next section.

2.3.3 The mechanism: managerial incentives

Following the theoretical mechanism proposed by Anton et al., 2022, our hypothesis is that common owners cause lower productivity by setting less performance-sensitive incentives for managers, and managerial slack leads to a reduction in productivity. The link between weak managerial incentives and lower productivity, also referred to as "enjoying the quiet life", has been proposed theoretically by Hicks, 1935 and empirically validated by Bertrand and Mullainathan, 2003.

Initial empirical evidence on this mechanism comes from Anton et al., 2022, who find a significant negative and causal effect of common owners on managerial incentives. Their study examines the link between common ownership and managerial incentives on a restricted data set, ignoring insider ownership for the sample period 2000-2017. Using a measure of common ownership that is based on complete ownership data and extending the sample period to 2020, we can ascertain the negative relationship between common ownership and managerial incentives. Panel results in Table B.8 and difference-in-difference results in Table 2.6 suggest that common ownership significantly reduces the wealth-performance sensitivity of managerial pay. The index addition of a competitor leads to a 17% reduction in managerial wealth-performance sensitivity, in line with the estimates of Anton et al., 2022.

With regards to the second part of the mechanism, Holmstrom and Milgrom, 1991 are the first to explain why managerial incentives matter for corporate performance and productivity, and our data provides supporting empirical evidence. Results in Table B.9 demonstrate that lower managerial incentives via lower wealth-performance sensitivity are associated with significantly lower productivity levels.

To test if common owners reduce productivity via their impact on managerial incentives, we extend the difference-in-difference model one step further. We use the index addition of a competitor to shock common ownership and estimate the variation in managerial incentives caused by this shock. Using this as first stage, we regress productivity on the instrumented variation in incentives due to the common ownership shock. The event window is unchanged at 4 years pre- and post-treatment and we include industry and year fixed effects, cluster standard errors by year and have the same controls for firm and ownership characteristics as before.

$$wps_{ft} = Post_{ft} * Treat_{ft} + Post_{ft} + Treat_{ft} + \Phi_1 X_{ft} + \Phi_2 Post_{ft} * X_{ft} + \alpha_t + \alpha_s + \varepsilon_{ft} \tag{2.14}$$

$$\tilde{\omega}_{ft} = \widehat{wps}_{ft} + \Phi X_{ft} + \alpha_t + \alpha_s + \varepsilon_{ft} \tag{2.15}$$

The results in Table 2.7 provide the first and second stage estimated coefficients. The treatment has, as expected, a significantly negative impact on incentives. The Kleibergen-Paap test for underidentification in the first stage is rejected, while a Sargan-Hansen test for the validity of over-identifying restrictions is not rejected at the 5% significant level. This means that our instrument is sufficiently strong and valid. The instrumented variation in wealth-performance sensitivity has a highly significant (at the 1% level) positive effect on productivity. This positive relationship between instrumented variation in incentives and productivity supports the panel evidence from Table B.9. The first stage treatment affects incentives negatively, while the relationship between incentives and productivity is positive, implying a negative effect of the common ownership increase on productivity of 1.65% on average.

$$\Delta logTFP = (-0.131) * 0.126 = -1.65\%$$

Comparing the raw difference-in-difference results from Table 2.6 to the instrumented difference-in-difference results above, the coefficient size for the raw effect of index addition on productivity is slightly smaller. This supports our hypothesis that the overall effect confounds common ownership and competition effects, but common ownership actually impacts productivity negatively, and at least in part via managerial incentives.

Next, we ascertain whether the effect of common ownership on productivity via managerial incentives translates into an analogous effect on actual (quantity) productivity and is not only capturing markup variation. To do so, we investigate the causal impact of common ownership variation on markups, again using raw and instrumental variable difference-in-difference models. Both models yield negative and more significant effects of common ownership on markups than on productivity. The index addition of a competitor reduces markups directly by about 1% (Table 2.6), while the variation in managerial incentives caused by common ownership shocks reduces markups by - 1.66% (Table 2.7).

$$\Delta markups = (-0.131) * 0.127 = -1.66\%$$

These results suggest that the estimated negative effect of common ownership on our productivity estimates captures mainly a negative impact on markups and the concurrent effect on actual (quantity) productivity may be null or mildly negative. However, referring back to the possible combinations of changes in productivity and markups outlined in the data section, we know that $\tilde{\omega}$ and μ are decreasing, and evidence in the literature suggests that prices are either positively affected or unaffected by common ownership. Combining these results, we conclude that actual (quantity) productivity must also be negatively affected by common ownership, although we cannot quantify this effect.

2.4 Robustness

Our main results are based on the cost shares approach to estimating total factor productivity. Alternative strategies to derive productivity estimates are based on the proxy approach (Ackerberg et al., 2015) and the dynamic panel approach (Blundell & Bond, 2000), which estimate the production function to arrive at factor elasticity estimates. Cost shares likely yield the least biased estimates of TFP in our setting and are therefore the baseline of our analysis. Using alternative estimation methods, we find that our panel and diff-in-diff results hold up qualitatively and in significance for the proxy approach-based estimates (Columns (5)-(8) in Table B.11). For the dynamic panel approach-based estimates all coefficients are rendered insignificant (Columns (1)-(4) in Table B.11). This collective insignificance may be due to a limited sample size and high residual uncertainty inherent to the dynamic panel approach.

Another robustness exercise considers TFP and markup estimates based on industry-median adjusted cost shares, which impose the same technology on all firms in an industry and remove some idiosyncratic variation from the outcome estimates. The panel results for profit weights in Table B.15 remain unchanged in significance and size for productivity but become insignificant for markups. To ascertain that our findings are not due to outliers, we also investigate the panel effects of ownership similarity again (Table B.16) and find that the negative association with both productivity and markups remains significant. The results for profit weights may therefore be driven by variation in ownership structure concentration, which we are not sufficiently controlling for. The difference-in-difference results for instrumented changes in managerial incentives on productivity in Tables B.17 and B.18, instead are consistently significant and larger than with unrestricted cost shares estimates (i.e. unrestricted technologies). One caveat to this approach for the markup estimates is that the only remaining variation in markups using industry-adjusted cost shares and industry-by-year fixed effects comes from the firm-specific COGS-to-Sales ratio (see equation 2.10). We consider this a significant limitation of this estimation approach.

An important concern with our panel analysis is the potential for reverse causality, where more productive firms attract more common owners than less productive firms. We address this in addition to the difference-in-difference analysis outlined above, by running the panel regressions with lagged dependent and control variables, estimating the effect of last period common ownership on current productivity and markups. Our conclusions remain unaffected by this time lag, as the coefficients on profit weights and ownership similarity remain significant and increase in absolute size (see Table B.19).

To ascertain that it is not the choice of industry classification that drives our results we also estimate the panel and diff-in-diff regressions using profit weights and industry fixed effects for current NAICS-3 industries and for SIC-3 industries. The results are reported in Tables B.21-B.24 in the appendix. The panel results do not change in significance or size using these alternative averages of profit weights, ownership similarity and fixed effects. However, while the raw and instrumented difference-in-difference results are qualitatively unchanged, the estimates are statistically insignificant or confounded by weak instruments. Considering the sample size of both analyses, this change is likely related to the reduction in the number of treated firms, especially for the SIC-3 industry analysis.

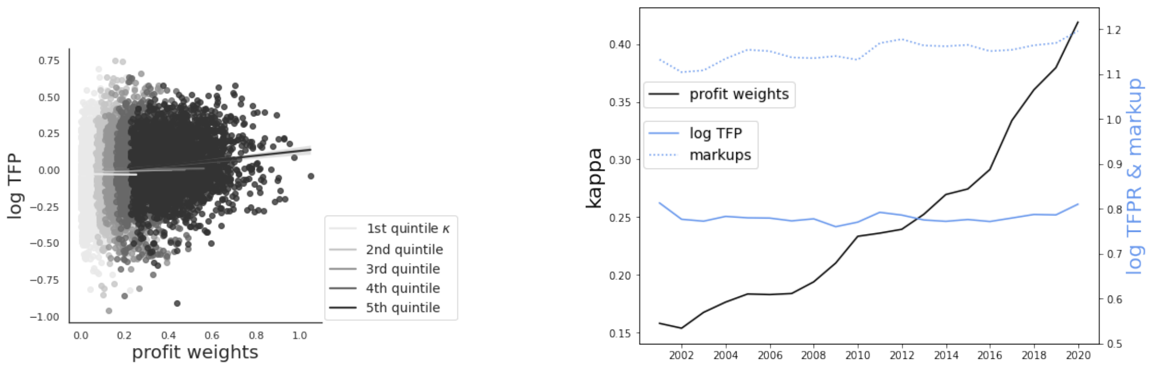
2.5 Conclusion

In this paper, we investigate empirically whether common ownership affects corporate productivity and if changes in managerial incentives are the underlying mechanism. Our measures of common ownership are based on a novel and uniquely comprehensive data set of corporate ownership for U.S. public firms. The estimates of total factor productivity and markups are derived from balance sheet data using the standard cost shares approach in the literature. We examine the relationship between common ownership and corporate outcomes using panel analysis and a difference-in-difference model of changes in response to the index addition of a competing firm. Both specifications provide evidence of a negative effect of common ownership on total factor productivity. Further, we test the mechanism suggested by Anton et al., 2022 in which common owners allow for less performance-sensitive managerial compensation and thereby lead to lower productivity. Combining the difference-in-difference model with an instrumental variable approach we find that the exogenous increase in common ownership significantly reduces managerial incentives, which, in turn, is associated with a significant reduction in productivity. This result corroborates our hypothesis that common ownership negatively affects productivity at least in part via managerial incentives.

Our findings contribute to the ongoing debate on anti-competitive effects of common ownership by providing the first large-sample evidence for an effect of common ownership on corporate productivity. Our findings suggest that common ownership induces lower productivity by setting less performance-sensitive managerial incentives. One limitation of our analysis is that the data available only allows us to estimate the effect of common ownership on total factor "revenue" productivity, which confounds variation in actual (quantity) productivity and markups. By estimating the effect of common ownership on revenue productivity *and* markups, however, we are able to infer the directional effect on actual (quantity) productivity. We find that actual productivity is also negatively affected by common ownership via the reduction of managerial incentives. Since we are not able to quantify the impact of common ownership on actual productivity, we invite future research based on quantity input and output data to do so. While we have made the first step in this direction, much remains to be done.

To encourage future research on the effects of common and universal ownership not only on competition, but also on real economic outcomes such as productivity and long-run growth in greater depth, we are making our ownership data publicly available. We hope this will allow many more researchers to comprehensively investigate the economic effects of common owners and also answer other broader research questions on corporate ownership structures.

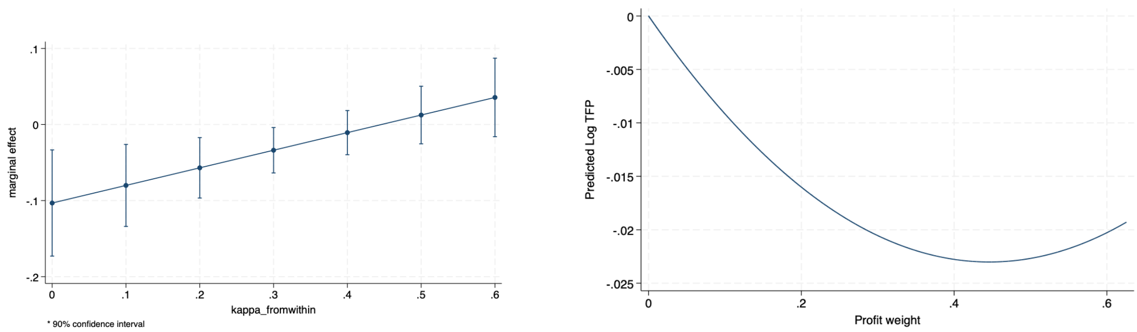
2.6 Figures & Tables



(a) Scatter & trend of TFP on kappa (b) Time trend in kappa & TFP

Figure 2.1: Trends in common ownership and productivity.

Figure (a) scatters productivity estimates residualized on NAICS-3-by-year fixed effects over common ownership profit weights for all firm-year observations and estimates a linear relationship between the two variables separately by quintile of the profit weight distribution. Figure (b) plots the annual average profit weight across all sample firms on the left y-axis and the annual average log-total factor productivity and markup estimates across all firms on the right y-axis. The sample covers Q4 2000 until Q4 2019.



(a) Marginal effect of κ on log TFP (b) Predict productivity with κ

Figure 2.2: Effect of common ownership (κ) on productivity.

Figure (a) plots the marginal effect of profit weights on productivity, at discrete levels of profit weights (0-0.7 at every 10 basis points). Figure (b) plots log productivity predicted with profit weights on the right y-axis and a density plot of profit weights on the left y-axis. The underlying regressions control for ownership and firm characteristics, industry#year fixed effects, and cluster standard errors by year.

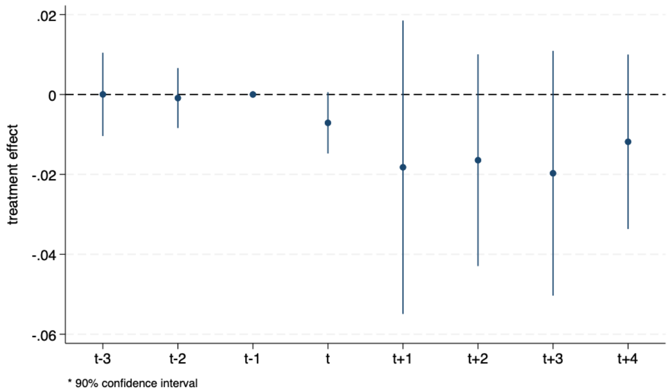


Figure 2.3: Dynamic treatment effect on productivity.
This figure plots the treatment effect of index addition on treated firms' productivity in the three years pre-treatment, the treatment year itself (t) and the 4 years post-treatment. The underlying regression interacts annual dummies with the treatment indicator, and controls for ownership and firm characteristics, industry and year fixed effects, and clusters standard errors by year and firm.

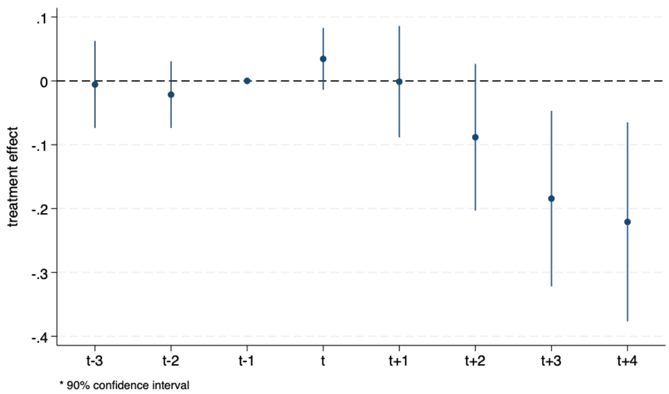


Figure 2.4: Dynamic treatment effect on managerial incentives.
This figure plots the treatment effect of index addition on treated firms' wealth-performance sensitivity in the three years pre-treatment, the treatment year itself (t) and the 4 years post-treatment. The underlying regression interacts annual dummies with the treatment indicator, and controls for ownership and firm characteristics, industry and year fixed effects, and clusters standard errors by year and firm.

Table 2.2: Summary statistics

	mean	std deviation	5th	median	95th
log TFP	0.751	0.227	0.385	0.750	1.139
markups	1.285	0.657	0.762	1.101	2.468
log TFP (BB)	0.748	1.138	-0.755	0.571	3.077
log TFP (DL)	-1.709	1.865	-4.414	-1.871	1.118
log WPS	1.851	1.522	-0.451	1.753	4.500
kappa (ew)	0.183	0.150	0.005	0.156	0.470
kappa (vw)	0.008	0.021	0.000	0.002	0.038
kappa (sw)	0.008	0.020	0.000	0.002	0.036
cosine sim	0.172	0.119	0.013	0.156	0.395
agg votes CO	0.701	0.330	0.111	0.751	1.172
HHI votes CO	0.032	0.040	0.002	0.027	0.070
log market cap	20.496	2.005	17.296	20.439	23.899
log sales	19.078	1.788	16.286	19.001	22.172
age	20.487	18.772	1.000	15.000	57.000
firms per naics3	117.428	124.981	9.000	64.000	395.000
marketshare (mcap)	0.035	0.101	0.000	0.004	0.186
market concentration (mcap)	0.167	0.136	0.048	0.126	0.404
top votes insider	0.117	0.155	0.005	0.059	0.465
agg votes insider	0.263	0.217	0.023	0.208	0.711
top votes activist	0.032	0.051	0.001	0.014	0.114
agg votes activist	0.050	0.067	0.002	0.027	0.171
top votes Big3	0.042	0.035	0.003	0.029	0.111
agg votes Big3	0.081	0.072	0.004	0.053	0.219

This table provides summary statistics, comprising the equally-weighted mean, standard deviation, 5th, 50th and 95th percentile across the whole sample for our key dependent and independent variables, and all control variables. Common ownership measures are firm-level averages and consider firms as competitors if they were classified into the same historical NAICS-3 industry in a given year.

Table 2.3: Correlation table

	log TFP	markup	log WPS	kappa	kappa_sw	cosinesim	aggCO
log TFP	1.000						
markup	0.721**	1.000					
log WPS	0.111**	0.128**	1.000				
kappa	0.087**	0.189**	-0.135**	1.000			
kappa_sw	-0.035**	0.017**	0.004	0.488**	1.000		
cosinesim	0.061**	0.172**	-0.188**	0.906**	0.413**	1.000	
aggCO	0.113**	0.194**	-0.145**	0.439**	0.065**	0.561**	1.000

This table provides pairwise correlation coefficients of our key independent and dependent variables. Common ownership measures are firm-level averages and consider firms as competitors if they were classified into the same historical NAICS-3 industry in a given year. Significance is indicated by stars, with p-values: ** $p<0.05$, * $p<0.1$.

Table 2.4: Productivity on equal-weighted profit weights

VARIABLES	(1) log TFP	(2) log TFP	(3) log TFP	(4) log TFP
κ	**-0.0735*** **	**-0.156*** **	**-0.0668*** **	**-0.149*** **
	(0.018)	(0.041)	(0.019)	(0.040)
κ^2		**0.122***		**0.123***
		(0.062)		(0.061)
log WPS			0.00464***	0.00464***
			(0.001)	(0.001)
All Ownership	0.00824	0.0116	0.0119	0.0152*
Insiders	-0.0425**	-0.0484***	-0.0484***	-0.0543***
Activists	-0.127***	-0.131***	-0.121***	-0.124***
Eng Activists	0.166***	0.163***	0.177***	0.175***
Universal O	-0.00707	0.00858	-0.00224	0.0135
HHI control	-0.0947***	-0.121***	-0.0937***	-0.120***
log Market Cap	0.0479***	0.0479***	0.0467***	0.0467***
Firm age	-0.000625***	-0.000627***	-0.000580***	-0.000582***
Dual dummy	-0.00115	-0.000339	-0.00118	-0.000367
Market share	-0.196***	-0.201***	-0.198***	-0.204***
Controlled	0.0145	0.0217*	0.0182*	0.0254**
Observations	15,166	15,166	15,166	15,166
R-squared	0.415	0.416	0.416	0.416
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3
Cluster	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

This table provides results for our main regression specification of firm-level productivity estimates regressed on common ownership. The key independent variables are firm-level profit weights (κ) averaged across all industry competitors and equally weighted, its squared term and log wealth-performance sensitivity as proxy for managerial incentives. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table 2.5: Treatment effect on profit weights & similarity

VARIABLES	(1) Δ kappa	(2) Δ cosinesim
treat	0.0499*	0.0329*
	(0.0260)	(0.0180)
Observations	2,152	2,152
R-squared	0.058	0.089
Controls	Yes	Yes
Cluster	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

This table provides regression results for the shock to common ownership due to treatment, measured by the percentage change in profit weights and ownership structure similarity between Q4 in the year before addition and Q4 in the year of addition. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The treatment indicator is 1 for all treated firms and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. Controls are omitted but include firm characteristics and ownership concentration in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.6: Treatment effect on productivity & markups

VARIABLES	(1) log WPS	(2) log TFP	(3) markup
post#treat	-0.174***	-0.011	-0.012*
	(0.059)	(0.011)	(0.007)
post	-2.136***	0.0800	-0.0634
	(0.336)	(0.057)	(0.039)
Observations	10,720	10,099	10,099
R-squared	0.394	0.533	0.468
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the treatment effect on log wealth-performance sensitivity, log productivity and markups. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

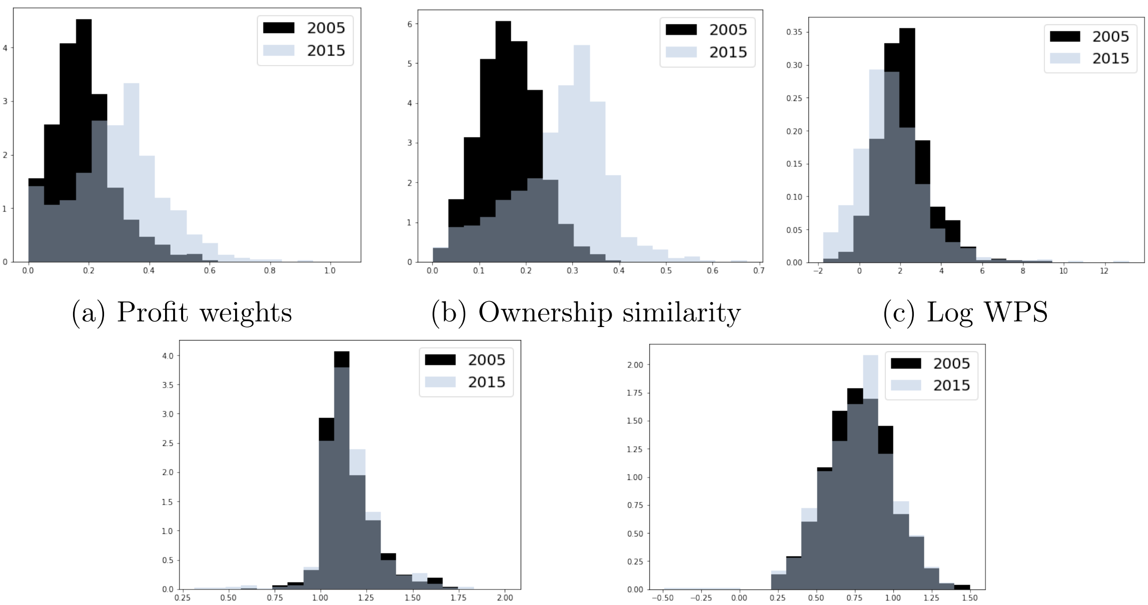
Table 2.7: Instrumented treatment effect on productivity & markups

VARIABLES	(0) log WPS	(1) log TFP	(2) markup
post#treat	-0.131**		
	(0.066)		
$\widehat{logWPS}$		0.126***	0.127***
		(0.015)	(0.016)
Observations	10,035	10,035	10,035
R-squared		-0.563	-1.164
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the instrumented treatment effect of managerial incentives on log productivity and markups. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The first stage regresses log wealth-performance sensitivity on the treatment#post interaction. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. The second stage regresses log productivity and markups (from the 3-input Cobb-Douglas function, columns (1)+(3) or from the 2-input Cobb-Douglas function, columns (2)+(4)) on instrumented wealth-performance sensitivity. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Appendices of Chapter 2

Appendix 2.A Figures & Tables

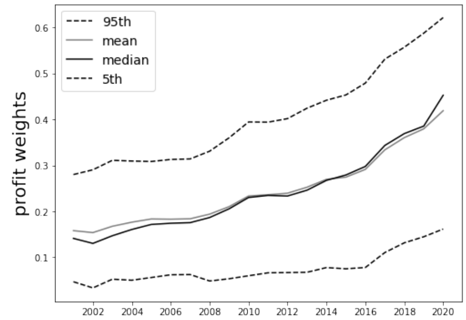


(a) Profit weights (b) Ownership similarity (c) Log WPS

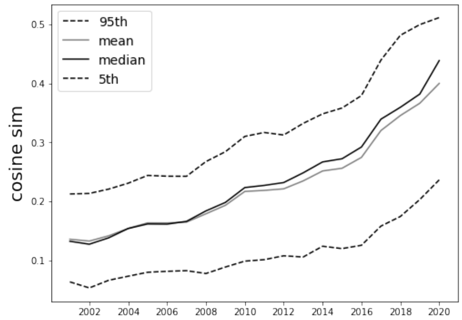
(d) Markups (e) Log TFP

Figure B.1: Histograms of key variables in 2005 and 2015.

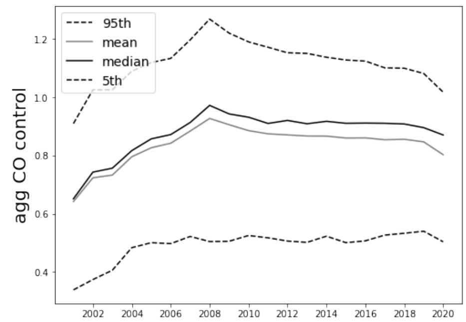
This figure plots the density histogram of common ownership measures (profit weights and cosine similarity of ownership structures), and outcome variables (log wealth-performance sensitivity, markups, log total factor productivity) for Q4 2005 in black and for Q4 2015 in light blue. The grey area is the overlap between both distributions.



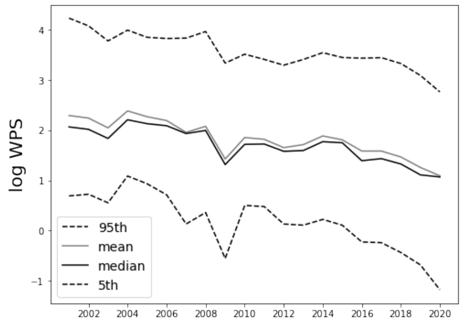
(a) Profit weights



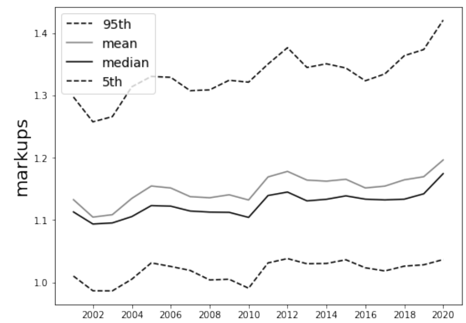
(b) Ownership similarity



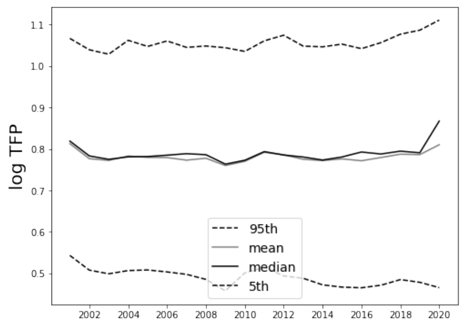
(c) Common owner control



(d) Log WPS



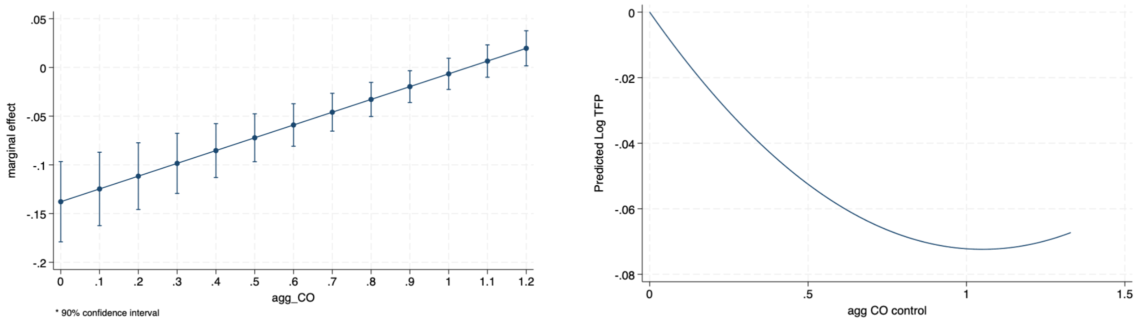
(e) Markups



(f) Log TFP

Figure B.2: Time trends of key variables 2000-2020.

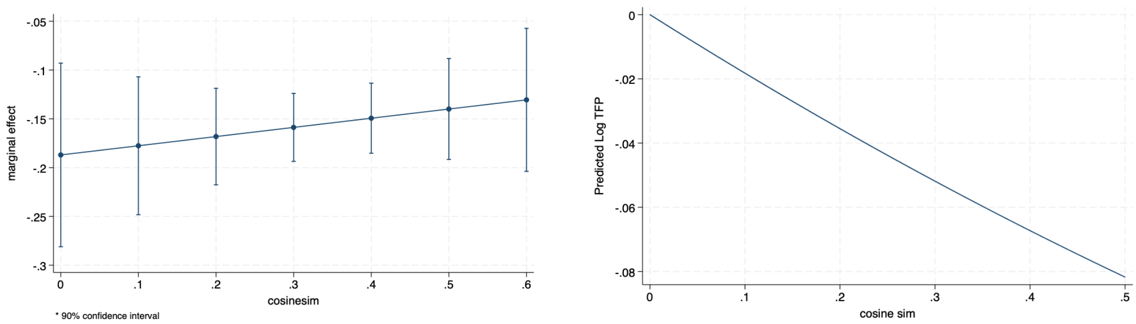
This figure plots the annual mean, median, 5th and 95th percentile across all sample firms for the key independent variables (profit weights/kappas (A), ownership structure similarity (B), aggregate common owner control (C)) and the key dependent variables (log wealth-performance sensitivity (D), markups (E), log productivity (F)).



(a) Marginal effect of aggCO on log TFP (b) Productivity predicted by aggCO

Figure B.3: Effect of aggregate CO control on productivity.

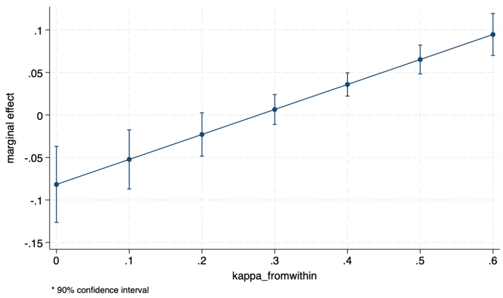
Figure (a) plots the marginal effect of aggregate common owner control on productivity, at discrete levels of aggregate common owner control (0-1.3 at every 10 basis points). Figure (b) plots log productivity predicted with aggregate common owner control on the right y-axis and a density plot of aggregate common owner control on the left y-axis. The underlying regressions control for ownership and firm characteristics, industry#year fixed effects, and cluster standard errors by year.



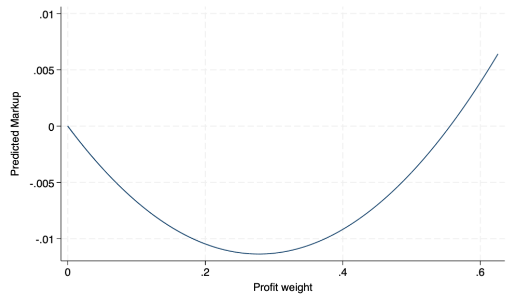
(a) Marginal effect of *cosinesim* on log TFP (b) Productivity predicted by *cosinesim*

Figure B.4: Effect of ownership similarity on productivity.

Figure (a) plots the marginal effect of ownership similarity on productivity, at discrete levels of ownership similarity (0-0.8 at every 10 basis points). Figure (b) plots log productivity predicted with ownership similarity on the right y-axis and a density plot of ownership similarity on the left y-axis. The underlying regressions control for ownership and firm characteristics, industry#year fixed effects, and cluster standard errors by year.



(a) Marginal effect of κ on markups



(b) Markups predicted by profit weights

Figure B.5: Effect of common ownership (κ) on markups.

Figure (a) plots the marginal effect of profit weights on markups, at discrete levels of profit weights (0-0.7 at every 10 basis points). Figure (b) plots markups predicted by a polynomial function of profit weights. The underlying regressions control for ownership and firm characteristics, industry#year fixed effects, and cluster standard errors by year.

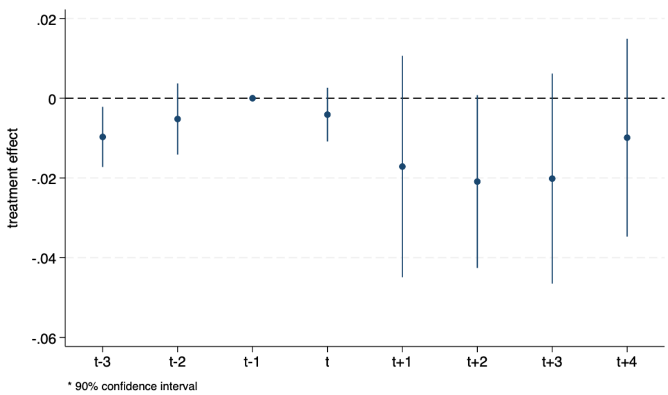


Figure B.6: Dynamic treatment effect on markups.

This figure plots the treatment effect of index addition on treated firms' markups in the three years pre-treatment, the treatment year itself (t) and the 4 years post-treatment. The underlying regression interacts annual dummies with the treatment indicator, and controls for ownership and firm characteristics, industry and year fixed effects, and clusters standard errors by year and firm.

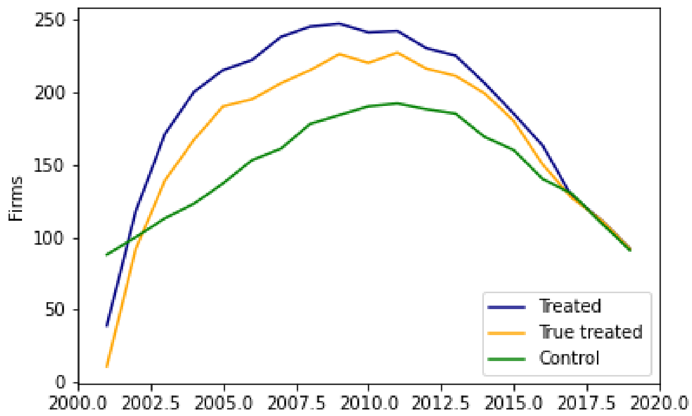


Figure B.7: Number of treated firms over time.
This figure plots the number of control, treated and true treated firms across our whole sample and all pre- and post-treatment years.

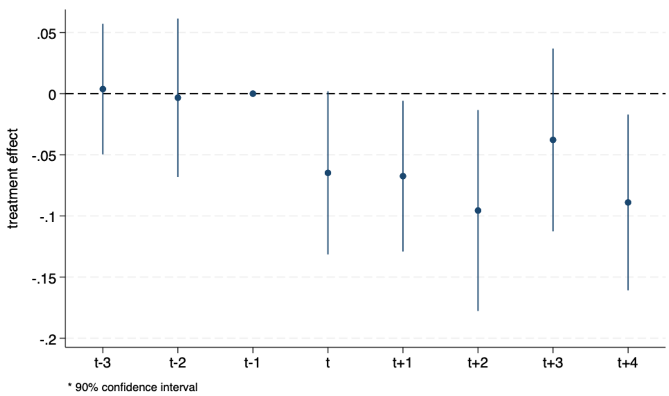
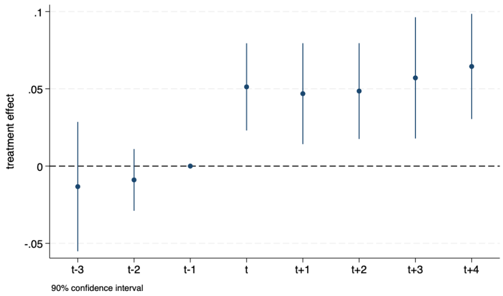
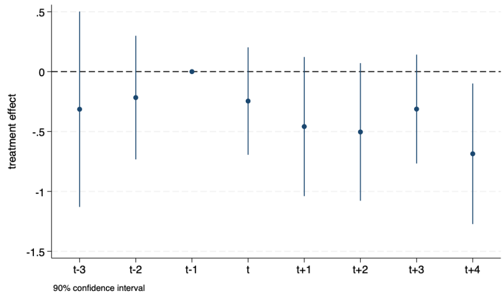


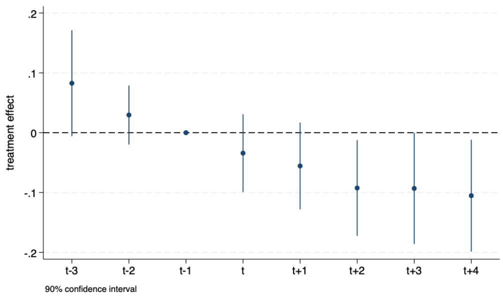
Figure B.8: Dynamic treatment effect on industry-adjusted TFP.
This figure plots the treatment effect of index addition on treated firms' median-cleaned productivity in the three years pre-treatment, the treatment year itself (t) and the 4 years post-treatment. The underlying regression interacts annual dummies with the treatment indicator, and controls for ownership and firm characteristics, industry and year fixed effects, and clusters standard errors by year and firm.



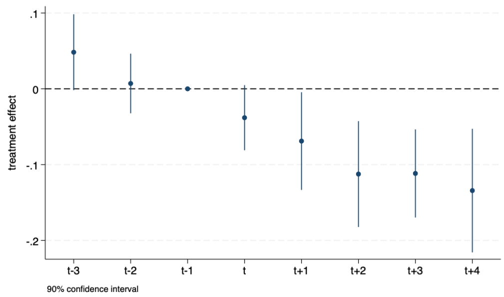
(a) Profit weights



(b) Managerial incentives



(c) Productivity



(d) Markups

Figure B.9: Treatment effects on added firms.

This figure plots the treatment effect of index addition on added firms' profit weights, wealth-performance sensitivity, productivity and markups in the three years pre-treatment, the treatment year itself (t) and the 4 years post-treatment. The underlying regression interacts annual dummies with the addition indicator, and controls for ownership and firm characteristics, industry and year fixed effects, and clusters standard errors by year and firm.

Table B.1: Markups on equal-weighted profit weights

VARIABLES	(1) markup	(2) markup	(3) markup	(4) markup
κ	-0.0224**	-0.111***	-0.0151	-0.104***
	(0.009)	(0.020)	(0.010)	(0.020)
κ^2		0.133***		0.133***
		(0.027)		(0.026)
log WPS			0.00513***	0.00513***
			(0.001)	(0.001)
All Ownership	0.0360***	0.0396***	0.0400***	0.0437***
Insiders	-0.0325***	-0.0389***	-0.0390***	-0.0454***
Activists	-0.0835**	-0.0874***	-0.0764**	-0.0804**
Eng Activists	-0.0442	-0.0473	-0.0314	-0.0344
Universal O	0.0140	0.0309	0.0193	0.0363
HHI control	-0.00833	-0.0369	-0.00730	-0.0360
log Market cap	0.0444***	0.0444***	0.0431***	0.0431***
Firm age	-0.000746***	-0.000748***	-0.000697***	-0.000699***
Dual dummy	-0.0109	-0.0100	-0.0110	-0.0101
Market share	-0.165***	-0.170***	-0.168***	-0.173***
Controlled	3.97e-05	0.00776	0.00410	0.0119
Observations	15,166	15,166	15,166	15,166
R-squared	0.402	0.402	0.404	0.405
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3
Cluster	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

This table provides results for our main regression specification of firm-level markup estimates regressed on common ownership. The key independent variables are firm-level profit weights (κ) averaged across all industry competitors and equally weighted, its squared term and log wealth-performance sensitivity as proxy for managerial incentives. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.2: Productivity & markups on equal-weighted ownership similarity

VARIABLES	(1) log TFP	(2) log TFP	(3) log TFP	(4) log TFP	(5) markup	(6) markup	(7) markup	(8) markup
cosinesim	-0.212***	-0.170**	-0.202***	-0.161**	-0.113***	-0.170***	-0.101***	-0.160***
	(0.022)	(0.061)	(0.022)	(0.058)	(0.009)	(0.034)	(0.009)	(0.034)
$cosinesim^2$		-0.0908		-0.0884		0.123*		0.125*
		(0.105)		(0.104)		(0.064)		(0.063)
log WPS			0.00441***	0.00440***			0.00492***	0.00493***
			(0.001)	(0.001)			(0.001)	(0.001)
Observations	15,166	15,166	15,166	15,166	15,166	15,166	15,166	15,166
R-squared	0.417	0.417	0.417	0.417	0.403	0.403	0.405	0.405
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for our main panel regression specification. The dependent variables are log productivity in columns (1)-(4) and markups in columns (5)-(8), the key independent variables are firm-level average ownership structure similarity with competitor firms, their squares and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls are omitted but include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.3: Productivity & markups on aggregate CO control

VARIABLES	(1) log TFP	(2) log TFP	(3) log TFP	(4) log TFP	(5) markup	(6) markup	(7) markup	(8) markup
aggCO	-0.102***	-0.165***	-0.0960***	-0.162***	-0.0404***	-0.0787***	-0.0332***	-0.0744***
	(0.013)	(0.032)	(0.013)	(0.032)	(0.008)	(0.019)	(0.009)	(0.019)
$aggCO^2$		0.0372**		0.0387**		0.0225**		0.0243**
		(0.017)		(0.017)		(0.009)		(0.009)
log WPS			0.00414***	0.00420***			0.00483***	0.00486***
			(0.001)	(0.001)			(0.001)	(0.001)
Observations	15,217	15,217	15,217	15,217	15,217	15,217	15,217	15,217
R-squared	0.419	0.419	0.420	0.420	0.405	0.405	0.407	0.407
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for our main panel regression specification. The dependent variables are log productivity in columns (1)-(4) and markups in columns (5)-(8), the key independent variables are firm-level average aggregate control fraction of common owners, their squares and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls are omitted but include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.4: Productivity & markups on sales-weighted profit weights

VARIABLES	(1) log TFP	(2) log TFP	(3) log TFP	(4) log TFP	(5) markup	(6) markup	(7) markup	(8) markup
κ_{sw}	-2.036***	-4.113***	-2.007***	-4.068***	-0.815***	-1.793***	-0.779***	-1.733***
	(0.140)	(0.224)	(0.142)	(0.226)	(0.065)	(0.128)	(0.064)	(0.133)
κ_{sw}^2		10.80***		10.71***		5.091***		4.956***
		(1.339)		(1.331)		(0.832)		(0.830)
log WPS			0.00384**	0.00337**			0.00477***	0.00455***
			(0.001)	(0.001)			(0.001)	(0.001)
Observations	15,166	15,166	15,166	15,166	15,166	15,166	15,166	15,166
R-squared	0.426	0.432	0.426	0.432	0.406	0.409	0.408	0.411
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for key outcome variables regressed on sales-weighted profit weights. The dependent variables are log productivity in columns (1)-(4), and markups in columns (5)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and weighted with the sales share of each respective competitor, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.5: Productivity & markups on profit weights - young vs old firms

	Below median age				Above median age			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	log TFP	log TFP	markup	markup	log TFP	log TFP	markup	markup
κ	-0.0845***	-0.111*	-0.0253	-0.140***	-0.0320**	-0.119*	0.00873	-0.144***
	(0.026)	(0.056)	(0.020)	(0.046)	(0.015)	(0.060)	(0.009)	(0.049)
κ^2		0.0516		0.222***		0.0592		0.225***
		(0.082)		(0.070)		(0.087)		(0.075)
Observations	16,634	16,634	16,634	16,634	15,815	15,816	15,815	15,816
R-squared	0.343	0.343	0.297	0.298	0.425	0.351	0.425	0.301
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for key outcome variables regressed on equal-weighted profit weights, for all below-median age firms in columns (1)-(4), and for all above median age firms in columns (5)-(8). The median is evaluated separately for each year. The dependent variables are log productivity in columns (1)-(2)/(5)-(6), and markups in columns (3)-(4)/(7)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and equally weighted and its squared term. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.6: Productivity & markups on profit weights - high vs low agg CO control

	Below median aggCO				Above median aggCO			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	log TFP	log TFP	markup	markup	log TFP	log TFP	markup	markup
κ	-0.0121	-0.134**	-0.00516	-0.120***	-0.0708**	-0.141**	0.0282	-0.130***
	(0.025)	(0.052)	(0.016)	(0.034)	(0.027)	(0.055)	(0.017)	(0.035)
κ^2		0.198***		0.187***		0.203**		0.194***
		(0.069)		(0.039)		(0.072)		(0.041)
Observations	16,072	16,072	16,072	16,072	16,466	15,259	16,466	15,259
R-squared	0.349	0.349	0.328	0.329	0.400	0.356	0.341	0.335
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for key outcome variables regressed on equal-weighted profit weights, for all below-median common owner control firms in columns (1)-(4), and for all above median common owner control firms in columns (5)-(8). The median is evaluated separately for each year. The dependent variables are log productivity in columns (1)-(2)/(5)-(6), and markups in columns (3)-(4)/(7)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and equally weighted and its squared term. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.7: Productivity & markups on profit weights - large vs small firms

	Below median market cap				Above median market cap			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	log TFP	log TFP	markup	markup	log TFP	log TFP	markup	markup
κ	-0.0643***	-0.150**	-0.0200	-0.0836**	-0.0124	-0.162***	0.0285**	-0.0942**
	(0.019)	(0.054)	(0.013)	(0.036)	(0.022)	(0.056)	(0.013)	(0.036)
κ^2		0.177*		0.131*		0.196*		0.142**
		(0.092)		(0.063)		(0.095)		(0.065)
Observations	16,402	16,402	16,402	16,402	16,062	15,566	16,062	15,566
R-squared	0.327	0.327	0.250	0.250	0.361	0.330	0.319	0.251
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for key outcome variables regressed on equal-weighted profit weights, for all below-median market capitalization firms in columns (1)-(4), and for all above median market capitalization firms in columns (5)-(8). The median is evaluated separately for each year. The dependent variables are log productivity in columns (1)-(2)/(5)-(6), and markups in columns (3)-(4)/(7)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and equally weighted and its squared term. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.8: Common ownership measures on managerial incentives

VARIABLES	(1) κ	(2) κ	(3) *cosinesim*	(4) *cosinesim*	(5) *aggCO*	(6) *aggCO*
log WPS	-0.00534***	-0.00123	-0.00289***	-0.00153**	-0.00798***	-0.00421***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
log WPS^2		-0.000814***		-0.000268**		-0.000746***
		(0.000)		(0.000)		(0.000)
Observations	15,630	15,630	15,630	15,630	15,681	15,681
R-squared	0.728	0.729	0.831	0.831	0.874	0.874
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for various measures of common ownership regressed on log wealth-performance sensitivity. The dependent variables are equal-weighted profit weights in columns (1)-(2), equal-weighted ownership similarity in columns (3)-(4), and aggregate control rights of common owners in columns (5)-(6). The key independent variables are log wealth performance sensitivity and its squared term. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.9: Productivity & markups on managerial incentives

VARIABLES	(1) log TFP	(2) log TFP	(3) markup	(4) markup
log WPS	0.00488***	0.0106***	0.00508***	0.00980***
	(0.001)	(0.002)	(0.001)	(0.002)
log WPS^2		-0.00118***		-0.000972***
		(0.000)		(0.000)
Observations	15,217	15,217	15,217	15,217
R-squared	0.418	0.419	0.406	0.407
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

This table provides regression coefficients for key outcome variables regressed on log wealth-performance sensitivity only. The dependent variables are log productivity in columns (1)-(2), and markups in columns (3)-(4). The key independent variables are log wealth performance sensitivity and its squared term. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.10: Productivity & markups 2-input Cobb-Douglas on profit weights

VARIABLES	(1) log TFP2	(2) log TFP2	(3) log TFP2	(4) log TFP2	(5) markup2	(6) markup2	(7) markup2	(8) markup2
κ	-0.0730**	-0.264**	-0.0575*	-0.249**	0.0849	-0.250	0.113	-0.224
	(0.029)	(0.107)	(0.030)	(0.106)	(0.095)	(0.338)	(0.098)	(0.335)
κ^2		0.285*		0.286**		0.499		0.501
		(0.139)		(0.135)		(0.396)		(0.389)
log WPS			0.0109***	0.0109***			0.0193***	0.0193***
			(0.002)	(0.002)			(0.005)	(0.005)
Observations	15,166	15,166	15,166	15,166	15,166	15,166	15,166	15,166
R-squared	0.456	0.456	0.457	0.457	0.400	0.400	0.400	0.400
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for alternative outcome variables regressed on equal-weighted profit weights. The dependent variables are log productivity estimates based on a 2-input Cobb-Douglas production function in columns (1)-(4), and markup estimates based on a 2-input Cobb-Douglas production function in columns (5)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and weighted with the sales share of each respective competitor, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.11: Productivity (alternative approaches) on profit weights

	Cost shares				Dynamic panel				Proxy approach			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP	log TFP
κ	-0.0268***	-0.120***	-0.0174*	-0.111***	0.0488	-0.0312	0.0694*	-0.0127	-0.120***	-0.200**	-0.0775**	-0.162*
	(0.009)	(0.021)	(0.009)	(0.021)	(0.033)	(0.085)	(0.034)	(0.083)	(0.035)	(0.072)	(0.033)	(0.078)
κ^2		0.139***		0.140***		0.119		0.122		0.120		0.126
		(0.026)		(0.026)		(0.121)		(0.120)		(0.114)		(0.124)
log WPS			0.00584***	0.00585***			0.0128***	0.0128***			0.0263***	0.0264***
			(0.001)	(0.001)			(0.003)	(0.003)			(0.002)	(0.002)
Observations	15,630	15,630	15,630	15,630	15,630	15,630	15,630	15,630	15,630	15,630	15,630	15,630
R-squared	0.580	0.580	0.581	0.581	0.825	0.825	0.825	0.825	0.981	0.981	0.982	0.982
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for alternative productivity estimates regressed on equal-weighted profit weights. The dependent variables are log productivity estimates based on the dynamic panel approach in columns (1)-(4), and productivity estimates based the De Loecker et al (2020) proxy approach in columns (5)-(8). The key independent variables are firm-level profit weights averaged across all industry competitors and weighted with the sales share of each respective competitor, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.12: Treatment effect on productivity & markups 2-input Cobb-Douglas

VARIABLES	(1) log WPS	(2) log TFP2	(3) markup2
post#treat	-0.174***	-0.0234	-0.0484
	(0.059)	(0.016)	(0.045)
post	-2.136***	0.191*	0.168
	(0.336)	(0.103)	(0.338)
Observations	10,720	10,099	10,099
R-squared	0.394	0.595	0.572
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the treatment effect on log wealth-performance sensitivity, log productivity and markups estimates based on a 2-input Cobb-Douglas production function. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.13: Treatment effect on productivity (alternative approaches)

		Dynamic panel	Proxy approach
	(1)	(2)	(3)
VARIABLES	log WPS	log TFP	log TFP
post#treat	-0.174***	-0.104	-0.453**
	(0.059)	(0.093)	(0.174)
post	-2.136***	0.0821	-2.654*
	(0.336)	(0.613)	(1.426)
Observations	10,720	10,786	10,786
R-squared	0.394	0.486	0.700
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the treatment effect on log wealth performance sensitivity and productivity estimates based on alternative estimation approaches. The dependent variables are managerial incentives in column (1), log productivity estimates based on the dynamic panel approach in column (2) and log productivity estimates based on the De Loecker et al (2020) proxy approach in column (3). The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.14: Instrumented treatment effect on productivity (alternative approaches)

		Dynamic panel	Proxy approach
	(0)	(1)	(2)
VARIABLES	log WPS	log TFP	log TFP
post#treat	-0.173***		
	(0.059)		
$\widehat{logWPS}$		0.0300	-0.0290
		(0.097)	(0.065)
Observations	10,720	10,720	10,720
R-squared	0.004	0.015	
Fstat		15.70	19.65
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the instrumented treatment effect of managerial incentives on alternative log productivity estimates. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The first stage regresses log wealth-performance sensitivity on the treatment#post interaction. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. The second stage regresses log productivity estimates based on the dynamic panel approach in column (2) and log productivity estimates based on the De Loecker et al (2020) proxy approach in column (3) on instrumented wealth-performance sensitivity. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.15: Industry-adjusted productivity & markups on profit weights

VARIABLES	(1) κ	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
κ		0.00480	-0.103***	0.00866	-0.0997***	-0.0236	-0.284	-0.00999	-0.271
		(0.009)	(0.025)	(0.008)	(0.025)	(0.051)	(0.192)	(0.053)	(0.192)
κ^2			0.161***		0.162***		0.388		0.389
			(0.030)		(0.030)		(0.234)		(0.230)
log WPS	-0.00534***			0.00269***	0.00270***			0.00949**	0.00951**
	(0.000)			(0.001)	(0.001)			(0.004)	(0.004)
Observations	15,618	15,154	15,154	15,154	15,154	15,154	15,154	15,154	15,154
R-squared	0.728	0.833	0.834	0.833	0.834	0.246	0.246	0.246	0.246
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for alternative outcome variables regressed on equal-weighted profit weights. The dependent variables are log productivity in columns (2)-(5), and markups in columns (6)-(9), both estimated from the cost shares approach but where cost shares are standardised to the industry-level median for all firms within an industry. The key independent variables are firm-level profit weights averaged across all industry competitors and equally weighted, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.16: Industry-adjusted productivity & markups on ownership similarity

VARIABLES	(1) cosinesim	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
cosinesim		-0.0840***	-0.156***	-0.0782***	-0.151***	-0.165**	-0.660**	-0.143*	-0.641**
		(0.013)	(0.047)	(0.013)	(0.047)	(0.076)	(0.248)	(0.078)	(0.246)
$cosinesim^2$			0.156		0.157		1.067**		1.072**
			(0.094)		(0.092)		(0.438)		(0.429)
log WPS	-0.00289***			0.00244***	0.00244***			0.00915**	0.00918**
	(0.000)			(0.001)	(0.001)			(0.004)	(0.004)
Observations	15,618	15,154	15,154	15,154	15,154	15,154	15,154	15,154	15,154
R-squared	0.831	0.834	0.834	0.834	0.834	0.246	0.246	0.246	0.246
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides regression coefficients for alternative outcome variables regressed on equal-weighted ownership structure similarity. The dependent variables are log productivity in columns (2)-(5), and markups in columns (6)-(9), both estimated from the cost shares approach but where cost shares are standardised to the industry-level median for all firms within an industry. The key independent variables are firm-level ownership structure similarity averaged across all industry competitors and equally weighted. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.17: Treatment effect on industry-adjusted productivity & markups

VARIABLES	(1) log WPS	(2) log TFP	(3) markup
post#treat	-0.174***	-0.0504*	-0.0543**
	(0.059)	(0.025)	(0.025)
post	-2.136***	-0.154	0.213
	(0.336)	(0.116)	(0.239)
Observations	10,720	10,099	10,099
R-squared	0.394	0.674	0.420
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the treatment effect on log wealth performance sensitivity and productivity estimates based on a variation of the cost shares approaches. The dependent variables are managerial incentives in column (1), log productivity in column (2) and markups in column (3), both estimated from the cost shares approach but where cost shares are standardized to the industry-level median for all firms within an industry. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.18: Instrumented treatment effect on industry-adjusted productivity & markups

VARIABLES	(0) log WPS	(1) log TFP	(2) markup
post#treat	-0.131**		
	(0.066)		
$\widehat{logWPS}$		0.112***	0.213***
		(0.031)	(0.058)
Observations	10,035	10,035	10,035
R-squared		-0.304	-0.218
Fstat		20.45	82.56
Industry	naicsh3	naicsh3	naicsh3
True Inclusions	Yes	Yes	Yes
Unique Treated Firms	264	264	264
Unique Control Firms	223	223	223
Controls	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table provides regression results for the instrumented treatment effect of managerial incentives on log productivity and markup estimates, both estimated from the cost shares approach but where cost shares are standardized to the industry-level median for all firms within an industry. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The first stage regresses log wealth-performance sensitivity on the treatment#post interaction. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. The second stage regresses log productivity estimates in column (2) and markups in column (3) on instrumented wealth-performance sensitivity. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.19: Productivity & markups on lagged profit weights

VARIABLES	(1) κ	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
Lag κ		-0.0599***	-0.171***	-0.0545***	-0.164***	-0.0267***	-0.136***	-0.0202**	-0.129***
		(0.016)	(0.049)	(0.017)	(0.048)	(0.008)	(0.030)	(0.009)	(0.030)
Lag κ^2			0.170*		0.168*		0.168***		0.166***
			(0.086)		(0.084)		(0.041)		(0.040)
Lag log WPS	-0.00536***			0.00406**	0.00404**			0.00483***	0.00481***
	(0.001)			(0.001)	(0.001)			(0.001)	(0.001)
Observations	13,725	13,341	13,341	13,341	13,341	13,341	13,341	13,341	13,341
R-squared	0.672	0.419	0.420	0.420	0.420	0.401	0.402	0.403	0.404
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides results for key outcome variables regressed on lagged equal-weighted profit weights. The dependent variables are log productivity in columns (1)-(4), and markups in columns (5)-(8). The key independent variables are previous-year firm-level profit weights averaged across all industry competitors and equally weighted, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.20: Productivity & markups on lagged ownership similarity

VARIABLES	(1) *cosinesim*	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
Lag *cosinesim*		-0.191***	-0.188**	-0.182***	-0.180**	-0.120***	-0.238***	-0.108***	-0.229***
		(0.021)	(0.075)	(0.021)	(0.073)	(0.012)	(0.043)	(0.012)	(0.043)
Lag $cosinesim^2$			-0.00669		-0.00346		0.265***		0.269***
			(0.135)		(0.133)		(0.081)		(0.079)
Lag log WPS	-0.00314***			0.00379**	0.00379**			0.00462***	0.00463***
	(0.000)			(0.001)	(0.001)			(0.001)	(0.001)
Observations	13,725	13,341	13,341	13,341	13,341	13,341	13,341	13,341	13,341
R-squared	0.798	0.420	0.420	0.421	0.421	0.402	0.402	0.404	0.404
Industry Def	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3	naicsh3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides results for key outcome variables regressed on lagged equal-weighted ownership structure similarity. The dependent variables are log productivity in columns (1)-(4), and markups in columns (5)-(8). The key independent variables are previous-year firm-level ownership structure similarity averaged across all industry competitors and equally weighted, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical NAICS-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.21: Productivity & markups on profit weights, current NAICS-3 industries

VARIABLES	(1) κ	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
κ		-0.0668***	-0.206***	-0.0598***	-0.197***	-0.0171*	-0.126***	-0.0101	-0.118***
		(0.017)	(0.043)	(0.018)	(0.043)	(0.009)	(0.023)	(0.010)	(0.022)
κ^2			0.211***		0.209***		0.166***		0.164***
			(0.066)		(0.064)		(0.031)		(0.030)
log WPS	-0.00483***			0.00505***	0.00503***			0.00508***	0.00506***
	(0.000)			(0.001)	(0.001)			(0.001)	(0.001)
Observations	15,488	15,013	15,013	15,013	15,013	15,013	15,013	15,013	15,013
R-squared	0.727	0.403	0.403	0.404	0.404	0.397	0.398	0.399	0.400
Industry Def	naics3	naics3	naics3	naics3	naics3	naics3	naics3	naics3	naics3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides results for key outcome variables regressed on equal-weighted profit weights based on alternative indsutry classifications. The dependent variables are log productivity in columns (1)-(4), and markups in columns (5)-(8). The key independent variables are firm-level profit weights averaged across all industry current NAICS-3 competitors and equally weighted, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same current NAICS-3 industry. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.22: Productivity & markups on profit weights, historical SIC-3 industries

VARIABLES	(1) κ	(2) log TFP	(3) log TFP	(4) log TFP	(5) log TFP	(6) markup	(7) markup	(8) markup	(9) markup
κ		-0.0499**	-0.175***	-0.0419**	-0.166***	0.00749	-0.0481**	0.0150	-0.0396*
		(0.019)	(0.041)	(0.020)	(0.041)	(0.008)	(0.021)	(0.009)	(0.020)
κ^2			0.177***		0.176***		0.0784***		0.0770***
			(0.046)		(0.045)		(0.027)		(0.025)
log WPS	-0.00544***			0.00597***	0.00595***			0.00565***	0.00564***
	(0.000)			(0.001)	(0.001)			(0.001)	(0.001)
Observations	14,680	14,205	14,205	14,205	14,205	14,205	14,205	14,205	14,205
R-squared	0.765	0.546	0.546	0.547	0.548	0.464	0.464	0.467	0.467
Industry Def	sich3	sich3	sich3	sich3	sich3	sich3	sich3	sich3	sich3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table provides results for our key outcome variables regressed on equal-weighted profit weights based on alternative industry classifiations. The dependent variables are log productivity in columns (1)-(4), and markups in columns (5)-(8). The key independent variables are firm-level profit weights averaged across all SIC-3 industry competitors and equally weighted, its squared term and log wealth performance sensitivity. Firms are considered competitors and subject to common ownership if they were classified into the same historical SIC-3 industry in a given year. Controls include ownership and firm characteristics, industry#year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.23: Instrumented treatment effect on outcomes, current NAICS-3 industries

VARIABLES	(0) log WPS	(1) log TFP	(2) log TFP2	(3) markup	(4) markup2
post#treat	-0.061				
	(0.051)				
$\widehat{logWPS}$		0.131***	0.285***	0.115***	0.540***
		(0.021)	(0.049)	(0.017)	(0.114)
Observations	10,072	10,072	10,072	10,072	10,072
R-squared		-0.603	-0.885	-0.955	-0.465
Fstat		38.40	28.36	35.84	35.80
Industry	naics3	naics3	naics3	naics3	naics3
True Inclusions	Yes	Yes	Yes	Yes	Yes
Unique Treated Firms	262	262	262	262	262
Unique Control Firms	224	224	224	224	224
Controls	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table provides regression results for the instrumented treatment effect of managerial incentives on log productivity and markups. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The first stage regresses log wealth-performance sensitivity on the treatment#post interaction. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a NAICS-3 industry competitor being added to the S&P 500 index in a given year (based on current NAICS-3 industry), and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. The second stage regresses log productivity and markups (from the 3-input Cobb-Douglas function, columns (1)+(3) or from the 2-input Cobb-Douglas function, columns (2)+(4)) on instrumented wealth-performance sensitivity. Controls are omitted but include firm and ownership characteristics in the year before treatment, industry (current NAICS-3) and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** p<0.01, ** p<0.05, * p<0.1 .

Table B.24: Instrumented treatment effect on outcomes, historical SIC-3 industries

VARIABLES	(0) log WPS	(1) log TFP	(2) log TFP2	(3) markup	(4) markup2
post#treat	-0.057				
	(0.076)				
$\widehat{logWPS}$		0.132***	0.171***	0.140***	0.314***
		(0.021)	(0.036)	(0.019)	(0.087)
Observations	12,123	12,123	12,123	12,123	12,123
R-squared		-1.018	-0.519	-1.840	-0.227
Fstat		11.71	9.783	11.85	24.34
Industry	sich3	sich3	sich3	sich3	sich3
True Inclusions	Yes	Yes	Yes	Yes	Yes
Unique Treated Firms	170	170	170	170	170
Unique Control Firms	300	300	300	300	300
Controls	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table provides regression results for the instrumented treatment effect of managerial incentives on log productivity and markups. The treatment window for all treated and control firms is 4 years pre- and post-treatment, implying the sample is restricted to treatments between 2004-2015. The first stage regresses log wealth-performance sensitivity on the treatment#post interaction. The variable post is a dummy equal to 1 in the treatment year and 4 consecutive years and otherwise 0. The treatment indicator is 1 for all true treated firms (added competitor was not previously part of the S&P 400 Mid-Cap) and 0 for all control firms. Treated firms observe the addition of a SIC-3 industry competitor being added to the S&P 500 index in a given year, and are not themselves dropped the following year. Control firms do not observe a competitor addition to the index in the respective treatment year, nor in the previous or following year. The second stage regresses log productivity and markups (from the 3-input Cobb-Douglas function, columns (1)+(3) or from the 2-input Cobb-Douglas function, columns (2)+(4)) on instrumented wealth-performance sensitivity. Controls are omitted but include firm and ownership characteristics in the year before treatment, SIC-3 industry and year fixed effects. Standard errors are clustered by year, and significance is indicated by stars, with p-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Chapter 3

Activist Portfolios

Abstract This paper provides the first comprehensive study of activist portfolios and their implications for activist campaigns. Contrary to common perception activists are highly diversified, not only across targeted firms, but also across competing firms which are never formally targeted. I show that the abnormal returns to a campaign generated by the activist portfolio of target and competing firms significantly outperform returns to the target firm only. Further analysis documents concurrent performance improvements at activist owned competitors, while target firms disappoint relative to matched controls. Overall these findings suggest that the effects of activist investors may be more extensive than previously established and arise as portfolio spillovers are internalized.

3.1 Introduction

Hedge fund activism has become a frequent governance intervention at U.S. corporations over the past twenty years and is considered an important mechanism to discipline firms and managers. Despite the ongoing discussion about the governance impact of hedge fund activists on individual target firms, we have not paid much attention to spillover effects on related, non-target portfolio firms, which may constitute an important fraction of activists' holdings.

As an example, Table 3.1 shows a subset of Carl Icahn's portfolio at the end of 2008-Q2, which demonstrates that a well-known hedge fund activist can be diversified across multiple competing firms, not all of which eventually become campaign targets. In 2008-Q2, Carl Icahn started a campaign at Amylin Pharmaceuticals, in which he invested 2.7% of his assets under management giving him control of 5% of all shares outstanding. At the same time, Icahn held 0.4% of his portfolio in Enzon Pharmaceuticals, where he started an activist campaign in the previous quarter and still controls 6.9% of the votes. Concurrently, Icahn's portfolio in 2008-Q2 includes three other pharmaceutical firms: Regeneron Pharmaceuticals, Biogen Idec and Adventrx Pharmaceuticals. The total invested capital in these firms competing with the targeted firm, Amylin Pharma, corresponds to 3% of Icahn's assets under management. Neither firm is ever targeted by Icahn, yet, his stakes in them are substantial and nearing 5% of outstanding shares.

Firm	Campaign	AUM %	Control %
Amylin Pharma	Q2-2008	2.7%	5.0%
Enzon Pharma	Q1-2008	0.4%	6.9%
Regeneron Pharma		0.5%	3.2%
Biogen Idec		2.4%	4.3%
Adventrx Pharma		0.04%	4.8%

Table 3.1: Portfolio (subset) of Carl Icahn, 2008-Q2

The evidence suggests that this example is not an exception, but a common occurrence among hedge fund activism campaigns. Figure 3.1 depicts the total number of campaigns started per year in black, and the number of campaigns where the activist owns a stake in competitors never targeted in gray. Referring to the latter as "activist common ownership (ACO) campaigns", they constitute more than a third of all campaigns started between 2000-2020.

Hedge fund activists differ from other institutional investment managers because their incentives are directly linked to portfolio returns (Brav, Jiang, & Li, 2022). Hence, their campaigns should optimally maximize aggregate portfolio returns, instead of an individual firm's returns. The question arising from my novel evidence on diversified activist portfolios is: why hold competitors of a target firm? If an activist campaign aims to make *only* the target firm more valuable and competitive, this will reduce the returns to competing, non-target portfolio firms in a standard Bertrand competition model. If the activist internalizes spillover effects onto competing portfolio firms, these competitors should also improve their performance and aggregate portfolio returns would rise in response to the campaign.

In this paper I investigate the portfolio incentives of hedge fund activists and whether diversified activists internalize the positive externalities of their campaigns on commonly owned competitors.

This appears as an important question in the context of two branches of the governance literature, discussed in greater detail below. The existing hedge fund activism literature and commentary do not evaluate activist portfolios, motivations for diversification or resulting incentives to positively affect commonly owned firms at all. A void filled by this paper. At the same time, the academic common ownership literature studies portfolio incentives to internalize externalities without differentiating between investor types in most cases, while policy makers discuss the anti-competitive implications of the largest universal shareholders' highly diversified, indexed portfolios. Both neglect the more direct incentives and effects of selective and active investors. My contribution is an accurate assessment of the prevalence and implications of hedge fund activists' common ownership, that can guide specific policy action towards a distinctive group of investors, without undermining the benefits of broad-based indexing.

To answer the research question, I establish the first comprehensive data set of hedge fund activist portfolio holdings of U.S. public companies. Using the ownership data set of Amel-Zadeh et al., 2024 and the list of activism campaigns shared by

Brav, Jiang, and Li, 2022, I capture 2034 campaigns run by 486 hedge fund activists, for which I have consistent portfolio information between 2000 and 2020. The analysis focuses on hedge fund activists of limited size and diversification - henceforth, single strategy hedge fund investors - as I am interested in actively managed portfolios of value-seeking investors, and not the investments produced by other portfolio managers using quantitative analysis or algorithmic trading. Combining the portfolio holdings with pair-wise product similarity scores of firms made available by Hoberg and Phillips, 2016, I identify portfolio firms competing in the same product market as the target firms of all campaigns.

Based on this unique data set of activists' holdings of target firms and non-targeted competing or non-targeted non-competing firms, I assess the size and diversification of activist portfolios, as well as their financial interests in targeted and competing firms around campaign start. Campaigns are separated into those where an activist commonly owns competitors of the target firm at campaign start - henceforth, ACO (activist common ownership) campaigns - and campaigns where the activist does not hold a competitor of the target at campaign start (non-ACO campaigns).

The novel empirical fact I identify through my analysis is that hedge fund activist portfolios are more diversified than commonly appreciated with more than a third of all campaigns run by an activist owning competitors of the target which are never themselves targeted. Frequently the activists' financial interest in a single competitor, meaning the fraction of assets under management invested in this competitor, is larger than the interest in the campaign target itself (although control in the target is always larger), suggesting relevant incentives to care about the performance of the competitor. Overall targeted firms are smaller, less efficient and had lower recent returns than the average Compustat firm, mirroring previous results in the literature. In contrast, activist-commonly owned competitors are larger, more efficient, and better performing than the average Compustat firm, and the majority of their shares are held by common owners. These facts could imply that activist portfolio diversification is a passive constant state, and the diversified investments are unrelated to any campaign, meant only to benefit from the returns to the largest, most profitable firms in an industry regardless of the activism campaign. A more detailed analysis of activists' investments in target and competitor firms in the pre-and post-campaign announcement period, however, provides evidence that ownership of competitors varies systematically in relation to the campaign and can be associated with different campaign outcomes.

The first part of the analysis serves to understand if ownership of target's competitors improves the financial returns of the activist, providing an incentive to diversify the portfolio in the target's market. Buy-and-hold-abnormal returns to the activists' actual portfolio holdings of target firms and their competitors *jointly* outperform returns to the target firm *only*. Holdings in a target's competitors provide a hedge against the target's underperformance before campaign announcement, and reap excess returns in the second and third year post campaign announcement, implying significant financial incentives to diversify holdings across the target's competitors. At the same time diversification and target performance co-vary. When the target's long run return is in the top quintile of campaign returns, the activist reduces its holdings of competitors more quickly post-campaign announcement than in campaigns where the target's long run return is in the bottom quintile. An analysis of the Fama-French five factor alpha of calendar-time portfolios of targets and commonly-owned competitors corroborates these findings, implying that activists have a significant financial incentive to hold the competitors of target firms.

The second part of the analysis studies whether the excess returns to portfolio diversification among competitors are related to positive economic spillovers from the campaign target to commonly owned competitors, or arise regardless of the activists' engagement. Using a staggered difference-in-difference model in an annual event study setting, I compare the post campaign start performance of targets and competitors owned by the activist to the performance of matched non-owned competitors. To address concerns regarding the staggered nature of treatment (each year several campaigns commence), I employ a stacked data method as suggested by the recent econometrics literature (Baker et al., 2022) and use competitors never owned by the activist as control group.

Activist commonly owned competitors significantly outperform their matched controls with 1 percentage point higher return on assets and higher market power (1 percentage point higher markups and 5.1% higher sales shares) in response to the campaign. The targeted firms in contrast reduce their sales share and productivity relative to matched non-activist owned competitors. Further investigation suggests that less differentiation between targets' and activist commonly owned competitors' products (measured by higher product similarity scores) may give rise to the positive spillover effects for owned competitors while negatively impacting the targets of such campaigns. These results indicate that financial returns to diversified portfolio holdings are not only driven by selection, but are reinforced by positive spillover effects specific to activist owned competitors.

In an extension to the main results, I find that short-run announcement returns are higher for targets of non-activist common ownership campaigns than for targets of activist common ownership campaigns, suggesting that market expectations about the performance of activist commonly owned targets are slightly lower. It is unclear if that is due to lower average investments of diversified activists in the target firms or due to knowledge of the activists' diversified portfolio interest. There is no evidence of announcement returns to competitors held by the activist exceeding the returns to non-activist owned competitors, hence it seems that the market is unaware of the activists' portfolio diversification and potential positive spillovers to commonly owned competitors.

My results are consistent with the hypothesis that activists intentionally diversify their portfolio, investing in competitors of targeted firms and consequently internalize the positive spillover effects of their campaigns on these competing portfolio firms. Financially, this diversification provides a hedge against the target's underperformance pre-campaign announcement and yields positive excess returns in the long-run. Economically, I find evidence of a link between the activist campaign and positive performance changes at activist-commonly owned competitors, while targets are slightly negatively impacted.

The incentives and implications of hedge fund activism are clearly related to the activists' diversified portfolio interests, suggesting that knowledge of portfolio diversification is key to analyzing the effects of activism. This raises the question of whether reporting requirements for hedge fund activists should be expanded to include information on investments in competitors, in order to more accurately and comprehensively study the outcomes of activist engagements. A discussion of the economic desirability of activist ownership in targets' competitors, especially post-campaign start, may be warranted but would benefit from further evidence on internalized campaign spillover and welfare effects.

3.2 Related literature

This paper contributes mainly to two ongoing debates in the literature. First it addresses the question whether activist campaigns are maximizing short-run returns of target firms by extracting long run value from other stakeholders. Second, it offers new evidence to the search for empirical manifestations of the common ownership hypothesis, which proposes that diversified investors internalize spillovers between firms in line with their portfolio incentives.

Hedge fund activism, its institutional attributes and effects on long run firm performance have been studied actively in academic research. For a comprehensive review of the pertaining literature see Brav, Jiang, and Li, 2022. Positive announcement returns to activist engagements and a higher likelihood of successful mergers and takeovers after announcement are the generally accepted effects of activism (Boyson et al., 2017; Denes et al., 2017), while long run implications for firm performance are more contested. Whilst identification of a *causal effect of engagement* provides significant challenges because campaigns inherently start with an activist *selecting* the target firm, the existing evidence suggests that activists' returns do not come at the expense of long run financial or operating performance of targets. Instead activist campaigns lead to profitability improvements, higher productivity and more efficient innovation at the target firm relative to matched controls.

Further research has identified mechanisms through which activist campaigns can impact firms other than the respective target firm. Most closely related to my analysis of portfolio returns are Feng et al., 2023 and Gantchev, 2013, who estimate the returns to and impact on targeted and non-targeted firms in the activists' portfolios. Different from my analysis, they do not differentiate between competitors or non-competitors and do not study the mechanism of spillovers. Gantchev et al., 2019 show that the threat of becoming a future activism target may drive a related firm to improve its performance and payouts, implying a positive effect for other firms' stakeholders. Alternatively, a more competitive target firm implies lower market power and returns for a competing firm (Aslan & Kumar, 2016), leading to negative effects on competitors' returns. To date, there is no evidence on potential trade-offs between improving the target firm and causing spillover effects on other firms, chiefly because no awareness of activists' diversified financial interests in both target and competing firms exists.

While the activists' ownership of non-target firms has attracted little attention so far, a more recent selection of papers studies the relationships between hedge fund activists' ownership and engagement, and other institutional investors' ownership of target firms. Multiple analyses show that the likelihood of an activist engagement and its success are dependent on ownership by other, activism-friendly institutional or activist investors (Brav, Dasgupta, & Mathews, 2022; Brav et al., 2021; Kedia et al., 2021). Among these papers, two identify common ownership of institutional investors as a possible deterrent or reinforcing mechanism to activism (Goshen & Levit, 2024; Gu & Zhang, 2020). However, nobody has analyzed the portfolio incentives of activists themselves.

In this paper, I add this novel dimension to the analysis of hedge fund activism, providing empirical facts on activist portfolio holdings and a surprising degree of diversification across target firms and competing firms. Based on these portfolio incentives, I argue and find that an analysis of the long run effects of activism should evaluate the effects on target firms and activist-owned competitors jointly, as the latter are relevant for the activists' aggregate campaign returns and there may be a trade-off between the two.

Separately, this paper draws on and contributes to the debate on the Common Ownership Hypothesis. This hypothesis was first theoretically established by Rotemberg, 1984 in a model of diversified investors, where managers optimally maximize the joint value of their corporations, by internalizing externalities on other firms, in order to maximize the diversified shareholders' utility. A common owner is defined as an investor in multiple firms competing for the same product market. The implications of this hypothesis for competition, innovation and growth have been studied in numerous settings and with varying results. For a comprehensive summary of findings and methodologies see Backus et al., 2021c; Schmalz, 2021 or Gerardi et al., 2023.

Virtually none of the empirical literature differentiates between different types of investors who may or may not have common ownership incentives. Due to data availability limitations and the concentration of stock holdings in a small group of institutional investors, most results are driven by common ownership of large institutional asset managers, such as BlackRock and Vanguard. These owners are so widely diversified that they can arguably be called "universal owners". Because of their ownership across all industries and their passive governance style, it is unclear whether the common ownership hypothesis applies to these investors at all and how they would interact differently with commonly owned firms. The only analysis of common ownership incentives among smaller and more selective investors, such as insiders and activists, is provided by Amel-Zadeh et al., 2022. I base my analysis on the comprehensive ownership data set compiled by Amel-Zadeh et al. and investigate the common ownership incentives and implications of hedge fund activists in more detail.

Selective theoretical work has attempted to predict the consequences of common ownership by investors with different investment horizons and engagement styles (Annabel et al., 2022). However, to the best of my knowledge, no empirical analysis of common ownership incentives of active investors exists to date. This paper provides a unique assessment of how prevalent common ownership incentives among engaged hedge fund activists are, and the first analysis of the relationship between activist common ownership and campaign effects on target firms and activist commonly owned competitors.

3.3 Data

3.3.1 Activist identification & portfolios

An activist is commonly defined as a specialized hedge fund that builds a minority stake in a large public corporation in order to change its strategic outlook, to improve its valuation and finally to sell the stake at a premium. The public announcement of the activist's significant minority stake and his strategic objective investing in the targeted firm marks the start of the activist campaign. This announcement regularly coincides with the hedge fund filing a SC 13-D report with the Securities Exchange Commission (SEC) and, sometimes concurrently, publishing a letter to management outlining desired changes. The SC 13-D filing is required by the SEC within 10 days of an investor acquiring more than 5% of the outstanding shares of a firm[1]. In the report, the investor states his aggregate holdings, source of funds and the objective or purpose of the investment in the firm.

An analysis of these SC 13-D filings and the stated objectives of activists is provided by Brav, Jiang, and Li, 2022. To distinguish between the different objectives of activists, their different tactics and outcomes, Brav, Jiang, and Li compile a comprehensive list of activist campaigns between 2000 and 2016[2]. Using their dataset, which comprises the activist's name, target firm identifiers, and the SC 13-D filing date initiating the campaign start, I identify the activist investors' quarterly portfolio holdings in the ownership data set assembled by Amel-Zadeh et al., 2024.

First, I match each investor name to its corresponding owner-"central index key" (*ownercik*), a unique identifier attributed by the SEC to any investor or firm reporting to it. A fuzzy name match followed by an extensive manual search of the SEC investor name list yields 508 *ownercik*-identified activists. Using the activists' unique *ownercik*, I restrict the ownership data set to portfolios pertaining to identified activists. With the unique target firm identifier and SC 13-D filing date provided by Brav, Jiang, and Li, I identify the portfolio firm targeted by an activist, and the quarter when the respective campaign starts. Overall I am able to identify quarterly portfolio holdings for 486 activist investors, comprising 2034 activist campaigns between 2000 and 2020.

For each campaign, meaning a unique activist-target firm-date combination, I know what other firms were in the activist's portfolio and what fraction of assets under management was invested in the current target and all other portfolio firms. This information is available for the quarter of campaign starts, but also for the

[1]From September 2024 onward the filing is required within 5 days of breaching the 5% threshold.
[2]My thanks to Brav, Jiang, and Li for sharing their data with me.

quarters before and afterwards, allowing an analysis of how the activist changed his holdings in targeted and competing firms around the SC 13-D filing.

In order to determine whether other portfolio firms of the activist are competitors of the target at the time of campaign start, I require a measure of markets or product similarity. As historical industries identified by SIC or NAICS codes are highly incomplete, fluctuating in size and lack the continuous competition measure required for one aspect of the analysis, I utilize the pairwise product similarity scores made available by Hoberg and Phillips, 2016. Comparing firms' product descriptions which are reported annually on their 10-K filing using NLP methods, Hoberg and Phillips construct a continuous measure of how similar the products of any given firm-pair are at annual frequency. To limit the dimensions of my competitive network, I restrict these similarity scores to be larger than 0.1%, which drops about a quarter of the firm-pairs from the TNIC-2 data set available on the authors' website. The firms in my data set have a minimum of 1 and a maximum of 1112 competitors in any given year, and the average number of competitors is 174 per firm-year. This is an intermediate size for a competitive network, smaller than most SIC-2 digit industry cohorts, but larger than the average SIC-3 digit industry, thereby well within the commonly used industry bands.

Using these similarity scores I determine for each campaign (activist-target firm-date) which other portfolio firms of the activist are competitors of the target. A competitor is defined as a firm with a similarity score in excess of 0.1% and a firm that is not itself targeted by an activist at any point. All firms with lower similarity scores or targeted themselves are not considered competitors of the target firm. This classification yields on average 3.6 competing firms in the activist's portfolio across all campaigns, and 9.3 competitors in the portfolios of activist common owners. Additionally, I identify firms competing with the target but not owned by the activist at campaign start, categorizing firms in the data into the following five categories:

"ACO targets" (short for **A**ctivist **C**ommon **O**wnership targets), are firms targeted by an activist who at the time of campaign announcement holds a stake in at least one competitor of the target. "ACO competitors", the competitors of a target firm owned by the targeting activist. In contrast, non-ACO or "NACO targets" (non-**A**ctivist-**C**ommon **O**wnership targets) are firms targeted by an activist who at the time of targeting holds no stake in competing firms and "NACO competitors" are competitors of the target that are not concurrently owned by the activist. Finally, "never ACO competitors" are firms competing with a targeted firm, or possibly with targets of multiple campaigns, but which are never themselves targeted or simultaneously owned by the targeting activist. These firms serve as the primary control group.

The panel portfolio data is combined with firm-level data on balance sheet fundamentals from Compustat, securities returns from CRSP and the firm-pair similarity scores from Hoberg and Phillips. All variables of interest are winsorized at the 1st and 99th percentile (including the similarity scores), balance sheet items in US$ are deflated using the US Bureau of Labor Statistics GDP deflator data benchmarked to 2017. Firms that stopped trading during a quarter are dropped from the data although I may observe their ownership for some part of the quarter. Table C.1 provides details on the construction of all relevant variables.

3.3.2 Sample restrictions

Among the activists identified by Brav et al., 2008, many are multi-strategy hedge funds that hold a large, highly diversified portfolio at the investor family level, but not necessarily at the activist portfolio manager level. As my focus is on the holdings of selectively diversified, value-sensitive and engaged investors, I restrict the analysis to what I refer to as single-strategy activist investors. Formally this means that all investors for whom I observe less than 5 portfolio firms across the whole sample are dropped, as they are often incorrectly captured (not consolidated in fund family or incorrect ownership data), and all investors with more than 200 portfolio firms in any given quarter or more than 100 portfolio firms in their median quarterly portfolio are removed, as they are likely multi-strategy hedge funds. Varying these cut-offs either leads to large, well-known activists like Nelson Peltz (Trian) or Dan Loeb (Third Point) being dropped from the sample, or large multi-strategy funds and market makers like Millenium Management being included. Neither would serve the purpose of this project.

From the remaining sample of campaigns and portfolio firms, I exclude all firm-year observations for which fundamental and securities data is missing and remove campaigns without any competitors. The latter only affects very small targeted firms, frequently also missing securities data. My analysis focuses on campaigns started in the years 2005-2016, as the event study set-up requires a pre- and post-treatment period of 4 years during which I observe firm performance and ownership.

The final data sample comprises 306 activist investors and 1238 campaigns, of which 183 activists and 537 campaigns are subject to activist common ownership, meaning the targeting activist concurrently holds the target firm and at least one competitor that is never itself targeted. The number of campaigns and the subset where the activist is a common owner, varies significantly across activists (see Figure C.5). Some activists only ever run one campaign, which may be an ACO campaign if they are diversified within the sector, others run more than 50 campaigns, of which maybe a third are ACO campaigns. The activists running many campaigns are over-represented in my sample and analysis, but this is controlled for and should not affect the interpretation of my findings.

3.4 Results

3.4.1 Activist portfolio diversification

Many activists engage in multiple campaigns over the twenty year sample horizon, but few engage solely in ACO or solely in non-ACO campaigns. The likelihood of running an ACO campaign depends on the portfolio size and specialization of the activist, and to a smaller degree on the number of competitors of the target firm. Across the 997 firms targeted in the total sample of 1238 campaigns, the average number of competitors per target firm is 164. The 468 target firms of the 537 ACO campaigns instead have 276 competitors on average, suggesting that ACO target firms' products are on average more similar to others and therefore subject to stronger competition.

The second determinant, the portfolio size of activist investors, is limited by my sample restriction to single-strategy hedge fund activists. In 2004 this leaves 21 activist investors in the sample, which rises to 79 in 2016 (Table C.3). The average activist holds 30 firms and \$1765 mio assets under management across all quarters, over time portfolio size is increasing in both dimensions. As the number of portfolio firms increases, the number of campaigns started per year and the number of ACO campaigns per year is rising from 43 and 18 in 2004 to 107 and 51 in 2016, respectively. This overall growth in activism corroborates previous work by Brav, Jiang, and Li, 2022 highlighting the proliferation of activism campaigns in recent years.

The portfolios of the 183 ACO activists are on average larger measured by number of portfolio firms and by assets under management. In any quarter where a campaign is started the portfolio of an activist comprises the target firm, previous and future target firms, possibly current competitors of the target, and other firms that are neither targeted at any time, nor competitors of the target. Across the activist-targeting quarters portfolio size varies significantly, from five portfolio firms to 194 portfolio firms, corresponding to \$0.34m and more than \$2000m assets under management respectively. Figure C.4 plots for each campaign on the horizontal axis the number of portfolio firms held by the activist corresponding to the bar height. Differently colored portions of each bar refer to different types of portfolio firms. The distribution of portfolio firms across current and non-current targets, competitors and non-competitors is highly heterogeneous, with some activists owning only current, previous and future target firms, and others owning the target and multiple competitors never themselves treated. A few activists hold many unrelated firms, that are neither targets nor competitors (large black portion of the bar), which could indicate that I have not removed all multi-strategy hedge funds from my sample. On the other hand, at more than half the campaign starts, the activists primarily hold current and non-current targets (light gray bar proportion), and then a few additional competitors and non-competitors of the current targets. The main variation in portfolio size is driven by the number of non-competitors owned. Once these portfolio firms are removed, Figure 3.2 shows activists do not hold any untargeted competitors of the current targets (i.e. these are non-ACO campaigns) in about 60% of campaigns, but they do own a number of previous and future targets. The remaining 40% of campaign starts involve an activist holding the current ACO target, alongside non-current targets and untargeted competitors. Zooming in on the 537 campaigns with activist common ownership, a substantial degree of variation in the portfolio size and diversification across competitors and targets remains. The largest ACO portfolios (furthest to the left) typically comprise a limited number of non-current targets and many competitors.

Taking a closer look at the investments of activist common owners in the respective targeted firm vis-a-vis the competing firms at campaign start, a surprisingly high heterogeneity arises. Whereas one might expect that the activists' investments in target firms, measured as a fraction of assets under management, will be larger than the investments in the most significant untargeted competitor, the empirical facts are different. Figure 3.3 plots the fraction of assets under management held in the target firm (black bar) and in the most significant competitor (gray bar) at campaign start for each ACO campaign on the horizontal. The average stake size in an ACO target is 7.9%, in the biggest ACO competitor it is 9.7%, and the average *aggregate* holdings in ACO competitors amount to 23.7%. The average fraction of shares outstanding controlled by the activist is slightly larger in targeted firms (8.2%) and somewhat lower in ACO competitors (8.0%) (see Table 3.2). The left tail of Figure 3.3 contains activists that invest more than half of their assets (up to 95% of AUM) into the target firm and hence hold a small stake in the most meaningful competitor. Further to the right, the fraction of AUM invested in the target firm declines to less than 5%, while holdings in the competitor reach up to 90%. For almost half of the ACO campaigns, the gray bar is higher than the black bar, implying that the fraction of AUM held in the competitor at campaign start is larger than the holdings in the target firm. Following the Common Ownership Hypothesis, such excess financial interests in the competitor can imply an incentive for the activist to "tunnel" resources from the target to the competitor firm, in order to increase its share price which is of greater value to the activist. However, the activist may not be able to capture a larger fraction of the competitor's valuation improvements because it is significantly larger (by market capitalization) than the targeted firm. Hence the fraction of cash flow rights (i.e. shares outstanding) held in the ACO competitor is actually smaller (average fractional ownership 8.2% for targets but 8.0% for ACO competitors).

Table 3.3 presents a comparison of the median characteristics of all sample firms, ACO and non-ACO target firms, as well as ACO and non-ACO competitor firms in the year before a campaign begins. Comparing target firms to the average sample firm the well-established features of target firms are identified: targets are on average older and smaller, have had lower returns recently and poorer valuations, which makes them attractive to activist investors. Being on average smaller, a lower fraction of AUM invested in the target will yield a larger control stake for the activist, implying more influence over corporate strategies and a larger fraction of cash flow rights than in ACO competitors. In addition, targeted firms have a high fraction of institutional ownership, which fits the literature studying the positive relationship between institutional ownership and activist campaign success (Brav et al., 2021; Kedia et al., 2021). Distinguishing between ACO and non-ACO targets does not show meaningful differences between median firm characteristics. ACO targets are a bit larger and poorer performing than non-ACO targets, and are more commonly owned, which could be due to their larger size or due to the common ownership of the activist itself.

Studying competitors, the distinction between ACO or non-ACO competitors matters much more. The median ACO competitor is more than twice as large as the average firm in the sample and more than three-times the size of a non-ACO competitor. ACO competitors are also characterized by higher recent returns, higher valuations, and much higher common ownership than non-ACO competitors and the average sample firm. Overall ACO competitor firms are well-performing, large corporations that are in the portfolios of most diversified institutional investors.

So far, the empirical evidence suggests that activists are more diversified than previously assumed, and frequently invest in large, well-performing competitors of target firms. However, we have not yet seen any evidence of a connection between the investments in competitors and an ongoing target campaign. Given the ACO competitor firms' characteristics, diversified investments by the activists may be completely unrelated to any campaign. For example, they may be motivated to hold large-cap, high-return corporations that are key drivers of financial market returns. Alternatively, activists may want to align their portfolio interests with those of large institutional investors, on whom they rely for support in any shareholders' vote. Aligned portfolio interests may give the activist a better chance to convince the institutional investor that "what's good for the activist is good for the institutional investor". The connection between activist investors and large institutional investors is the subject of Brav et al., 2021 and others, but will not be the topic of the following analysis. I focus on the activists' own financial incentives to alter target and competing portfolio firms' performance and investigate if concurrent investments in targets and competitors are strategically enhancing the activists' financial returns.

Portfolio diversification as a means to capture general market trends or to align portfolio incentives with large institutional managers would imply that the activist's investments in competitors are relatively stable over the quarters pre- and post-campaign start. If, instead, the investments in competitors are strategic with an aim to benefit from campaign spillover effects, the holdings of competing firms should vary around campaign start and return realization. Figure 3.4a plots the median fraction of assets under management or fraction of cash flow rights (dashed line) held by an activist in the target firm and Figure 3.4b plots the same for holdings in the top competitor, from 12 quarters before campaign start to 12 quarters after. The graph for target firms depicts a steady and significant increase of the activists' investments in targeted firms in the year leading up to campaign start, with a jump in the quarter of SC 13-D filing. At its peak, two quarters after campaign announcement, the median activist invests 5.3% of AUM into the target and holds 8.4% of all shares outstanding. Afterwards, his portfolio and control shares in the target firm decline very gradually and are still at more than 3% and 5%, respectively, after three years. The activists' ownership of the top competitor also follows a surprisingly dynamic pattern. In the year before campaign announcement, both the portfolio and the control share in the top competitor are increasing substantially. The median activist invests a maximum of 3.8% of AUM in the top ACO competitor at campaign start, while peak holdings of shares outstanding reach 2.5% two quarters after campaign start. Post-campaign start, the activists' investments as a fraction of AUM decline within two years back to the level held two years before the campaign. The share ownership falls belatedly, three quarters post-campaign start, but more sharply to its pre-campaign 1% level. A very similar picture arises when aggregating the fraction of assets invested in all competitors of the target, instead of focusing on the most significant competitor only (Figure C.8).

In light of this active increase and decrease of ownership stakes in both target and competitor firms, the activists' diversified investments do not seem completely uncorrelated from the campaign itself, but suggest strategic concurrent ownership of multiple competing firms. Before the campaign is announced, holdings in several firms in the same market increase and once a target is determined the holdings in this firm remain high, whilst holdings of non-target competitors decline. Multiple hypotheses may rationalize these patterns. One might infer that the choice of the target firm was uncertain until the quarter of campaign announcement and the activist was preparing to engage in any one of the commonly owned competitors. Once the target is chosen, holdings in non-chosen firms decline as they are a distraction. This hypothesis is at odds with the different characteristics of ultimately chosen target firms and untargeted competitors. Alternatively, the parallel increase in ownership of multiple firms may serve to enhance the "perceived threat of activism", which according to Gantchev et al., 2019 can be associated with performance improvements at non-target firms. Performance improvements in such "threatened" competitors may benefit the activist common owner in the longer run. Finally, the activist may not seek to influence the competitor at all, but wants to hedge against the downside risk in the target's pre-campaign start returns, which can be significantly negative. Once the campaign is announced, this hedge is wound down as the target is expected to outperform. The next section will evaluate to what extent the activists derive pecuniary benefits from their diversified portfolio holdings and which hypothesis is supported by the data.

3.4.2 Returns to activism

As selective and value-oriented investors, hedge fund activists are assumed to invest in firms which they perceive as undervalued, where investor engagement or another change in the firms' environment leads to valuation improvements and pecuniary benefits to the activist. The literature has traditionally focused on the financial returns to investments in targeted firms, meaning those firms in which an activist publicly announces a significant control stake and engagement objective. This paper accounts for the diversified portfolio held by activists and the potential gains from spillover effects of the campaign on non-target portfolio firms. To determine whether the activist benefits from such spillover effects and diversification strategies in the long run, I analyze the returns to the activist portfolio of target and competing firms, and compare them to the target-only returns.

Following the literature (Kedia et al., 2021) I construct buy-and-hold abnormal returns to the activist portfolio-weighted holdings over a 12 quarter horizon pre- and post-campaign announcement for each ACO campaign (537 in total). The baseline portfolio encompasses all securities in the activist's holdings. The main portfolio of interest is the ACO portfolio, a subset of the overall portfolio which comprises only the target firm and competing firms held by the activist (ACO competitors) at campaign start. Finally, the ACO target-only portfolio contains a single firm, the portfolio weighted target investment. For each portfolio, I calculate period-specific, weighted returns using the portfolio weight (fraction of AUM, α_{st}) of all relevant securities ($s \in p$) and then compound returns from 12 quarters pre-announcement up to 12 quarters post-campaign announcement. To capture the abnormal part of buy-and-hold returns, I subtract the cumulative returns on the CRSP value-weighted market portfolio over the same horizon.

$$BHAR^{p}(-12,\tau) = \left(\prod_{t=-12}^{\tau} (1 + \sum_{s \in p} \alpha_{st} R_{st}) \right) - \left(\prod_{t=-12}^{\tau} (1 + R_t^m) \right) \tag{3.1}$$

Figure 3.5 plots the mean buy-and-hold abnormal returns (BHAR, henceforth) to each of the three portfolios over the 24 quarters surrounding campaign announcement, and their respective 95% confidence intervals. The mean BHAR to the ACO target-only portfolio are substantially negative for the quarters leading up to campaign announcement, in line with a deterioration of target performance before the activist engages. Surprisingly, this trend is not reversed by the activist's entry over the following 12 quarters. The negative returns become smaller in absolute value, and stabilize just above zero after six quarters, but three years after campaign announcement the mean BHAR to the ACO target-only portfolio remains significantly negative at -42.9%. This does not change when the observation period is extended to five years post campaign announcement (see Figure C.10).

In stark contrast, both the mean ACO portfolio and complete portfolio BHAR are positive and increasing from three quarters post-announcement onward. The mean ACO portfolio's BHAR grow especially quickly after six quarters and exceed (although statistically insignificantly) the mean complete portfolio BHAR after eleven quarters. From three years pre- to three years post-campaign announcement, the ACO portfolio buy-and-hold-abnormal returns are marginally (10% level) significant and positive at 26.04%. The ACO portfolio statistically and economically significantly outperforms the ACO target-only portfolio, with a difference in mean BHAR three years after campaign start of 68%. The results are robust to extending the window to five years post-announcement and when using equal-weighted portfolio and market returns.

The diversified investments in competing firms significantly improve the activists' financial returns to the campaign, chiefly by hedging the activist portfolio against the downside risk pre-campaign announcement. In the four quarters leading up to campaign start the ACO portfolio begins to outperform the ACO target-only portfolio significantly. The successful hedge is probably due to the activist selecting stocks that are likely to perform better than the target, regardless of whether the activist invests in them or not.

More interestingly, the ACO portfolio mean BHAR rise more quickly than the complete portfolio BHAR between three and nine quarters after campaign announcement, despite negative returns to the target. In this setting, it is difficult to tell whether the outperformance is a result of selection or a result of activist-owned competitors benefiting from positive spillovers caused by the campaign, but this will be analyzed in detail in the next section.

As an alternative measure of financial performance I estimate Jensen's alpha for several calendar-time portfolios constructed of value-weighted ACO target-only, ACO portfolios (comprising ACO target and competitors) and non-ACO competitor portfolios. Specifically, the analysis comprises six portfolios of the above-mentioned subsets of firms for the period 36-25 months before, 24-13 months before, 12-1 months before and the same periods after campaign announcement. A firm is included for example in the ACO target-only portfolio for 24-13 months pre-announcement, if it is the target of an ACO campaign beginning 24 months later. The firm is dropped from the portfolio when the campaign start is only 12 months away and added instead to the 12-1 month pre-portfolio. For each calendar-time monthly portfolio return I subtract the risk-free rate and regress the "excess returns" on the Fama-French 5 factor model (market, value, size, robust profitability and conservative investment) to generate an estimate of the respective monthly portfolio "alpha" (coefficient on the intercept).

$$r_t^p - r_t^f = \alpha + \beta_1 mkt_t + \beta_2 value_t + \beta_3 size_t + \beta_4 rmw_t + \beta_5 cma_t + \varepsilon_t \quad (3.2)$$

To test the financial performance of each portfolio, Table 3.4 compares the alpha for the ACO target-only, the ACO portfolio and the non-ACO portfolio over the three pre- and post-periods. The results are not as readily interpreted as the buy-and-hold-returns, because they cannot be weighted by the actual portfolio weight attributed to each firm by the activist and are weighted by fraction of market capitalization instead. Hence, it will over-weight the largest firms and under-weight smaller firms, which are possibly more responsive to activist engagement and a larger fraction of the activists' actual portfolios. The broad findings are in line with the BHAR results. The non-ACO portfolio has a significantly positive alpha for all six time horizons, which declines in absolute value after campaign start. A portfolio of ACO targets-only derives an insignificantly positive alpha for most years around campaign announcement. In the 12 months post campaign announcement its alpha is insignificantly negative, but turns positive the following 12 months, and afterwards becomes significantly positive for the first time.

The ACO portfolio, comprising both ACO targets and ACO competitors, performs better than the target-only portfolio with a significantly positive alpha in all three periods before campaign announcement and substantially better in the 12 months after campaign announcement with a highly significant alpha of 0.006. Two and three years post campaign start, the ACO portfolio stops outperforming the ACO target-only portfolio, and returns positive but smaller alphas. Overall this calendar-time portfolio analysis supports my previous findings that the ACO portfolio hedges against target-only underperformance to the activist. In the longer run, there is less evidence of the ACO portfolio's outperformance than in the BHAR analysis. This is likely due to the incorrect weighting of portfolio firms.

The detailed study of campaign returns to diversified activist portfolios demonstrates that there is a pecuniary benefit to owning the competitors of targeted firms. Three-year buy-and-hold abnormal returns to the portfolios of activist commonly owned targets and competitors significantly outperform the target-only campaign returns. Before the campaign announcement, portfolio diversification provides a hedge against the downside risk from deteriorating target performance. After campaign start, the portfolio of target and ACO competitors outperforms the market and the activists' overall portfolio.

An interesting extension to these findings considers the relationship between the size of activist portfolio investments in targets and competitors and the respective portfolio performance.

First, the activists' ownership of the targets at campaign start is related to the overall campaign returns of targets and ACO competitors. Figure 3.6 plots the mean buy-and-hold abnormal returns to the target, ACO portfolio and total portfolio of campaigns where the fraction of AUM invested in the target at campaign start is within the top quintile of campaign start ownership, versus campaigns with target ownership in the bottom quintile. The trends depict markedly lower target BHAR for the bottom quintile target investments, both before and after campaign announcement. In contrast to the top quintile target investments, there is no reversal in target BHAR for the bottom quintile. High target ownership is thus positively related to target returns, suggesting the size of the activist's financial incentives matter to the campaign outcome.

The findings regarding ACO portfolio returns for different target investments are more ambiguous. Whereas pre-announcement returns to the ACO portfolio are substantially higher for top quintile target investments, the post-announcement returns are initially negative for both top and bottom quintile target investments. For campaigns with low target investments the ACO portfolio return increases consistently between 3-10 quarters after campaign start, but then drops again. For campaigns with high target investments, the ACO portfolio return is overall flat for 10 quarters post-campaign start and only begins to increase substantially afterwards, coinciding with an improvement in target returns. At face value this suggests that the ACO portfolio provides a more important hedge against target underperformance in portfolios where the target investment at campaign start is smallest.

Second, the changes of activists' ownership of targeted and competing firms during the campaign are related to the campaign returns. Figure 3.7 plots the average fraction of AUM invested in the ACO target and in all competitors jointly across all campaigns, across campaigns where the target buy-and-hold-abnormal return over three years pre- and post-campaign start is in the top and bottom quintile.

The gray lines show that not only is the activists' ownership of top performing targets higher than their ownership of lowest performers at campaign start, it is also increasing in the long run for top performers. Thus, higher BHAR are driven both by better performance and by more investment in the targets. At the same time, activists' ownership of ACO competitors is the same for campaigns with top and least performing targets at campaign start. In the following quarters, however, ownership of ACO competitors declines more quickly when the target is high performing. The assets freed-up when reducing the hedge position do not seem to be re-invested in the target, but seem to flow into unrelated investments.

These findings do not establish a causal relationship between activist investments in targets and competitors, and the respective campaign returns, but clearly demonstrate that there is a positive association between activist investments in target firms and target returns, while the relationship with ACO competitor ownership and ACO portfolio returns is more ambiguous.

To establish a causal link between activist common ownership and firm performance, the next section analyzes whether there is evidence of positive spillovers specific to the activist commonly owned competitors in response to the activist engagement.

3.4.3 Fundamentals, competition and activism

Empirical design

To determine whether hedge fund activism affects target firm performance directly or whether the target firm would have outperformed in the future regardless of the activists' engagements, existing studies compare the performance of target firms post-campaign announcement to the performance of matched firms in the same industry and over the same time frame. The question for causal activist effects on commonly owned competitors is analyzed analogously in the following sections.

On the one hand, the activist might selectively invest in the largest, best performing corporations competing with the target firm. These competitors have outperformed the average firm in the past (see Table 3.3) and provide a hedge against target underperformance leading up to the campaign start (see Figure 3.5). Post campaign start the activist unwinds the hedging position (see Figure 3.4b) and any continued outperformance by the competitors is intrinsic and not related to the activists' engagement in the target firm.

The alternative explanation is that the activist initially invests in competitors as a hedge that performs better than the target regardless of the activist-common ownership. Post campaign start, however, the activist holds on to its stake in the competitors, albeit a smaller stake, as he expects his campaign to have positive spillover effects on the activist-commonly owned competitors. Comparable competitors not owned by the activist instead should not be affected by such spillovers.

Multiple mechanisms can give rise to positive spillover effects and are discussed and analyzed in greater detail in section 3.4.3. The first step, as seen in the following paragraphs, is to determine whether target and ACO competitors actually perform differently than comparable non-ACO competitors in response to the activism campaign.

The empirical strategy employed to distinguish between campaign effects and trends that would have affected targets and ACO competitors regardless of activist engagement utilizes an event study setting, with staggered treatment, matched controls and a difference-in-difference-in-difference comparison. The diff-in-diff-in-diff model compares the post-campaign announcement change in ACO target performance to the post-campaign announcement change in performance of ACO competitors of the same campaign, to the post-campaign announcement change in performance of comparable non-activist owned competitors of the target, who act as industry benchmark.

$$y_{eit} = \gamma_1 post_{eit} * treattarget_{ei} + \gamma_2 post_{eit} * treataco_{ei} + X_{eit} + a_{\tau i} + a_{\tau t} + \varepsilon_{eit} \quad (3.3)$$

A campaign announcement constitutes an event (e) and I am comparing the firms' (i) performance in the four years before the announcement year (eventyear, τ) to the performance in the year of announcement and four years after. Every event comprises the target firm, activist commonly owned competitor(s) and non-ACO competitors.

The *post* dummy variable is equal to 1 for the year of campaign announcement and the four following years, and 0 for the four preceding years. The *treattarget* dummy is equal to 1 for the target firm in each event, and 0 for all competitors. The *treataco* dummy, instead, is 1 for the target and the ACO competitors in a given event, but is 0 for the non-ACO competitors of the event. Thus the coefficient γ_2 corresponds to the change in performance of the activist owned competitors after the campaign announcement, relative to the non-ACO competitors, and the sum of the two coefficients $\gamma_1 + \gamma_2$ is an estimate of the effect on the target firm relative to the non-ACO competitors. γ_1 on its own reflects how the target performs compared to the ACO competitors.

In order to estimate a clean treatment effect, I restrict the sample of campaigns and treatment and control firms in various dimensions. Campaigns included in this analysis are all ACO campaigns, as I require the existence of at least one ACO competitor. When a firm is the target of multiple campaigns, where each campaign can be an ACO or non-ACO campaign, the corresponding campaign is dropped. I only consider firms as competitors that are never targeted themselves and, as mentioned before, consider a firm a competitor if the product similarity score in the year of campaign announcement is larger than 0.1%. Competitors that are never held by an activist in the year of campaign announcement are considered as "never treated" and serve as controls (i.e. the non-ACO competitor baseline in the regression).

On average, I find nine ACO competitors per campaign. However, a firm can be a competitor of multiple targets, sometimes activist-commonly owned and sometimes not, implying an unclean treatment. Unfortunately, if I only kept firms that are competitors in a single campaign, 95% of all ACO competitors would be dropped. Hence, I choose to focus on the most relevant ACO competitors in each campaign, reducing the incidence of multiple treatments significantly. A firm is therefore considered an ACO competitor of a campaign if its weight in the activist's portfolio is larger than 1%, or, whenever all ACO competitors have portfolio weights below 1%, I take the one ACO competitor with the largest portfolio weight. Given these restrictions, I have a unique treatment of targets, never treated non-ACO control firms, and between 1 and 4 treated ACO competitors per ACO campaign.

Based on summary statistics reported in Table 3.3, this leads to a major concern, because treated ACO targets, treated ACO competitors and non-ACO competitor controls differ substantively in their fundamental characteristics, such as size, leverage and profitability. If left unchecked, a claim that the activist campaign causes differential trends in treatment and control firms instead of underlying fundamental differences between firms would be doubtful.

To address this concern, I follow the literature in matching a control firm to the target and to the ACO competitors (with replacement) on characteristics including size, R&D expenses, return on assets, book-to-market ratio, leverage, cumulative return over past 12 months, dividend yield and aggregate institutional ownership. The matching procedure is based on an unsupervised nearest neighbor nonparametric method.

The resulting fit between matched target and control firms and matched ACO competitors and control firms is reported in Tables C.6 and C.5 and plotted jointly in Figure C.6. While the match between target and control firms is good (i.e. insignificant differences in most cases), there remain several significant differences between ACO competitors and control firms. This is to be expected given the substantial differences in firm characteristics reported before. However, the distribution of key variables is not excessively distinct.

The diff-in-diff-in-diff setting would nevertheless compare ACO targets to ACO competitors of the same campaign, which are highly distinct firms by the fundamentals. To account for this concern, I estimate another diff-in-diff model where the treated firms are ACO targets and control firms are the non-ACO competitors matched to the targets. The treatment dummy *treataco* is dropped in this regression and the *treattarget* dummy takes the value 1 for targets and 0 for matched non-ACO competitors. All other aspects of the regression are unchanged.

$$y_{eit} = \gamma_1 post_{eit} * treattarget_{ei} + X_{eit} + a_{\tau i} + a_{\tau t} + \varepsilon_{eit} \tag{3.4}$$

The matching procedure drops further target and ACO competitors for which no control firm could be found, resulting in an overall sample size of 258 treated target firms, 474 treated ACO competitors and 641 matched control non-ACO competitors. The number of controls does not correspond to the sum of all treated firms because control firms can be matched multiple times to different treated firms. If matched multiple times, the control firm is repeatedly included in the sample.

Finally, the estimation procedure needs to address concerns regarding the staggered treatment timing. The analysis contains campaign events in each year between 2005 and 2016 (see Table C.3). Although I take care to use as controls only firms that are *never* treated, a heterogeneous treatment effect over time can cause biased results when estimating a simple average treatment effect in a two-way fixed effects diff-in-diff model. With staggered treatment, the estimated treatment effect is a weighted average of multiple treatment events, where the weights attributed to each event can distort the average to have the wrong sign and the period fixed effects can be contaminated because, for example, 2006 is the treatment year for some events but a year before treatment for other events. For a more detailed discussion of these concerns see Baker et al., 2022; Callaway and Sant'Anna, 2021.

In line with the most recent contributions discussing remedies for these issues in the econometrics literature research, I utilize the stacked regression approach. For each event, I create a separate data set containing the four pre- and five post-periods for each treated and control firm and then stack these 258 data sets into one big data set, where an event-firm-relative time row is always unique. The repeated data set structure addresses the weighting issues identified in the literature. When running the diff-in-diff-in-diff regression model on the data, I include eventyear-by-year ($a_{\tau t}$) and eventyear-by-firm ($a_{\tau i}$) fixed effects, implying that the year 2006 has a separate dummy if it is attributed to an event happening in 2005 or in 2007, removing concerns about biased fixed effects.

This estimation technique remains imperfect as it does not yield dynamic and heterogeneous treatment effects per eventyear. However, I also estimate the model for each eventyear separately (only including year and firm fixed effects per regression) and spot check the resulting estimates to see if the aggregate effect is plausible given the individual estimates. Figures C.12-C.15 in the appendix provide the corresponding regression results.

Performance & competition changes in response to activism campaign

Using the stacked data set, the restricted sample of matched treated targets, treated ACO competitors and control non-ACO competitors, I estimate equation 3.3 for firm-level markup, log sales share, return on assets and log total factor revenue productivity (TFP henceforth) as measures of performance. For details of the respective variable construction see Table C.1.

The results reported in Table 3.6 are highly consistent and statistically, as well as economically, significant. ACO competitors on average increase their markups, sales shares and return on assets by 1.1 percentage points, 5.2% and 1.2 percentage points, respectively, compared to matched non-ACO competitors in the four years following an activist campaign. Only TFP is insignificantly different after treatment. Thus the evidence suggests that firms competing with the target firm and owned by the activist benefit from positive spillover effects, not affecting other competitors.

In contrast, ACO targets perform worse than ACO competitors in all variables, with on average 3.7 percentage points lower markups, 16% lower sales shares, 1.9 percentage points lower return on assets and 3.2% lower TFP. As explained in the previous section, the comparison of the ACO targets and ACO competitors is likely biased by fundamental differences between these firms. More informative is the effect on ACO targets relative to the effect on matched non-ACO competitor controls. Table 3.7 provides the results for estimating equation 3.4, implying control firms are only those non-ACO competitors matched to the ACO targets. The overall effect on ACO targets is still significantly negative for markups (-2.6pp), sales shares (-12%) and productivity (-3.5%), but insignificantly positive for return on assets.

To square these results with previous findings in the literature, it is important to note that the negative effect on targets' markups and ROA is at least partially driven by the choice of pre-treatment period. My analysis compares post-announcement performance to the four years pre-campaign performance, which implies a higher starting performance level, than other studies comparing post-announcement performance to the year before campaign start only. Figure 3.9 plots the dynamic diff-in-diff-in-diff estimates for the four pre- and post-treatment periods, while Figure 3.10 plots the results for the diff-in-diff results of targets vs matched controls. Both markups and productivity of targets deteriorate from a highly positive level in t-4 and t-3, to an insignificant level post-campaign. Comparing t-1 levels with post-treatment levels the average treatment effect would not be significantly negative. In contrast, the sales shares of ACO targets decline significantly post-campaign regardless of the chosen pre-treatment baseline.

The productivity improvements and small but highly significant sales share growth of ACO competitors, combined with the reduction in ACO targets' sales shares, suggest that positive campaign effects on ACO competitors are partially "paid for" with negative effects on the target firm. Referring back to the analysis of financial incentives of the activist based on Figure 3.3, these findings are in line with the incentive to tunnel value to another portfolio firm, whenever the activist has a larger financial stake in ACO competitors than the targets.

The question is: how does this happen? Are ACO campaigns systematically disadvantageous to target firms, such that when comparing ACO to non-ACO campaigns, the outcomes for targets differ starkly? And how are the positive spillover effects on ACO competitors created - pro-actively or passively? The next section will discuss the possible underlying mechanisms and evidence thereof.

Mechanism for positive spillover effects of activism campaign

It may be the case that campaigns by diversified (ACO) activists are systematically different from non-ACO activists' campaigns, with different objectives, tactics and outcomes for targets. A study of stated objectives and tactics depending on the activist's portfolio incentives is beyond the scope of this paper, but certainly an interesting topic for future research. However, I can test whether performance outcomes differ for targets of ACO campaigns and targets of non-ACO campaigns.

Employing a similar event study and using a staggered diff-in-diff model (see Equ. 3.5) based on stacked data, I analyze whether ACO targets perform systematically worse in response to activist campaigns than their non-ACO counterparts, focusing on the same measures (markups, sales shares, ROA and TFP) as before. Unlike the previous section, the comparison is not perfectly clean as treated and control firms do not belong to the same campaign and activist. The treated firm is targeted by an ACO activist in the same year as a matched control firm is targeted by a non-ACO activist. To make sure that the target firms are comparable and do not behave differently simply because of fundamental differences, I employ a nearest neighbor matching procedure analogous to the one described above. The match fit is reported in Table C.7 and Figure C.7.

$$y_{eit} = \delta_1 post_{eit} * treat_{ei} + X_{eit} + a_{\tau t} + a_{\tau i} + \varepsilon_{eit} \tag{3.5}$$

Table 3.9 reports the estimated coefficients for the variable of interest δ_1, that highlights the difference in average post-targeting performance of treated ACO targets relative to control non-ACO targets. Targets do not differ in markups or ROA, however, ACO targets are less productive (-2.6%) and yet have higher sales shares (6.1%) after the campaign compared to non-ACO targets. These results are puzzling as lower productivity and higher costs would usually imply lower market shares captured or lower markups. The only way to rationalize a reduction in productivity and concurrently unchanged markups but higher sales shares is with a change in market power. If the activist common owner changes the target's product portfolio in a way that reduces the target's efficiency but increases the activist's market power across all commonly owned competitors, then markups and sales shares among the ACO firms may be more flexible, resulting in unchanged markups and higher sales share for the target.

This analysis certainly suggests that there exists a meaningful distinction between ACO and non-ACO campaigns' effects on target firms, which requires a change in the market's competitive structure to be rationalized. Another observable aspect of campaigns that may contribute to differential outcomes for ACO and non-ACO targets are differences in stated objectives at announcement or tactics deployed by the activist. The link between activist common ownership and stated activist objectives remains an open query to be analyzed in future research.

The second puzzle arising from the previous section, is the mechanism of positive spillovers from activist campaigns onto activist-commonly owned firms. In theory two channels seem plausible.

Positive spillover effects on ACO competitors may arise without any action by the activist to improve the commonly owned competitors' performance. Simply holding a stake in a firm competing with a current target, the activist may create the impression on management that it considers a future engagement in this firm. The perceived threat of future activism has been found to trigger performance and valuation improvements at competitors in order to preempt future activist engagement (Gantchev et al., 2019). Thus, without actions by the activist, the ACO competitors' performance can improve and benefit the activist through the common ownership stake. This mechanism does not imply any repercussion or follow-on effects for the target firm.

Specific actions of the activist to improve the competitive position of commonly owned firms, can also give rise to positive spillover effects, such as an increased market share and profitability of ACO competitors.

One way to improve the ACO competitors' competitive position is to increase differentiation between their products and the target's products. In a basic Bertrand competition in differentiated goods model this will soften competition between the activist owned firms, giving them a chance to capture a higher market share and increase overall profits. The target firm's move away from ACO competitors is undoubtedly positive for the ACO competitors' market share. The target also benefits from competing less with ACO competitors. However, if the similarity between target and non-ACO competitors rises, the target may face stiffer competition from this side. The change in the target's product portfolio may lead to changes in its total factor revenue productivity.

An alternative way to improve the competitive positions of commonly owned firms is by increasing joint market power, streamlining processes and sharing of best-practices. The higher the similarity between target and ACO competitors' products and processes, the more an activist common owner can use lessons learned across all portfolio firms to increase efficiency and reduce costs. The efficiency improvements should be especially visible at the target, with the strongest activist influence, but may affect ACO competitors in whom the activist holds a meaningful stake. Concurrent to cost reductions, an owner with influence over all firms producing a certain product range has more market power and the ability to increase his portfolio profits by increasing sales shares, markups and profitability. This mechanism follows the typical Common Ownership Hypothesis (Schmalz, 2021). Positive spillovers on ACO competitors and improvements in target performance may be the result of higher product similarity, efficiency improvements and increased market power.

This analysis will focus on the active channel of how product similarity can improve ACO competitors' performance and change the competitive structure in a way to reduce targets' market shares. The perceived threat of activism may contribute to the positive spillover effects on ACO competitors, but a formal analysis of this channel is left to future research. To analyze how the similarity between target and ACO competitors' products has changed in comparison to the similarity between target and non-ACO competitors' products, I adjust the empirical design and data set used in the previous section. Instead of running a diff-in-diff-in-diff model, I estimate a standard staggered diff-in-diff model, based on the subset of the stacked data set comprising only ACO and matched non-ACO competitors. All target firms and respective controls are removed.

$$score_{eit} = \delta_1 post_{eit} * treat_{ei} + X_{eit} + a_{\tau t} + a_{\tau i} + \varepsilon_{eit} \tag{3.6}$$

The *post* dummy has the same specification as before and the *treat* dummy is 1 for all ACO competitors, but 0 for matched non-ACO competitors. Fixed effects and controls are the same as before. The coefficient of interest is δ_1, which corresponds to the average change in product similarity between target and ACO competitors' products in the four years post-campaign announcement, relative to the respective change in the similarity between target and non-ACO competitors' products.

Results reported in Table 3.8, comprise the performance variables previously studied and the similarity score as key outcome of interest. The product similarity between activist owned firms *increases* relative to non-activist owned firms' similarity, implying that activist-owned target and competitor firms reduce their differentiation.

Activist engagement clearly does not improve the competitive position of commonly owned firms via increased differentiation. Instead, higher product and possibly process similarity can theoretically give rise to productivity gains. In Table 3.8 ACO competitors show no productivity differences relative to matched non-ACO competitors and targets are actually less efficient than controls (see Table 3.7), after the campaign. Thus positive productivity spillovers from product alignment are not realized.

Higher product similarity and joint influence over all relevant firms producing in this product segment can, however, increase the market power of the common owner, giving him the ability to increase markups and profitability. These positive spillover effects on ACO competitors are evident in Table 3.8. Furthermore the common owner can reallocate market shares among his portfolio firms, explaining the concurrent positive effect on ACO competitors' sales shares and negative effect on targets' sales shares. If the change in product range makes the target less productive and reduces its markups, it makes sense to reallocate more sales to the ACO competitors.

Refuting the differentiation hypothesis, I find evidence that increased product similarity among activist commonly owned firms raises the activist owned firms' market power and leads to positive spillover effects on ACO competitors, while imposing costs on the ACO target. Overall, the activist likely benefits through his cash flow interest in the ACO competitors.

The previous empirical analysis has identified positive consequences of activist common owners' campaigns on ACO competitors relative to non-ACO competitors. A plausible mechanism for these to be achieved are higher market power through product approximation and market share reallocation from the target to activist-commonly owned competitors. Although this could imply a systematic disadvantage for targets of ACO campaigns, there is limited evidence that such targets underperform vis-a-vis targets of non-ACO campaigns on average. The diversified activist benefits from positive spillovers of the campaign, while an undiversified activist will not realize the same benefit.

This analysis neglects potential differences in activists' objectives when starting campaigns with or without holdings in competitors. The different campaign outcomes suggest that objectives could differ, but a rigorous analysis is left to future research. The following section provides one final extension of this analysis, testing whether the market knows of activists' strategic portfolio diversification and treats ACO and non-ACO targets and competitors differently in response to the campaign announcement.

3.4.4 Market reactions to campaign announcements

Following the existing literature, I analyze the short run cumulative abnormal returns to target and competing firms in a 5 or 22 day window around the campaign announcement. Cumulative abnormal returns are calculated for each firm separately by compounding daily returns from t-5 or t-22 days before the day of SC 13-D filing, up to 5 or 22 days after the filing date. To capture the "abnormal" proportion of cumulative returns, henceforth CAR, I subtract the corresponding cumulative returns to the CRSP value-weighted market portfolio.

$$CAR_{ei\tau} = \left(\prod_{t=-22}^{\tau} (1 + R_{eit}) \right) - \left(\prod_{t=-12}^{\tau} (1 + R_t^m) \right) \tag{3.7}$$

The sample of campaigns, targets, ACO competitors and non-ACO competitors is restricted in the same way as for the key diff-in-diff-in-diff analysis in section 3.4.3 for ease of interpretation.

Figure 3.12a plots the CAR over a 22-day pre- and post-announcement window for targets and competitors, while Table 3.10 reports t-test results comparing the CAR of targets, ACO competitors and non-ACO competitors 22 days after campaign announcement. In line with existing analysis of the announcement returns to activist campaigns, I find that the CAR of target firms jump on the day of SC 13-D filing by about 3 percentage points, while competitor CAR remain flat. This holds regardless of whether the competitor is owned by the activist or not. 22 days after campaign start the CAR to targets remain statistically significantly larger than zero and significantly larger than both ACO competitors' and non-ACO competitors' CAR. All competitors' CAR are indifferent from zero for the post-announcement period until

22 days after. A t-test cannot reject the null hypothesis that ACO competitors' and non-ACO competitors' CAR are the same. Thus clearly the market does not know or expect any positive impact on the ACO competitors at campaign announcement.

To determine whether the market perceives a difference between targets of activist common owners' campaigns and non-common owners' campaigns, I adjust the sample to test the difference in CAR between matched ACO and non-ACO targets. The sample underlying this analysis is the same as in the previous fundamental comparison between ACO and non-ACO targets. Both types of targets have statistically significant, positive CAR over a 22 day horizon pre- and post-campaign announcement. The CAR to non-ACO targets are significantly larger than ACO targets' CAR (see Table 3.10), although highly volatile as Figure 3.12b depicts. While ACO targets generate on average 3.7% cumulative abnormal returns by the 22nd day post-announcement, the corresponding mean CAR of non-ACO targets is 22%. The market does react differently to ACO and non-ACO campaign targets. However, based on this analysis, it is unlikely that this is driven by the activist's common ownership, which does not affect ACO competitors, and may instead be due to larger activist investments in non-ACO than ACO targets on average (see Table 3.2).

All findings described above also hold if the cumulative abnormal returns are investigated over a shorter 5 day pre- and post-announcement window. Overall the market does not seem to know that activists hold competitors of targeted firms, and that these competitors may benefit from positive spillover effects. In contrast, the market does react positively to higher activist investments in the targeted firm, suggesting the market expects better target performance when the activist holds a larger stake in it.

3.5 Conclusion

In this paper, I examine the portfolio holdings of hedge fund activists and investigate if activists concurrently owning campaign targets and their competitors (**A**ctivist **C**ommon **O**wners) internalize any financial or economic spillover effects of these campaigns. The analysis is based on a novel data set of activists' portfolio holdings, combining activist campaigns identified by Brav, Jiang, and Li, 2022 with ownership data of U.S. common stocks compiled by Amel-Zadeh et al., 2024. Financial performance is measured as the buy-and-hold abnormal returns to portfolios of the activists' actual holdings of the target only, versus a portfolio of actual target and commonly owned competitor holdings (ACO portfolio). Over three years around campaign announcement, the ACO portfolio significantly outperforms the target-only portfolio by more than 60%, and also marginally significantly outperforms the market with 26% abnormal returns. Before campaign announcement, the common ownership of competitors provides a hedge against the deterioration in target returns, whilst after announcement, commonly owned competitors outperform the market despite the target's continued underperformance. To test if there is a direct impact of activist campaigns on commonly owned competitors and targets, I employ a staggered difference-in-difference model to estimate differential effects on these competitors and targets relative to matched non-commonly owned competitors. My results suggest that activist owned competitors significantly improve their markups, sales shares and return on assets in response to the campaign, while the corresponding targets' sales shares and productivity decline relative to matched controls. One underlying mechanism at work is lower product differentiation between targets and commonly owned competitors, leading to higher market power for the activist common owner and a reallocation of sales shares from the less productive target to commonly owned competitors.

These findings corroborate the hypothesis that activist common owners internalize positive spillover effects of their campaigns to derive a financial benefit. Adding to the existing activism literature, I show that activists are more diversified than previously assumed and this diversification matters for their incentives and campaign outcomes. Further research into the effects of hedge fund activism should take into account the portfolio incentives of activists when determining the long run implications on firm performance and market structure. Such academic and policy-relevant analyses would benefit from enhanced reporting requirements for hedge fund activists, including information on investments in competitors. With further evidence on how diversified activists shape the externalities of their campaigns, market structure and welfare, a policy re-evaluation of the economic desirability of activist ownership in targets' competitors, especially post-campaign start, may be necessary.

Two aspects left out of my analysis, to be studied in future research, relate to potential differences in activists' stated objectives for ACO and non-ACO campaigns and to the effects of ACO and non-ACO campaigns on merger outcomes. Theoretical models of common ownership have interesting, testable implications for both queries and empirical evidence on the effects of activist common ownership will contribute meaningfully to the policy debate started by this analysis.

3.6 Figures & Tables

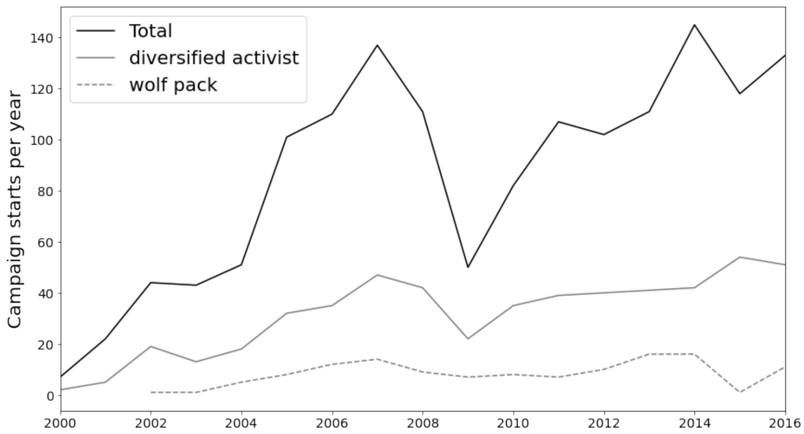


Figure 3.1: Types of campaigns over time.

This figure plots over the years 2000-2016, the total number of activist campaigns started per year in black, the number of activist-common owner campaigns started per year in gray, and the number of wolf pack activist campaigns started per year in a dashed line.

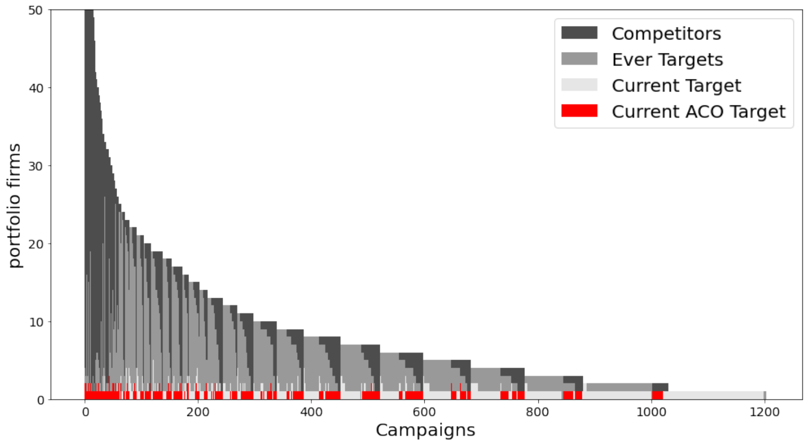


Figure 3.2: Campaign-specific relevant portfolio composition.

This figure plots a subset of the portfolio firms held by a targeting activist in the quarter of campaign start as a bar chart for each activist campaign in my sample on the horizontal, sorted by portfolio size from large to small. Non-target-non-competitor firms are discarded. Different colored bar proportions depict non-target-competitor portfolio firms (dark gray), non-current targets (mid gray), current target firms (light gray), current ACO targets (red).

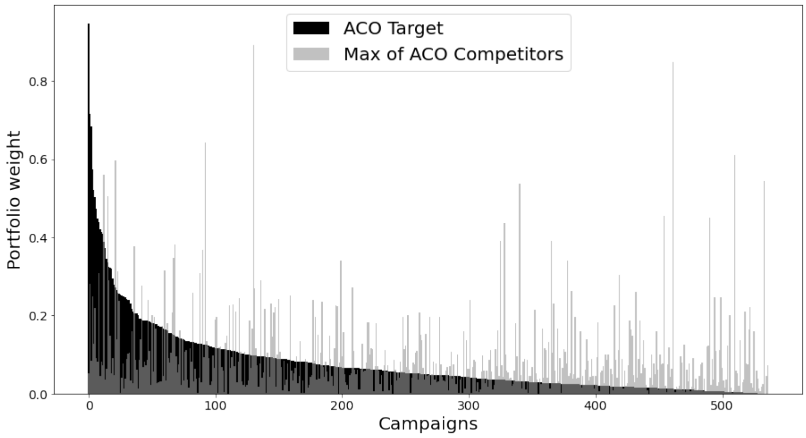
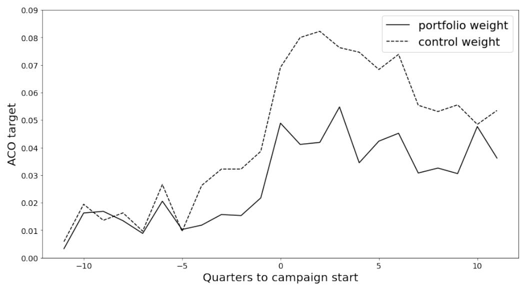
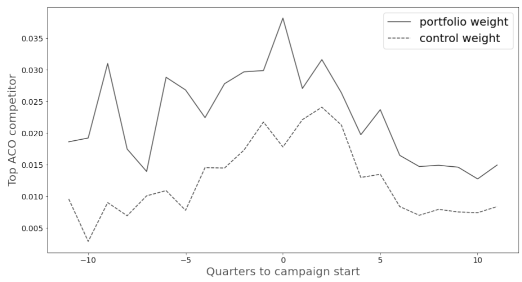


Figure 3.3: Portfolio share in targets vs top ACO competitors across campaigns. This figure plots the fraction of assets under management invested in the target firm and the most important competitor in the quarter of campaign announcement, across all ACO campaigns in my sample on the horizontal axis. Each black bar represents portfolio weight of the activist, and the gray bar the portfolio weight of the single largest ACO competitor for a given campaign.



(a) Target ownership



(b) Top competitor ownership

Figure 3.4: Ownership of target and top ACO competitor around campaign start. This figure plots the mean activists ownership of targeted firms (A) and the single most important ACO competitor (B) from 12 quarters before to 12 quarters after campaign announcement. The unbroken line depicts investment as fraction of assets under management, the dashed line depicts ownership as fraction of shares outstanding held.

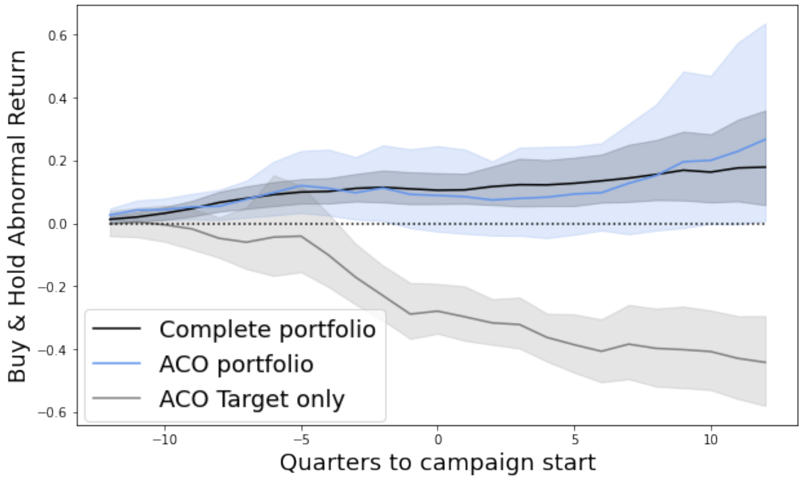


Figure 3.5: Value-weighted BHAR to ACO campaigns.
This figure plots the mean buy-and-hold abnormal returns to the activists' value-weighted holdings in ACO targets only (gray), in ACO targets & ACO competitors jointly (light blue), and in all portfolio firms (black) from 12 quarters pre-campaigns start to 12 quarters post-campaign start. 95% confidence intervals are shaded in the respective color. The calculation of buy-and-hold abnormal returns follows equation 3.1.

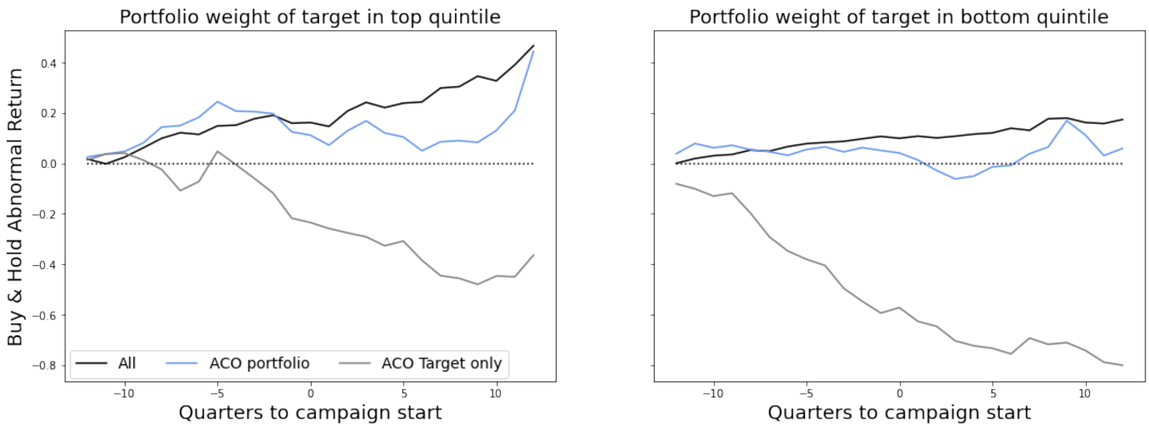


Figure 3.6: ACO target & portfolio BHAR across activist investment size.
This figure plots the mean buy-and-hold abnormal returns to the activists' value-weighted holdings in ACO targets only (gray), in ACO targets & ACO competitors jointly (light blue), and in all portfolio firms (black) from 12 quarters pre-campaigns start to 12 quarters post-campaign start, for a subset of ACO campaigns. The left graph considers ACO campaigns where the activist's investment in the target at campaign announcement is in the top 20% of target investments, the right graph considers ACO campaigns with target investments in the bottom 20%. 95% confidence intervals are shaded in the respective color. The calculation of buy-and-hold abnormal returns follows equation 3.1.

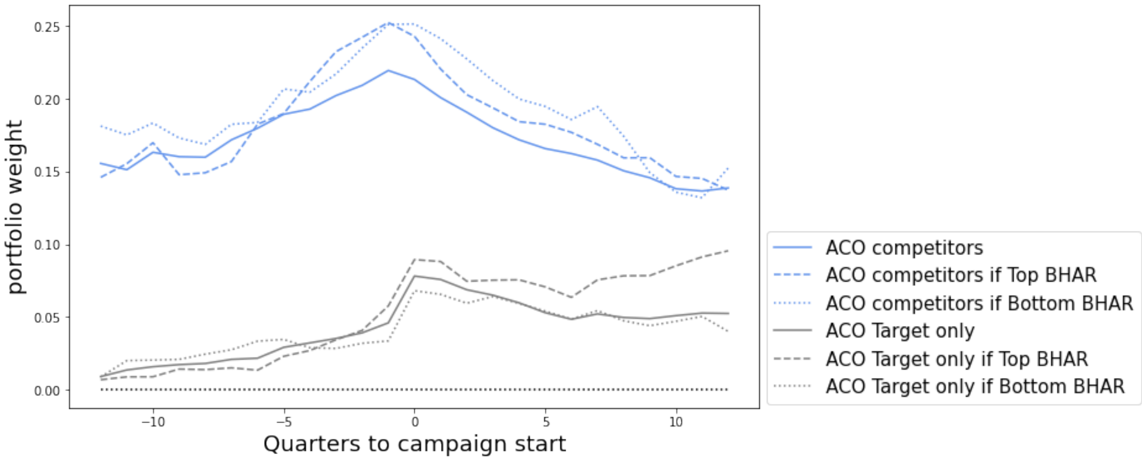


Figure 3.7: Portfolio weight of ACO target & competitors across BHAR.
This figure plots the mean portfolio weight (investment as % of AUM) in ACO targets (gray) and ACO competitors aggregated (blue) from 12 quarters pre-campaigns start to 12 quarters post-campaign start. The straight line takes the average across all ACO campaigns. The dashed line depicts the average across campaigns where the target's BHAR 12 months post-campaign start is in the top quintile or returns, while the dotted line depicts the average across campaigns with bottom quintile target BHAR. The calculation of buy-and-hold abnormal returns follows equation 3.1.

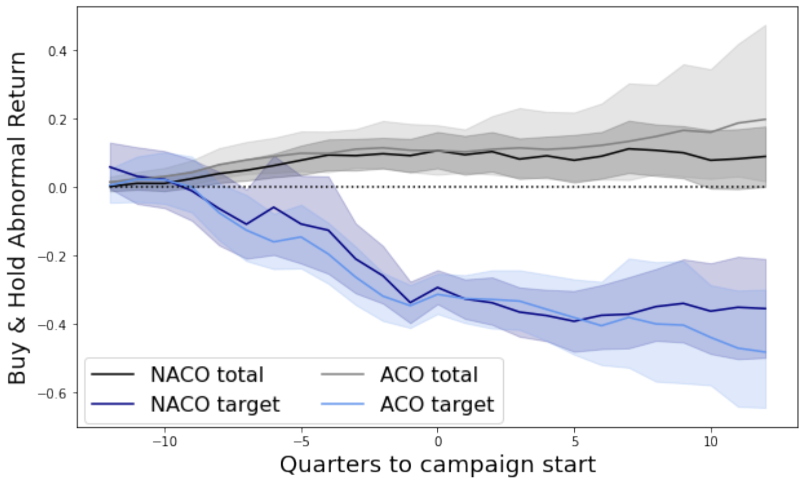
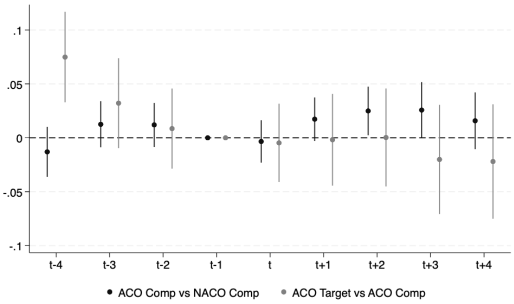
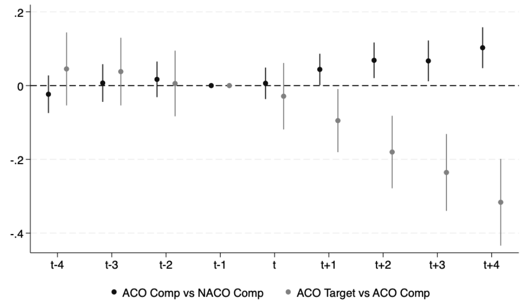


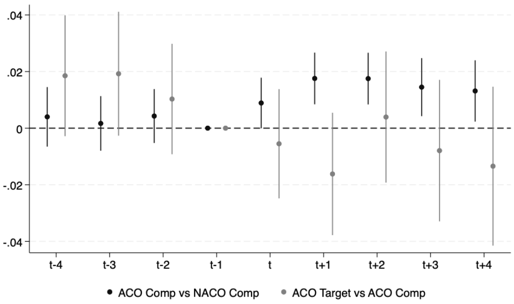
Figure 3.8: Value-weighted BHAR to ACO & NACO campaigns.
This figure plots the mean buy-and-hold abnormal returns to the activists' value-weighted total portfolio holdings (gray shades) and holdings in campaign targets only (blue shades), of ACO campaigns (light gray/blue) and matched non-ACO campaigns (dark gray/blue), from 12 quarters pre-campaigns start to 12 quarters post-campaign start. 95% confidence intervals are shaded in the respective color. The calculation of buy-and-hold abnormal returns follows equation 3.1.



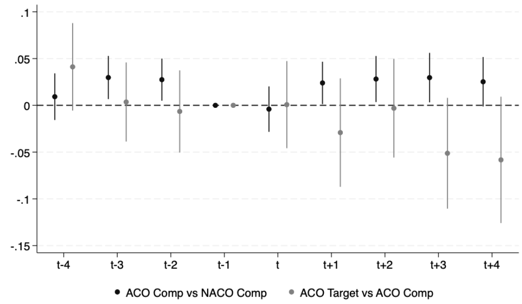
(a) Markups



(b) Sales share



(c) ROA

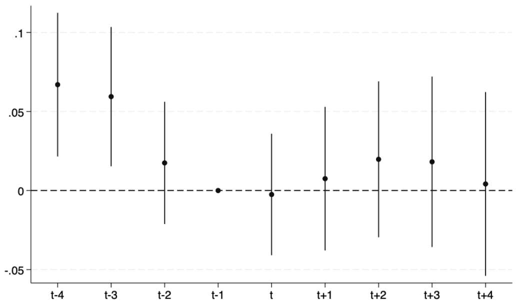


(d) Productivity

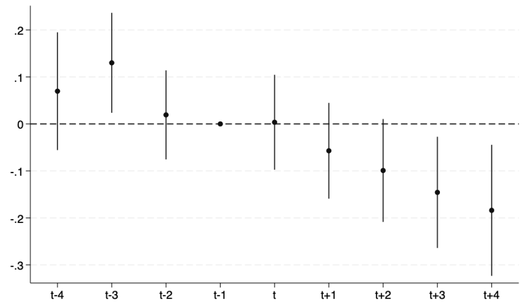
Figure 3.9: Dynamic Diff-in-Diff-in-Diff: Target vs ACO competitors vs NACO competitors.

This figure plots the estimated coefficients of a staggered diff-in-diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interactions of time-by-treattarget dummies (gray) and time-by-treataco dummies (black). The baseline are matched never treated non-ACO competitors, "treataco" firms are ACO competitors, and "treattarget" are ACO targets of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Below is the estimated regression equation:

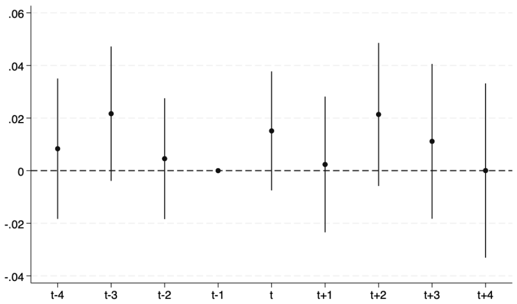
$y_{eit} = \sum_{s=-4}^{4} \gamma^1_{t+s} * d_{t+s} * treattarget_{ei} + \sum_{s=-4}^{4} \gamma^2_{t+s} * d_{t+s} * treataco_{ei} + X_{eit} + a_{ei} + a_{et} + \varepsilon_t$



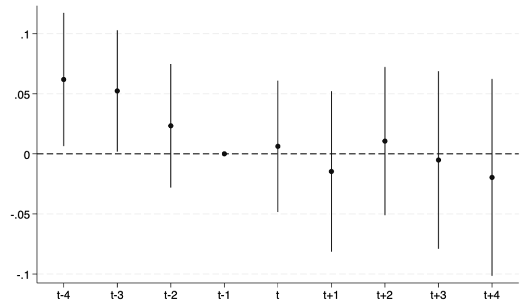
(a) Markups



(b) Sales share



(c) ROA



(d) Productivity

Figure 3.10: Dynamic Diff-in-Diff: Target vs NACO competitors.

This figure plots the estimated coefficients of a staggered diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interacted of time-by-treattarget dummies. The baseline are matched never treated non-ACO competitors, and "treattarget" are ACO targets of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Below is the estimated regression equation:

$y_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treattarget_{ei} + X_{eit} + a_{ei} + a_{et} + \varepsilon_t$

Table 3.2: Portfolio characteristics of hedge fund activists

	all Portfolios	ACO Portfolios
no of comp per target	164.0	277.000
no of comp owned (ACO)		9.000
% AUM in target	0.134	0.079
% control in target	0.078	0.082
% AUM in competitors agg		0.237
% AUM in top competitor		0.097
% control in top competitor		0.080
no of portf firms	29.28	41.099
AUM portfolio	1764.906	2056.705

This table summarizes the holdings of activists in targeted and competing firms at campaign start, activists' average portfolio size and target firms' average competitive network size at campaign start.

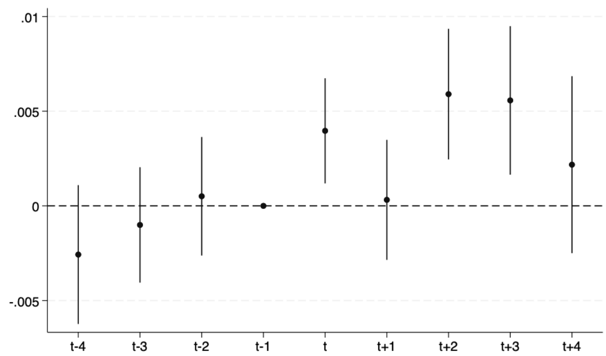
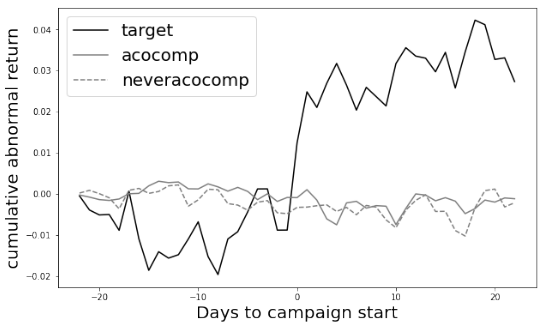
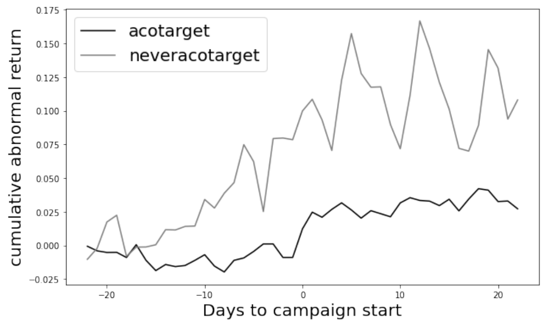


Figure 3.11: Dynamic Diff-in-Diff: ACO vs NACO competitor product similarity.
This figure plots the estimated coefficients of a staggered diff-in-diff regression of annual product similarity scores (Hoberg & Phillips, 2010) on interacted of time-by-treated dummies. The baseline are matched never treated non-ACO competitors, and "treated" are ACO competitors of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Below is the estimated regression equation:
$y_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_{ei} + a_{et} + \varepsilon_t$



(a) Target, ACO & NACO competitors



(b) ACO & NACO targets

Figure 3.12: Short run returns to campaign announcement.
This figure plots the short-run mean cumulative abnormal returns to various firms affected by activist campaigns from 22 days pre-campaign start to 22 days post-campaign start. The left graph depicts mean CAR of the campaign target (black), ACO competitors (gray), non-ACO competitors (dashed). The right graph distinguishes among targets of ACO campaigns (black) and targets of non-ACO campaigns (gray). The calculation of cumulative abnormal returns follows equation 3.7.

Table 3.3: Median firm characteristics

	All firms	ACO Targets	NACO Targets	ACO Competitor	NACO Competitor
Age	9.700	11.450	13.300	10.700	9.000
Market Cap (mn)	356.981	316.437	306.211	797.222	278.860
Book-to-Market	0.524	0.523	0.547	0.510	0.531
Tobins Q	1.495	1.462	1.473	1.558	1.474
ROA	0.061	0.065	0.087	0.028	0.067
Markup	1.118	1.066	1.072	1.192	1.104
TFP	2.209	2.139	2.038	2.459	2.152
Margin	1.168	1.124	1.110	1.241	1.152
Sales share (SIC2)	0.001	0.001	0.002	0.001	0.000
Sales HHI (SIC2)	0.041	0.043	0.048	0.044	0.041
Cash Flow	0.033	0.029	0.052	0.013	0.038
Cumulative Return (12m)	0.047	-0.014	-0.012	0.067	0.038
Leverage	0.376	0.398	0.292	0.465	0.353
Cash	0.100	0.154	0.114	0.100	0.100
Dividend yield	0.000	0.000	0.000	0.000	0.000
R&D expenses	0.000	0.000	0.000	0.000	0.000
Inst Ownership	0.617	0.869	0.872	0.819	0.512
Common Ownership	0.439	0.631	0.544	0.689	0.342
HHI Ownership	0.038	0.048	0.051	0.037	0.038

This table provides the median of key firm attributes across all firms in the sample, across ACO and non-ACO targets separately, and across ACO and non-ACO competitors separately.

Table 3.4: Alpha for calendar-time value-weighted portfolios

	(1)	(2)	(3)	(4)	(5)	(6)
	pre 3y	pre 2y	pre 1y	post 1y	post 2y	post 3y
Target only						
α	0.0112	0.0105	0.000203	-0.000473	0.00481	0.0106**
	(0.008)	(0.007)	(0.006)	(0.004)	(0.005)	(0.005)
ACO Portfolio						
α	0.00845*	0.00651*	0.00807*	0.00560**	0.00354	0.00851**
	(0.005)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
NACO Portfolio						
α	0.0115***	0.00943***	0.00853***	0.00333*	0.00616*	0.00522***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Fstat	37.11	30.37	25.33	30.54	46.83	32.33
Observations	167	167	167	167	167	167
Std Errors	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4

This table provides coefficient estimates for the intercept in a Fama-French-5 factor model, regressing calendar-time portfolio returns net of the risk-free rate on the five factors. The "target only" portfolio adds and drops ACO targets in the relevant time pre- and post-campaign start, the "ACO portfolio" adds and drops ACO targets and ACO competitors, and the "NACO portfolio" adds and drop matched non-ACO competitors, respectively. Standard errors in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.5: Alpha for calendar-time value-weighted target portfolios

	(1) pre 3y	(2) pre 2y	(3) pre 1y	(4) post 1y	(5) post 2y	(6) post 3y
All Targets						
α	0.0225	0.00283	0.000102	0.000156	0.00971***	0.0119***
	(0.016)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)
ACO Targets						
α	0.00559	-0.00198	-0.00710*	-0.00520	-0.00303	-0.00213
	(0.006)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)
NACO Targets						
α	0.00638	0.00455	-0.00613	-6.76e-05	0.00517	0.00109
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Fstat	37.78	76.26	32.06	42.18	55.74	33.06
Observations	167	167	167	167	167	167
Std Errors	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4

This table provides coefficient estimates for the intercept in a Fama-French-5 factor model, regressing calendar-time portfolio returns net of the risk-free rate on the five factors. The “all target” portfolio adds and drops any target in the relevant time pre- and post-campaign start, the “ACO target” portfolio adds and drops ACO targets, and the “NACO target” portfolio adds and drop matched non-ACO targets, respectively. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.6: Diff-in-Diff-in-Diff analysis: Target vs ACO competitors vs NACO competitors

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP
post#treattarget	-0.0365***	-0.163***	-0.0192***	-0.0319**
	(0.012)	(0.027)	(0.006)	(0.014)
post#treat	0.0117**	0.0519***	0.0118***	0.00240
	(0.006)	(0.013)	(0.002)	(0.006)
Observations	237,026	236,541	235,239	200,274
R-squared	0.850	0.964	0.836	0.841
Fstat	2236	2647	874.7	1157
Sample	All	All	All	All
Matched ACO Target	258	258	258	258
Matched ACO Comp	474	474	474	474
Matched NACO Comp	641	641	641	641
Std Errors	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes

This table provides coefficient estimates of a staggered diff-in-diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interactions of post-by-treattarget dummies and post-by-treat dummies. The baseline are matched never treated non-ACO competitors, "treated" firms are ACO competitors, and "targettreated" firms are ACO targets of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log firm age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.7: Diff-in-Diff analysis: Target vs NACO competitors

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP
post#treat	-0.0259**	-0.128***	0.00267	-0.0350**
	(0.013)	(0.032)	(0.007)	(0.017)
Observations	3,696	3,657	3,647	3,332
R-squared	0.818	0.974	0.820	0.774
Sample	All	All	All	All
Matched ACO Target	258	258	258	258
Matched NACO Comp	221	221	221	221
Std Errors	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes
Fstat	45.88	34.35	34.33	22.27

This table provides coefficient estimates of a staggered diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interactions of post-by-treat dummies. The baseline are matched never treated non-ACO competitors, and "treated" firms are ACO targets of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log firm age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.8: Diff-in-Diff analysis: ACO competitors vs NACO competitors

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP	(5) Similarity
post#treat	0.0116**	0.0517***	0.0117***	0.00240	0.00409***
	(0.006)	(0.013)	(0.002)	(0.006)	(0.001)
Observations	233,330	232,884	231,591	196,939	165,726
R-squared	0.851	0.964	0.836	0.842	0.703
Fstat	2927	3490	1133	1517	15.75
Sample	All	All	All	All	All
Matched ACO Comp	474	474	474	474	474
Matched NACO Comp	495	495	495	495	495
Std Errors	robust	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes	Yes

This table provides coefficient estimates of a staggered diff-in-diff regression of annual markups, log sales shares, return on assets, log TFP and product similarity scores on interactions of post-by-treated dummies. The baseline are matched never treated non-ACO competitors, "treated" firms are ACO competitors. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log firm age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.9: Diff-in-Diff analysis of ACO vs NACO target performance

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP
post#treat	0.00224	0.0612**	-0.00251	-0.0256*
	(0.012)	(0.029)	(0.006)	(0.014)
Observations	5,522	5,476	5,423	5,008
R-squared	0.756	0.975	0.765	0.782
Fstat	57.07	45.66	57.13	26.11
Sample	All	All	All	All
Matched ACO Target	258	258	258	258
Matched NACO Target	157	157	157	157
Std Errors	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes

This table provides coefficient estimates of a staggered diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interactions of post-by-treated dummies. The baseline are matched never treated non-ACO targets, "treated" firms are ACO targets. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log firm age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table 3.10: Comparison of mean 22-day pre & post return

	N	Mean		Mean	t-stat	p-value
Target	598	0.0429	null	0	6.0672	**0.0000**
Competitor	520	-0.0087	null	0	-1.4878	0.1371
Target		0.0429	Competitor	-0.0087	5.6146	**0.0000**
ACO Target	258	0.0323	null	0	2.9832	**0.0030**
NACO Target	157	0.1004	null	0	4.8008	**0.0000**
ACO Target		0.0323	NACO Target	0.1004	-3.1817	**0.0016**
ACO Comp	258	-0.0016	null	0	-0.4165	0.6771
NACO Comp	258	-0.0034	null	0	-0.9845	0.3250
ACO Target		0.0323	ACO Comp	-0.0016	3.7098	**0.0002**
ACO Target		0.0323	NACO Comp	-0.0034	4.0015	**0.0001**
ACO Comp		-0.0016	NACO Comp	-0.0034	0.3569	0.7212

This table reports results of a t-test comparing the cumulative abnormal returns of targets (all, ACO & NACO) and competitors (all, ACO, NACO) over the 45-day period from 22 days pre-campaign start to 22 days post-campaign start, among each other and against null. Differences that are statistically significant at the 5% level are highlighted in bold.

Appendices of Chapter 3

Appendix 3.A Details on variables & data

Table C.1: Variable explanations

Variable	Description	Source
firm age	time since incorporation or first date CRSP	CRSP
market cap	price multiplied by common stock outstanding	CRSP
btm	book value of equity over market capitalization	Compustat
markup	estimated based on cost shares approach (De Loecker & Syverson, 2021)	Compustat
omega	total factor revenue productivity estimate	Compustat
	based on cost shares approach (De Loecker & Syverson, 2021)	
roa	return on assets: ratio of EBITDA to lagged assets	Compustat
growth	percentage change in sales since last period	Compustat
leverage	ratio (book value current+long term debt) to book value equity	CRSP
divyield	common stock dividends over adj income before depr&amo	Compustat
cash	cash and equivalent assets over lagged assets	Compustat
xrd	expenditures on R&D over lagged assets	Compustat
xsga	expenditures on overhead	Compustat
margin	sales over cost of goods sold and overhead expenses	Compustat
saleshare	firm-level share of sales in SIC-3 industry aggregate	Compustat
salehhi	Herfindahl-Hirschman Index of sales at SIC-3 industry level	Compustat
beta inst	firm-level ownership fraction of financial institutions	Amel-Zadeh et al., 2022
CAR	cumulative firm return minus cum. CRSP vw portfolio return	CRSP
score	firm-pair product similarity score (cosine)	Hoberg and Phillips, 2016

This table reports for all relevant variables in this analysis the data source and method of construction.

Table C.2: Activist portfolio size by year and campaign type

	All campaigns		ACO campaigns	
	Mean portfolio firms	Mean portfolio AUM ($mio)	Mean portfolio firms	Mean portfolio AUM ($mio)
2000	19.00	737.76	6.00	1284.24
2001	12.84	521.70	40.33	593.17
2002	22.71	378.41	34.91	420.47
2003	23.73	362.46	52.89	541.53
2004	25.11	1203.39	34.25	1604.38
2005	34.24	1092.11	40.76	1320.60
2006	34.78	1386.63	50.94	1604.08
2007	39.94	1777.95	52.50	2108.67
2008	29.37	1531.38	43.29	1802.93
2009	29.34	1556.09	38.20	2298.26
2010	27.09	1598.43	41.78	1426.62
2011	27.79	1560.09	37.77	2077.63
2012	29.47	2119.36	45.13	2884.42
2013	30.12	2684.16	41.51	3279.66
2014	27.32	2925.35	47.77	3318.95
2015	28.16	2506.90	33.63	2071.38
2016	24.80	1574.05	29.76	1812.65

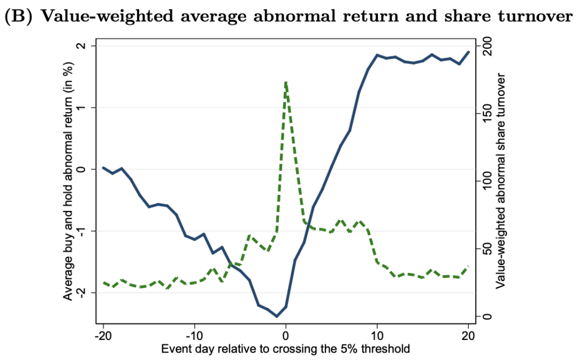
This table reports for each year and separately for all campaigns or for ACO campaigns the mean portfolio size of activists starting a campaign in a given year.

Table C.3: Activist campaigns by year and type

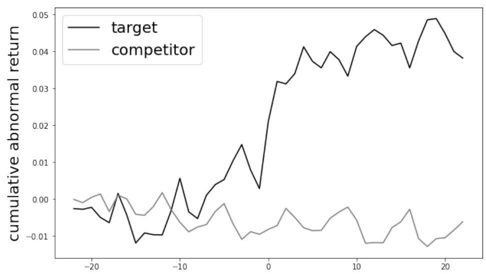
year	# Campaigns	# Activists	# ACO Campaigns	# ACO Activists
2000	6	6	2	2
2001	17	10	5	3
2002	39	22	19	10
2003	37	21	13	9
2004	43	27	18	17
2005	81	45	32	22
2006	89	59	35	30
2007	118	68	47	36
2008	98	68	42	33
2009	44	33	22	20
2010	70	44	35	26
2011	85	48	39	27
2012	84	50	40	26
2013	96	58	41	31
2014	121	60	42	25
2015	103	71	54	37
2016	107	79	51	43

This table reports for each year the number of campaigns started and number of campaigning activists, in total and in the subset of ACO campaigns.

Appendix 3.B Validation of existing literature



(a) Brav, Jiang, and Li, 2022: 22-days CAR

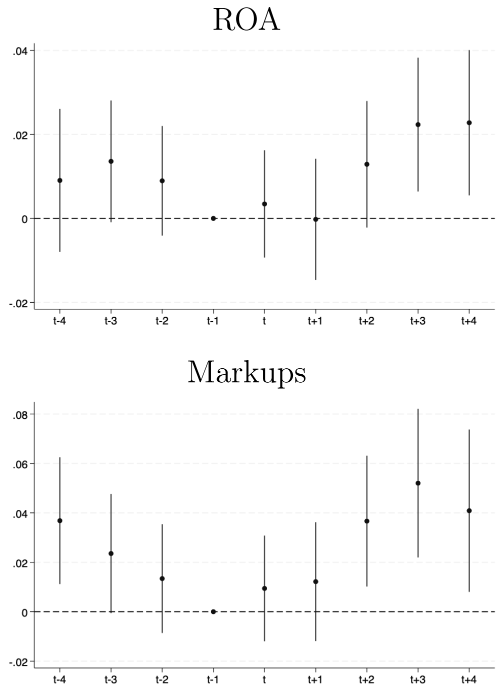


(b) Replication: 22-days CAR

Figure C.1: Validation: Short run target returns to campaign announcement.
This figure reports the 22 day pre & post announcement cumulative abnormal returns of target firms found by Brav, Jiang, and Li, 2022 in (A), and plots the respective CAR calculated on my sample of targets and matched competitors in (B).

Panel A: The p-score-matched sample				
	(1)	(2)	(3)	(4)
VARIABLES	Q	Q	ROA	ROA
$d \cdot t-3$	0.0809*	0.0165	0.0046	0.0030
	(1.65)	(0.35)	(1.21)	(0.85)
$d \cdot t-2$	0.0460	0.0121	-0.0044	-0.0043
	(1.19)	(0.33)	(-1.63)	(-1.64)
$d \cdot t$ Event Year	0.1137***	0.1099***	-0.0038	-0.0036
	(2.92)	(2.81)	(-1.41)	(-1.31)
$d \cdot t+1$	0.1966***	0.1828***	-0.0024	0.0017
	(3.94)	(3.77)	(-0.62)	(0.46)
$d \cdot t+2$	0.1633***	0.2119***	-0.0019	0.0026
	(2.75)	(3.83)	(-0.42)	(0.65)
$d \cdot t+3$	0.2296***	0.2670***	0.0055	0.0102**
	(3.47)	(4.29)	(1.06)	(2.26)
$d \cdot t+4$	0.2277***	0.2650***	0.0086	0.0152***
	(3.21)	(3.93)	(1.53)	(3.12)
$d \cdot t+5$	0.3174***	0.3281***	0.0024	0.0112**
	(4.11)	(4.63)	(0.38)	(2.08)
$\ln(MV)$	0.2435***	0.7038***	0.0339***	0.0441***
	(18.70)	(25.54)	(27.52)	(21.99)
$\ln(Age)$	-0.2747***	-0.2486***	0.0206***	0.0067
	(-9.25)	(-4.53)	(8.01)	(1.64)
$t+k$ Dummies	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SIC3 FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
N	42060	42060	42060	42060
R^2	0.232	0.631	0.355	0.763

(a) Brav, Jiang, and Li, 2022 Dynamic Diff-in-Diff



(b) Replication: Dynamic Diff-in-Diff

Figure C.2: Validation: Diff-in-Diff of Targets vs Matched Competitors.
This figure reports in panel (A) the regression results of Brav, Jiang, and Li, 2022 regressing Tobin's Q and ROA on time-by-treated dummies, where treated firms are campaign targets and control firms are matched competitors. Panel (B) reports analogous results for regressions of ROA and markups on my data set.

Panel A: Value-weighted target firm six-factor regressions						
	Holding period (in months)					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	-36 to -25	-24 to -13	-12 to -1	+1 to +12	+13 to +24	+25 to +36
α	-0.008	-0.010	-0.012	-0.000	0.001	0.004
	(-3.819)	(-4.579)	(-5.124)	(-0.132)	(0.606)	(1.868)
β_{RMRF}	1.008	1.125	1.004	0.981	1.072	0.897
	(17.506)	(14.024)	(14.829)	(17.956)	(20.860)	(16.591)
β_{SMB}	0.404	0.398	0.230	0.465	0.422	0.422
	(4.661)	(4.728)	(2.078)	(6.448)	(6.895)	(4.827)
β_{HML}	-0.161	-0.274	0.057	-0.052	-0.005	0.041
	(-1.695)	(-2.218)	(0.556)	(-0.515)	(-0.063)	(0.509)
β_{RMW}	-0.114	0.321	0.305	0.345	0.245	-0.169
	(-0.956)	(3.339)	(2.318)	(3.511)	(3.482)	(-1.596)
β_{CMA}	0.251	0.120	0.019	0.229	0.054	0.081
	(1.976)	(0.736)	(0.135)	(1.714)	(0.540)	(0.696)
β_{MOM}	-0.033	-0.112	-0.113	-0.129	-0.006	0.091
	(-0.783)	(-1.794)	(-1.239)	(-2.551)	(-0.137)	(1.981)
N	300	300	301	298	292	280
R^2	0.690	0.706	0.594	0.694	0.763	0.694

(a) Brav, Jiang, and Li, 2022: Jensen's alpha

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	pre 3y	pre 2y	pre 1y	post 1y	post 2y	post 3y
alpha	0.0225	0.00283	0.000102	0.000156	0.00971***	0.0119***
	(0.016)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)
mktrf	0.683*	1.019***	0.877***	1.053***	1.124***	0.916***
	(0.381)	(0.107)	(0.104)	(0.088)	(0.111)	(0.094)
smb	1.233	0.410**	0.267	0.409**	0.271**	0.406**
	(0.931)	(0.184)	(0.218)	(0.172)	(0.129)	(0.170)
hml	-0.318	0.0934	-0.315	-0.0936	-0.0308	-0.0349
	(0.225)	(0.228)	(0.241)	(0.181)	(0.167)	(0.137)
rmw	-0.973	-0.0398	-0.800**	-0.142	0.128	0.202
	(0.766)	(0.180)	(0.352)	(0.307)	(0.194)	(0.178)
cma	-1.462	-0.301	-0.0321	-0.204	0.0398	0.133
	(1.468)	(0.234)	(0.306)	(0.380)	(0.206)	(0.251)
Observations	167	167	167	167	167	167
Std Errors	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4	NW-L4
Fstat	37.78	76.26	32.06	42.18	55.74	33.06

(b) Replication: Jensen's alpha

Figure C.3: Validation: FF5 alpha of Targets vs Matched Competitors.
This figure reports in panel (A) the coefficient estimates of Brav, Jiang, and Li, 2022 for a Fama-French-5-factor model, regressing calendar-time target portfolio returns net of the risk-free rate on 5 factors and the intercept. Panel (B) reports analogous results for Fama-French-5-factor regressions on calendar-time target portfolio returns based on my data sample

Table C.4: Validation: Matched Targets and Competitors

variable	control	treated	t-stat	p-value
log Market Cap	20.025	19.967	0.513	0.608
Book-to-Market	0.623	0.663	-1.071	0.284
Tobin's Q	2.414	2.143	2.128	0.034
ROA	0.070	0.064	0.597	0.551
Cum Return (12m)	0.091	0.086	0.092	0.927
Leverage	0.652	0.604	0.302	0.763
Dividend yield	0.010	0.008	2.280	0.023
Cash	0.208	0.201	0.531	0.596
R&D expenses	0.060	0.054	0.953	0.341
log SG&A exp	18.492	18.655	-1.663	0.097
Profit margin	1.178	1.146	1.398	0.162
Inst ownership	0.783	0.818	-1.696	0.090
Markup	1.115	1.086	1.555	0.120
log TFPR	0.714	0.717	-0.139	0.890
sales shares	0.011	0.011	0.051	0.959

This table reports results of a t-test comparing the firm attributes of matched never targeted-competitor to those of matched targets in the year prior to campaign start.

Appendix 3.C Further robustness checks

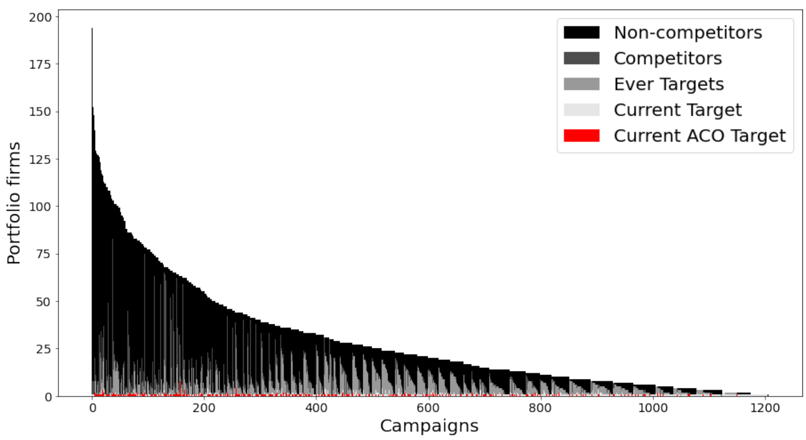


Figure C.4: Campaign-specific complete portfolio composition.

This figure plots the number of portfolio firms held by a targeting activist in the quarter of campaign start as a bar chart for each activist campaign in my sample on the horizontal, sorted by portfolio size from large to small. The height of each bar corresponds to the total number of portfolio firms, the black proportion, the dark gray proportion, the lighter gray proportions and the red proportion of each bar correspond to the number of non-target-non-competitor portfolio firms, non-target-competitor portfolio firms, non-current or current portfolio target firms and current ACO target firms, respectively.

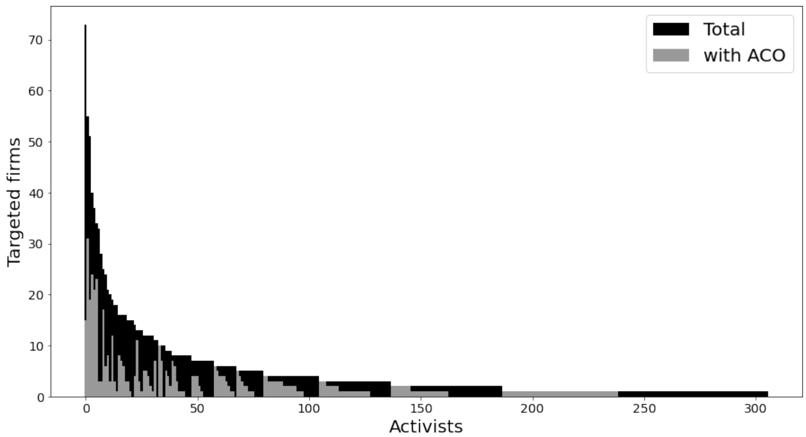


Figure C.5: Number of campaigns across ACO activists.

This figure plots the number of activist campaigns started represented by each bar's height, across all hedge fund activists in my sample on the horizontal axis, sorted from most to fewest campaigns. The proportion of each bar in black represents non-ACO campaigns started, the proportion in gray dpicts ACO campaigns started.

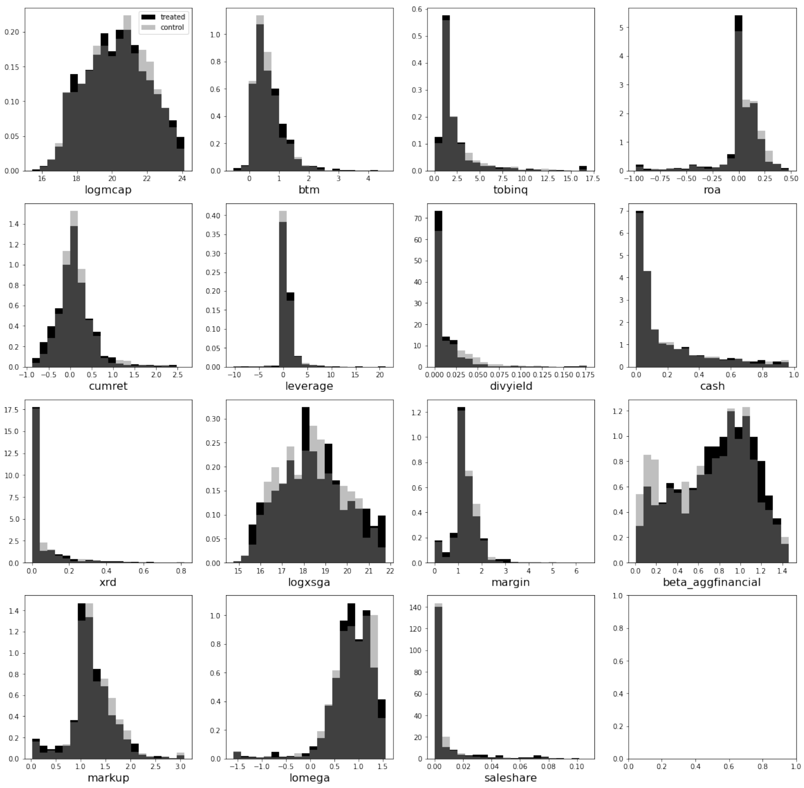


Figure C.6: Matched ACO portfolio to NACO competitors - fit distribution.

This figure plots the distribution of key attributes of matched and treated ACO targets & competitors in black, and the corresponding variable distribution of matched non-ACO competitors as controls in gray.

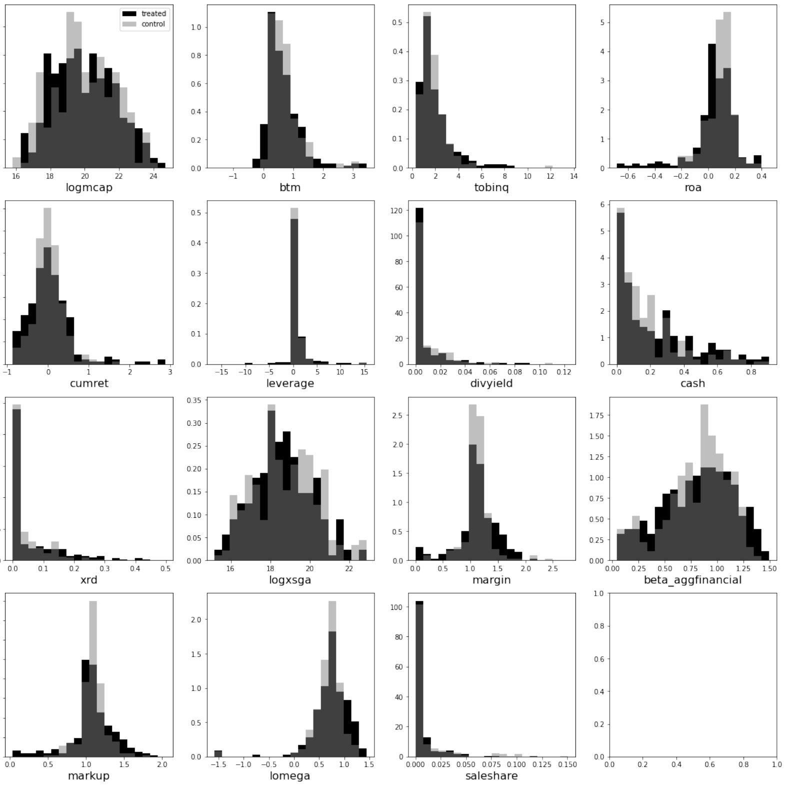


Figure C.7: Matched ACO targets to NACO targets - fit distribution.
This figure plots the distribution of key attributes of matched and treated ACO targets in black, and the corresponding variable distribution of matched non-ACO targets as controls in gray.

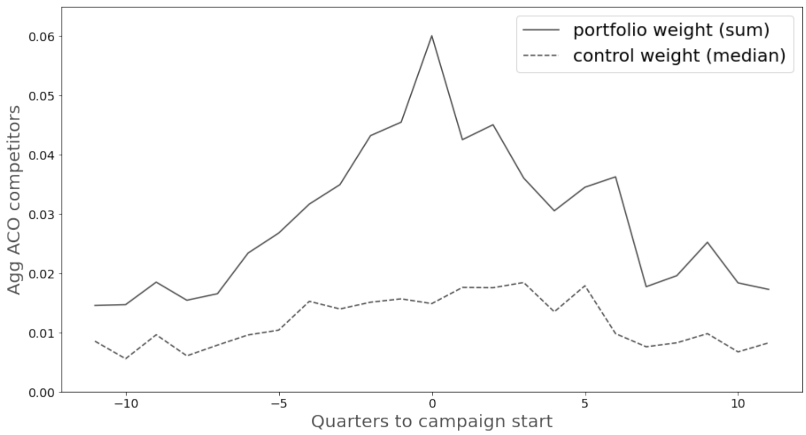


Figure C.8: Ownership of ACO competitors - aggregate - around campaign start.
This figure plots the median activist's aggregate ownership of ACO competitors from 12 quarters before to 12 quarters after campaign announcement. The unbroken line depicts investment as fraction of assets under management, summed across all ACO competitors, the dashed line depicts ownership as fraction of shares outstanding held, using the median across all ACO competitors.

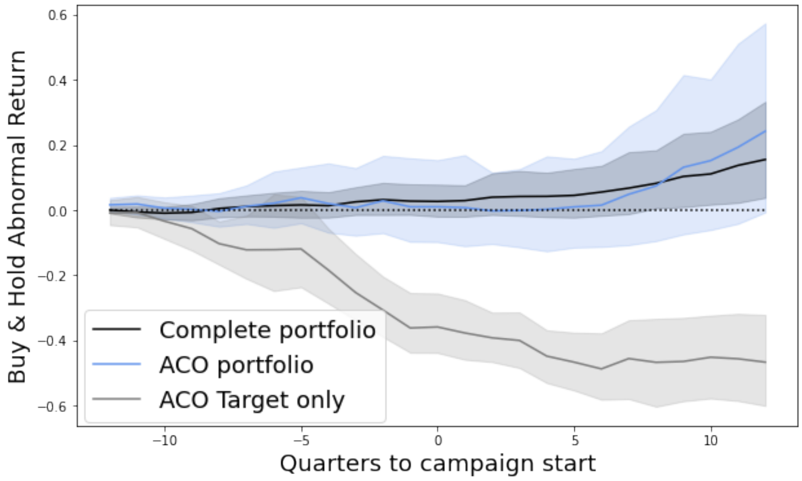


Figure C.9: Equal-weighted BHAR to ACO campaigns.

This figure plots the mean buy-and-hold abnormal returns to the activists' equal-weighted holdings in ACO targets only (gray), in ACO targets & ACO competitors jointly (light blue), and in all portfolio firms (black) from 12 quarters pre-campaigns start to 12 quarters post-campaign start. 95% confidence intervals are shaded in the respective color. The calculation of buy-and-hold abnormal returns follows equation 3.1.

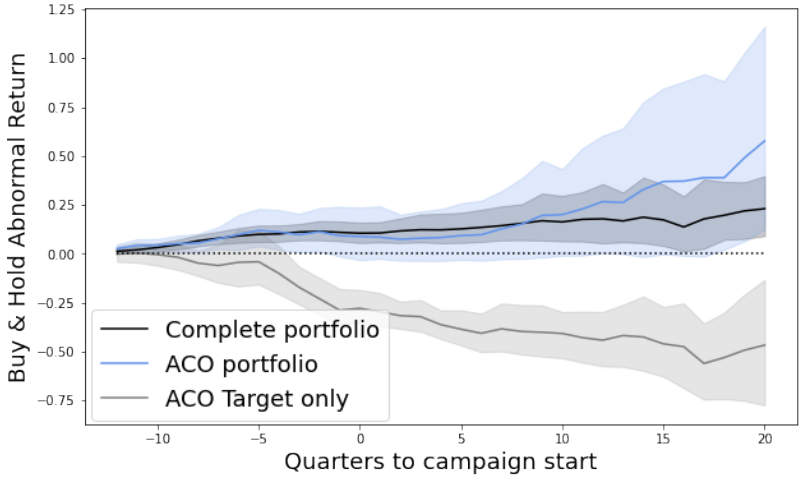
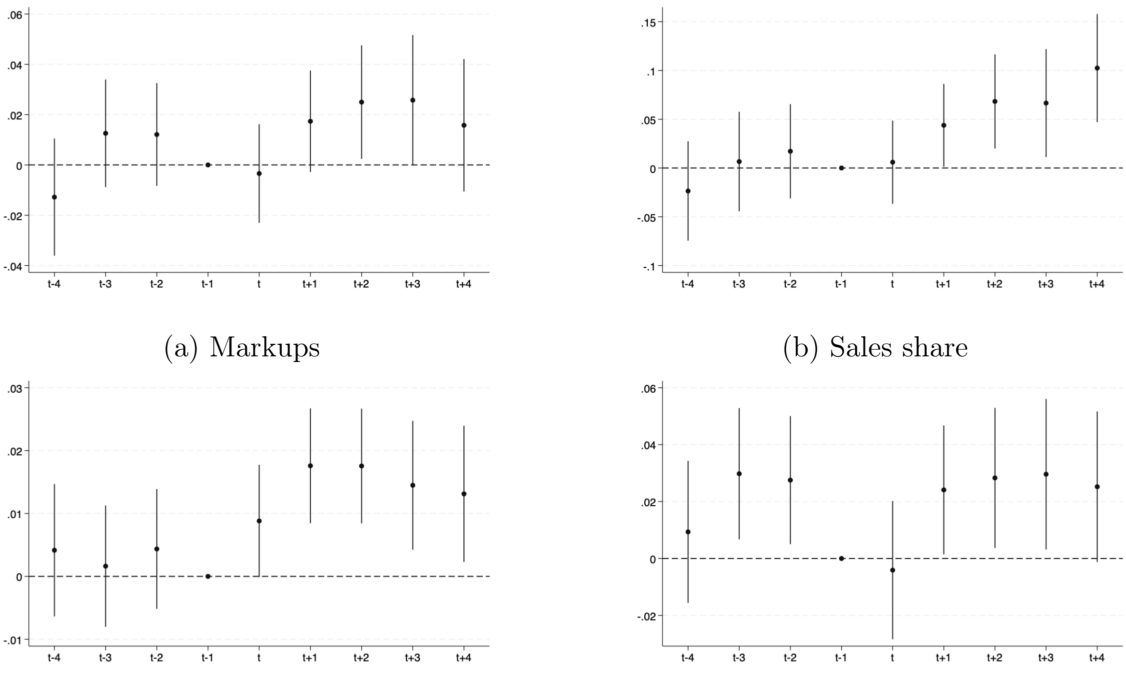


Figure C.10: Value-weighted BHAR to ACO campaigns for post-5 years.

This figure plots the mean buy-and-hold abnormal returns to the activists' value-weighted holdings in ACO targets only (gray), in ACO targets & ACO competitors jointly (light blue), and in all portfolio firms (black) from 12 quarters pre-campaigns start to 20 quarters post-campaign start. 95% confidence intervals are shaded in the respective color. The calculation of buy-and-hold abnormal returns follows equation 3.1.



(a) Markups

(b) Sales share

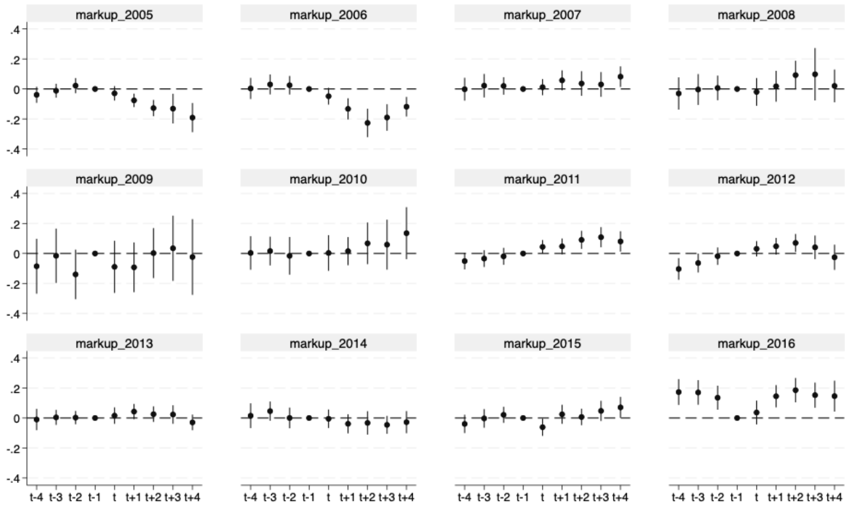
(c) ROA

(d) Productivity

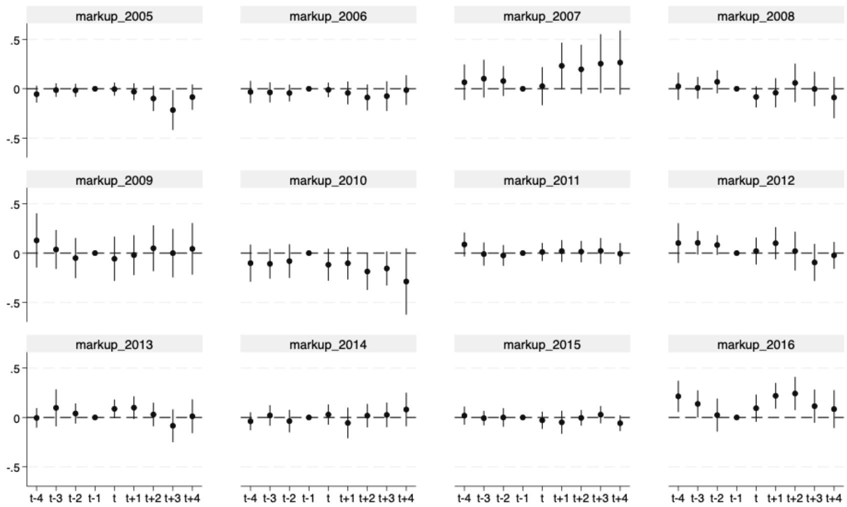
Figure C.11: Dynamic Diff-in-Diff: ACO vs NACO competitors.

This figure plots the estimated coefficients of a staggered diff-in-diff regression of annual markups, log sales shares, return on assets and log TFP on interacted of time-by-treated dummies. The baseline are matched never treated non-ACO competitors, and "treated" are ACO competitors of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Below is the estimated regression equation:

$y_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_{ei} + a_{et} + \varepsilon_t$



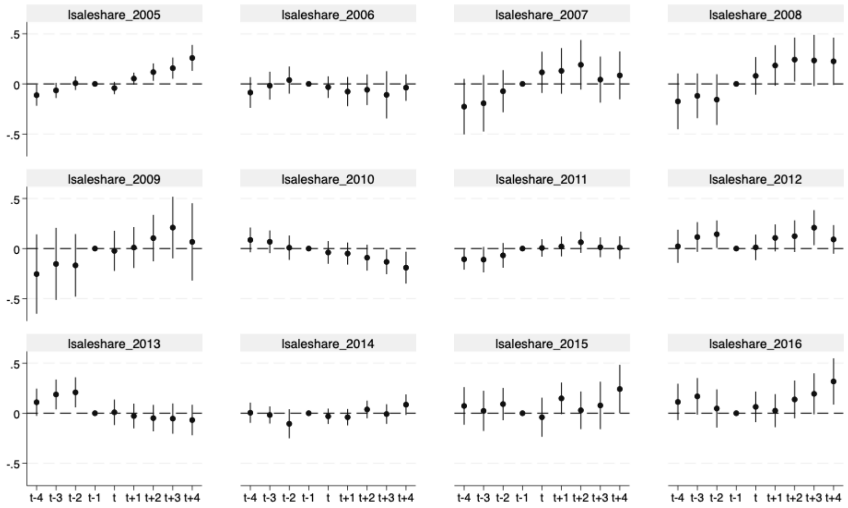
(a) ACO vs NACO competitors



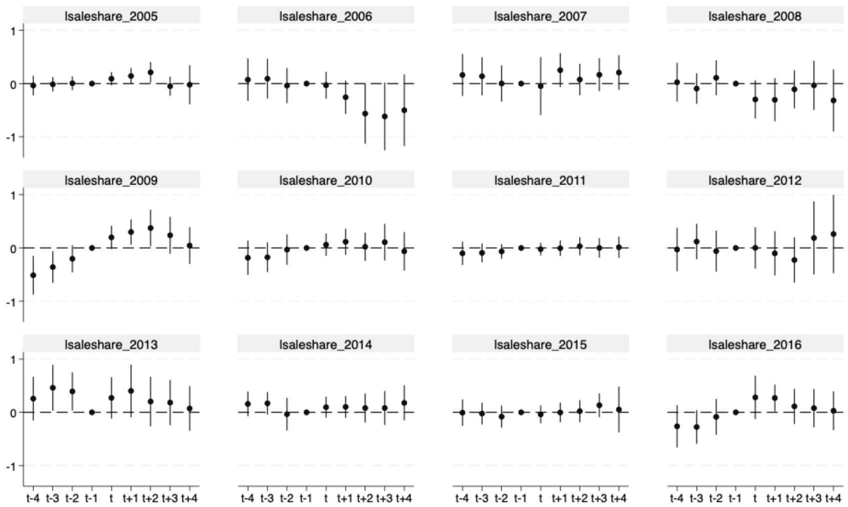
(b) ACO vs NACO targets

Figure C.12: Dynamic DiD by event-year of markups.

This figure plots the estimated coefficients of a diff-in-diff regression of markups on interacted time-by-treated dummies, separately for each year between 2005-2016 and all events in the given year. The baseline in (A) are matched never treated non-ACO competitors, and *treated* are ACO competitors of the same campaign. The baseline in (B) are matched never treated non-ACO targets, and *treated* are ACO targets of the event-year. Controls for market capitalization, firm age, as well as year and firm fixed effects are included. Below is the estimated regression equation: $\forall n \in [2005, 2016]$ if $e \in n$
$markup_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_i + a_t + \varepsilon_t$



(a) ACO vs NACO competitors

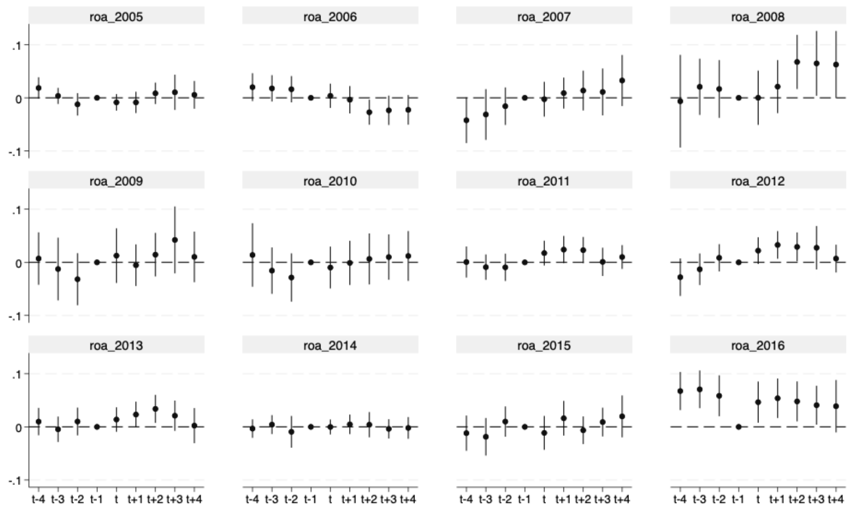


(b) ACO vs NACO targets

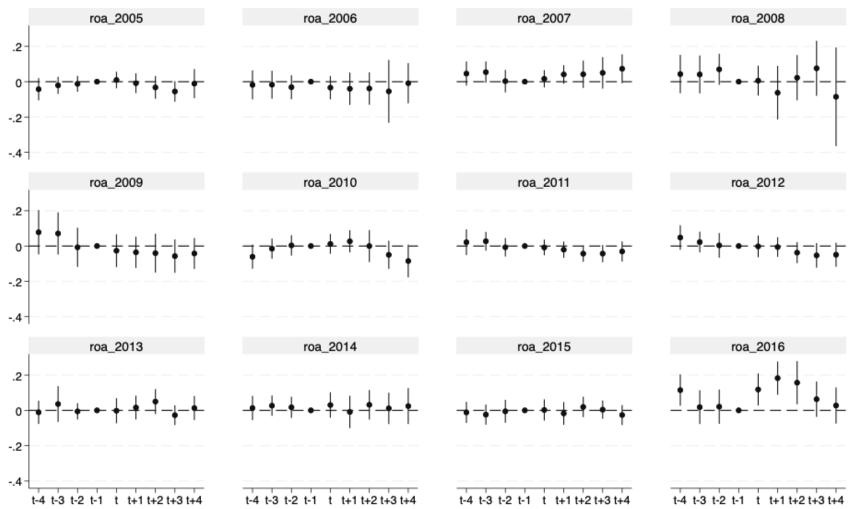
Figure C.13: Dynamic DiD by event-year of log sales share.

This figure plots the estimated coefficients of a diff-in-diff regression of log sales share on interacted time-by-treated dummies, separately for each year between 2005-2016 and all events in the given year. The baseline in (A) are matched never treated non-ACO competitors, and *treated* are ACO competitors of the same campaign. The baseline in (B) are matched never treated non-ACO targets, and *treated* are ACO targets of the event-year. Controls for market capitalization, firm age, as well as year and firm fixed effects are included. Below is the estimated regression equation: $\forall n \in [2005, 2016]$ if $e \in n$

$markup_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_i + a_t + \varepsilon_t$



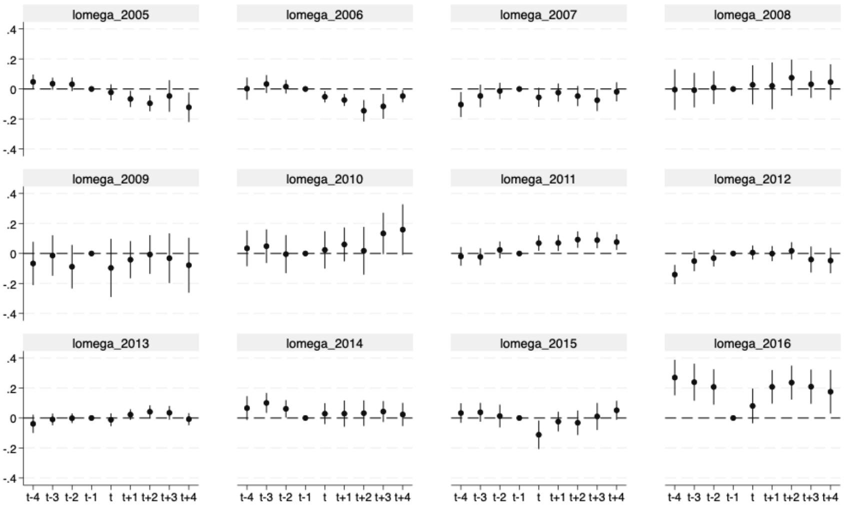
(a) ACO vs NACO competitors



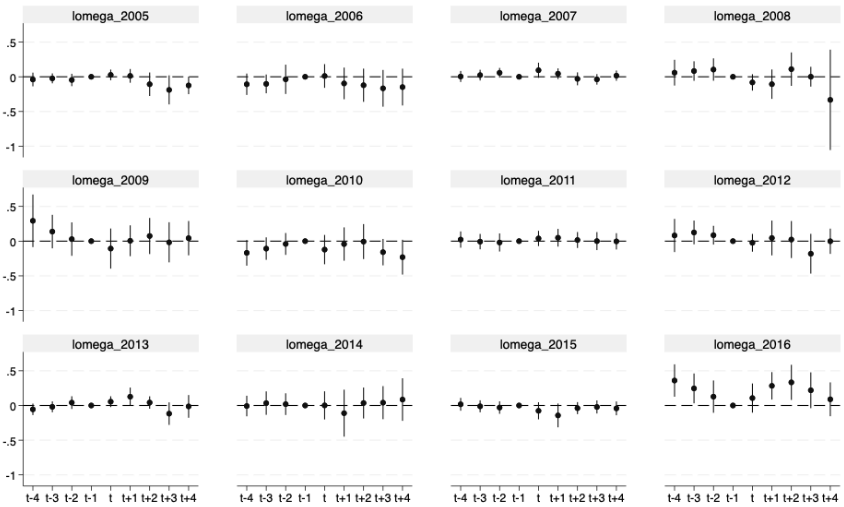
(b) ACO vs NACO targets

Figure C.14: Dynamic DiD by event-year of ROA.

This figure plots the estimated coefficients of a diff-in-diff regression of ROA on interacted time-by-treated dummies, separately for each year between 2005-2016 and all events in the given year. The baseline in (A) are matched never treated non-ACO competitors, and *treated* are ACO competitors of the same campaign. The baseline in (B) are matched never treated non-ACO targets, and *treated* are ACO targets of the event-year. Controls for market capitalization, firm age, as well as year and firm fixed effects are included. Below is the estimated regression equation: $\forall n \in [2005, 2016]$ if $e \in n$
$markup_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_i + a_t + \varepsilon_t$



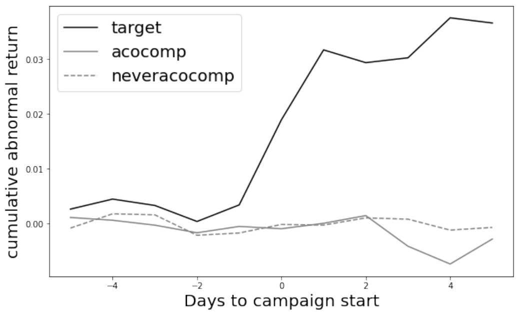
(a) ACO vs NACO competitors



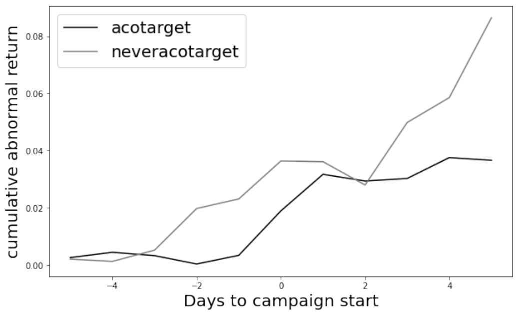
(b) ACO vs NACO targets

Figure C.15: Dynamic DiD by event-year of productivity.

This figure plots the estimated coefficients of a diff-in-diff regression of log TFP on interacted time-by-treated dummies, separately for each year between 2005-2016 and all events in the given year. The baseline in (A) are matched never treated non-ACO competitors, and *treated* are ACO competitors of the same campaign. The baseline in (B) are matched never treated non-ACO targets, and *treated* are ACO targets of the event-year. Controls for market capitalization, firm age, as well as year and firm fixed effects are included. Below is the estimated regression equation: $\forall n \in [2005, 2016]$ if $e \in n$
$markup_{eit} = \sum_{s=-4}^{4} \gamma_{t+s} * d_{t+s} * treat_{ei} + X_{eit} + a_i + a_t + \varepsilon_t$



(a) CAR to target, ACO, NACO



(b) CAR to ACO & NACO targets

Figure C.16: Short run returns to campaign announcement (5 day horizon).
This figure plots the short-run mean cumulative abnormal returns to various firms affected by activist campaigns from 5 days pre-campaign start to 5 days post-campaign start. The left graph depicts mean CAR of the campaign target (black), ACO competitors (grey), non-ACO competitors (dashed). The right graph distinguishes among targets of ACO campaigns (black) and targets of non-ACO campaigns (grey). The calculation of cumulative abnormal returns follows equation 3.7.

Table C.5: Match fit: ACO competitors to NACO competitors

Variable	Control firms	Treated firms	t-stat	p-value
log Market Cap	20.442	20.724	-2.934	0.003
Book-to-market	0.655	0.718	-1.358	0.175
Tobin's Q	2.499	2.442	0.434	0.665
ROA	0.052	0.023	2.845	0.004
Cum Return (12m)	0.150	0.151	-0.076	0.940
Leverage	1.884	5.126	-1.098	0.272
Dividend yield	0.018	0.012	4.391	0.000
Cash holdings	0.177	0.195	-1.637	0.102
R&D expenses	0.045	0.065	-2.780	0.005
log SG&A exp	18.369	18.786	-4.640	0.000
Profit margin	1.399	1.345	1.481	0.139
Inst ownership	0.706	0.775	-3.761	0.000
Markup	1.318	1.268	2.254	0.024
log TFPR	0.916	0.891	1.014	0.311
Sales share	0.008	0.013	-3.392	0.001

This table reports results of a t-test comparing the firm attributes of matched non-ACO competitors to those of matched ACO competitors in the year prior to campaign start.

Table C.6: Match fit: ACO Targets to NACO competitors

Variable	Control firms	Treated firms	t-stat	p-value
log Market Cap	20.033	20.027	0.038	0.970
Book-to-market	0.623	0.704	-1.325	0.186
Tobin's Q	2.379	2.303	0.373	0.710
ROA	0.043	0.031	0.645	0.519
Cum Return (12m)	0.100	0.138	-0.378	0.705
Leverage	0.568	0.633	-0.343	0.732
Dividend yield	0.012	0.007	2.653	0.008
Cash	0.231	0.234	-0.116	0.908
R&D expenses	0.068	0.072	-0.315	0.753
log SG&A exp	18.391	18.656	-1.926	0.055
Profit margin	1.196	1.128	1.851	0.065
Inst ownership	0.752	0.818	-2.132	0.033
Markup	1.128	1.064	1.999	0.046
log TFPR	0.742	0.727	0.396	0.692
Sales share	0.007	0.008	-0.278	0.781

This table reports results of a t-test comparing the firm attributes of matched non-ACO competitors to those of matched ACO targets in the year prior to campaign start.

Table C.7: Match fit: ACO targets to NACO target

Variable	Control firms	Treated firms	t-stat	p-value
log Market Cap	20.033	20.027	0.039	0.969
Book-to-market	0.686	0.704	-0.329	0.742
Tobin's Q	1.801	2.303	-2.901	0.004
ROA	0.089	0.031	3.983	0.000
Cum Return (12m)	0.033	0.138	-1.056	0.291
Leverage	0.699	0.633	0.366	0.715
Dividend yield	0.007	0.007	0.411	0.681
Cash	0.175	0.234	-3.165	0.002
R&D expenses	0.037	0.072	-3.643	0.000
log SG&A exp	18.697	18.656	0.283	0.777
Profit margin	1.128	1.128	0.022	0.983
Inst ownership	0.817	0.818	-0.060	0.952
Markup	1.078	1.064	0.604	0.546
log TFPR	0.680	0.727	-1.378	0.169
Sales share	0.010	0.008	1.345	0.179

This table reports results of a t-test comparing the firm attributes of matched non-ACO targets to those of matched ACO targets in the year prior to campaign start.

Table C.8: BHAR returns to Targets, ACO competitors & NACO competitors

BHAR	mean	BHAR	mean	t-stat	p-value
Target	-0.4289	null	0	-6.0381	**0.0000**
ACO portfolio	0.2604	null	0	1.6715	0.0950
Total portfolio	0.1721	null	0	2.2153	**0.0270**
Target	-0.4289	Total portfolio	0.1721	-5.0190	**0.0000**
ACO portfolio	0.2604	Total portfolio	0.1721	0.5282	0.5975
Target	-0.4289	ACO portfolio	0.2604	-3.2939	**0.0010**

This table reports results of a t-test comparing the buy-and-hold abnormal returns of activists' value-weighted holdings of ACO targets, ACO portfolios and their complete portfolios over the 6 year period from 12 quarters pre-campaign start to 12 quarters post-campaign start, among each other and against null. Differences that are statistically significant at the 5% level are highlighted in bold.

Table C.9: Dynamic Diff-in-Diff-in-Diff: Targets vs ACO competitors vs NACO competitors

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP
treat#t-4	-0.0130	-0.0235	0.00400	0.00925
	(0.012)	(0.026)	(0.005)	(0.013)
treattarget#t-4	0.0749***	0.0452	0.0185*	0.0412*
	(0.021)	(0.050)	(0.011)	(0.024)
treat#t-3	0.0125	0.00699	0.00167	0.0297**
	(0.011)	(0.026)	(0.005)	(0.012)
treattarget#t-3	0.0322	0.0379	0.0192*	0.00356
	(0.021)	(0.047)	(0.011)	(0.022)
treat#t-2	0.0120	0.0169	0.00428	0.0275**
	(0.010)	(0.025)	(0.005)	(0.011)
treattarget#t-2	0.00855	0.00570	0.0103	-0.00653
	(0.019)	(0.045)	(0.010)	(0.022)
treat(target)#t-1	0.0000	0.0000	0.0000	0.0000
	(-)	(-)	(-)	(-)
treat#t+0	-0.00341	0.00612	0.00889*	-0.00406
	(0.010)	(0.022)	(0.005)	(0.012)
treattarget#t+0	-0.00470	-0.0288	-0.00551	0.000752
	(0.019)	(0.046)	(0.010)	(0.024)
treat#t+1	0.0173*	0.0439**	0.0176***	0.0240**
	(0.010)	(0.022)	(0.005)	(0.012)
treattarget#t+1	-0.00179	-0.0950**	-0.0162	-0.0291
	(0.022)	(0.044)	(0.011)	(0.030)
treat#t+2	0.0249**	0.0686***	0.0175***	0.0281**
	(0.012)	(0.025)	(0.005)	(0.013)
treattarget#t+2	0.000298	-0.180***	0.00393	-0.00308
	(0.023)	(0.050)	(0.012)	(0.027)
treat#t+3	0.0258*	0.0670**	0.0145***	0.0297**
	(0.013)	(0.028)	(0.005)	(0.013)
treattarget#t+3	-0.0201	-0.235***	-0.00794	-0.0512*
	(0.026)	(0.053)	(0.013)	(0.030)
treat#t+4	0.0158	0.103***	0.0131**	0.0252*
	(0.013)	(0.028)	(0.006)	(0.013)
treattarget#t+4	-0.0220	-0.316***	-0.0134	-0.0583*
	(0.027)	(0.060)	(0.014)	(0.034)
Observations	237,026	236,541	235,239	200,274
R-squared	0.850	0.964	0.836	0.841
Sample	All	All	All	All
Matched ACO Target	258	258	258	258
Matched ACO Comp	474	474	474	474
Matched NACO Comp	641	641	641	641
Std Errors	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes

This table reports coefficient estimates of a staggered diff-in-diff-in-diff regression of markups, log sales shares, return on assets and log TFPR on interactions of time-by-treattarget dummies and time-by-treat dummies. The baseline are matched never treated non-ACO competitors, “treated” firms are ACO competitors, and “treattarget” firms are ACO targets of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table C.10: Dynamic Diff-in-Diff: ACO competitors vs NACO competitors

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP	(5)
treat#t-4	-0.0128	-0.0236	0.00416	0.00935	-0.00257
	(0.012)	(0.026)	(0.005)	(0.013)	(0.002)
treat#t-3	0.0126	0.00661	0.00163	0.0298**	-0.00101
	(0.011)	(0.026)	(0.005)	(0.012)	(0.002)
treat#t-2	0.0121	0.0172	0.00436	0.0275**	0.000507
	(0.010)	(0.025)	(0.005)	(0.011)	(0.002)
treat#t+0	-0.00342	0.00598	0.00882*	-0.00409	0.00396***
	(0.010)	(0.022)	(0.005)	(0.012)	(0.001)
treat#t+1	0.0174*	0.0438**	0.0176***	0.0241**	0.000317
	(0.010)	(0.022)	(0.005)	(0.012)	(0.002)
treat#t+2	0.0250**	0.0683***	0.0176***	0.0283**	0.00590***
	(0.012)	(0.025)	(0.005)	(0.013)	(0.002)
treat#t+3	0.0257*	0.0666**	0.0145***	0.0296**	0.00557***
	(0.013)	(0.028)	(0.005)	(0.013)	(0.002)
treat#t+4	0.0158	0.102***	0.0131**	0.0252*	0.00218
	(0.013)	(0.028)	(0.006)	(0.013)	(0.002)
Observations	233,330	232,884	231,591	196,939	165,726
R-squared	0.851	0.964	0.836	0.842	0.703
Sample	All	All	All	All	All
Matched ACO Comp	474	474	474	474	474
Matched NACO Comp	495	495	495	495	495
Std Errors	robust	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes	Yes

This table reports coefficient estimates of a staggered diff-in-diff regression of markups, log sales shares, return on assets, log TFPR and product similarity scores on interactions of time-by-treated dummies. The baseline are matched never treated non-ACO competitors, "treated" firms are ACO competitors of the same campaign. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table C.11: Dynamic Diff-in-Diff: ACO targets vs NACO targets

	(1) Markups	(2) Sales share	(3) ROA	(4) TFP
treat#t-4	0.0312	-0.0282	0.0169	0.0341
	(0.021)	(0.054)	(0.011)	(0.024)
treat#t-3	0.0253	0.0131	0.0164	0.0296
	(0.020)	(0.044)	(0.011)	(0.021)
treat#t-2	0.00615	0.000508	0.00400	0.0274
	(0.018)	(0.044)	(0.010)	(0.022)
treat#t+0	0.00776	0.0594	0.0143	-0.000317
	(0.018)	(0.047)	(0.010)	(0.023)
treat#t+1	0.0388*	0.0950**	0.00947	0.00933
	(0.022)	(0.044)	(0.012)	(0.031)
treat#t+2	0.0356	0.0441	0.0174	0.0338
	(0.024)	(0.051)	(0.013)	(0.028)
treat#t+3	-0.000921	0.0541	-0.0105	-0.0429
	(0.026)	(0.058)	(0.013)	(0.030)
treat#t+4	-0.00194	0.0161	-0.0164	-0.0421
	(0.028)	(0.064)	(0.016)	(0.036)
Observations	5,522	5,476	5,423	5,008
R-squared	0.756	0.975	0.765	0.783
Sample	All	All	All	All
Matched ACO Target	258	258	258	258
Matched NACO Target	157	157	157	157
Std Errors	robust	robust	robust	robust
Eventyear-Year FE	Yes	Yes	Yes	Yes
Eventyear-Firm FE	Yes	Yes	Yes	Yes

This table reports coefficient estimates of a staggered diff-in-diff regression of markups, log sales shares, return on assets and log TFPR on interactions of time-by-treated dummies. The baseline are matched never treated non-ACO targets, "treated" firms are ACO targets. Sample selection and matching follows the description in section 3.4.3. Controls for market capitalization and log age, and eventyear-by-year, eventyear-by-firm fixed effects are included. Standard errors reported in brackets. *, ** and *** denote coefficients significant at the 10%, 5%, and 1% level, respectively.

Table C.12: Comparison of mean 5-day pre & post return

	N	Mean		Mean	t-stat	p-value
Target	598	0.0317	null	0	8.9454	**0.0000**
Competitor	519	0.0001	null	0	0.0178	0.9858
target		0.0317	competitor	0.0001	6.8833	**0.0000**
ACO Target	258	0.0316	null	0	5.5984	**0.0000**
NACO Target	157	0.0463	null	0	4.9061	**0.0000**
ACO Target		0.0316	NACO Target	0.0463	-1.4270	0.1543
ACO Comp	258	-0.0037	null	0	-1.8024	0.0717
NACO Comp	258	-0.0003	null	0	-0.1487	0.8818
ACO Target		0.0316	ACO Comp	-0.0037	7.2299	**0.0000**
ACO Target		0.0316	NACO Comp	-0.0003	7.1617	**0.0000**
ACO Comp		-0.0037	NACO Comp	-0.0003	-1.3136	0.1891

This table reports results of a t-test comparing the cumulative abnormal returns of targets (all, ACO & NACO) and competitors (all, ACO, NACO) over the 11-day period from 5 days pre-campaign start to 5 days post-campaign start, among each other and against null. Differences that are statistically significant at the 5% level are highlighted in bold.

Conclusion

This dissertation contributes novel data and evidence to our understanding of ownership structures of U.S. public corporations, the portfolio incentives of these owners and their combined effect on corporate productivity and competition.

Chapter 1 establishes a comprehensive picture of the key shareholders of America's largest firms and to what extent they are universal owners of all firms, common owners of competing firms, or undiversified maverick investors. The appendix of Chapter 1 describes the construction of the underlying novel data set of corporate ownership, which accounts for all types of stock owners who report their holdings to the Securities Exchange Commission in the U.S.. I find that corporate insiders and non-financial blockholders are mostly undiversified mavericks, who reduce universal and common ownership, especially in the 10% of sample firms where they are the most influential shareholders. Institutional investment managers, chiefly among them the "Big Three", BlackRock, Vanguard and StateStreet, are highly diversified across virtually all sample firms, implying a positive contribution to universal and common ownership. Even controlling for indexing this positive effect remains significant and is likely driven by the centralization of control across multiple sub-funds and by consolidation in the asset management industry. Surprisingly, hedge fund activists are also frequently diversified across competitors and non-competitors, increasing measures of common and universal ownership. These findings overturn existing results on the drivers of common and universal ownership and re-open the question whether consolidation in the institutional investment management industry should continue unchecked in the future. In addition, our results show that accounting for all owners of common stock is key to avoid biased estimation of the average shareholders' portfolio incentives.

Chapter 2 investigates the effects of common ownership on corporate productivity and markups. Theoretically, common ownership has been modeled as a cause of softer competition and higher markups without an effect on corporate productivity. A recent paper by Anton et al., 2022 demonstrates how common ownership softens competition by causing less performance-sensitive compensation, thereby incentivizing managers to reduce their efforts towards efficiency improvements and ultimately reducing productivity. Combining measures of common ownership and managerial incentives with estimates of total factor revenue productivity and markups based on the cost shares approach, we find that common ownership is indeed correlated with lower productivity and markups, with larger effects on firms with initially lower levels of common ownership. An event study of index additions of competitors varies common ownership exogenously and thereby allows identification of a causal link with productivity. The difference-in-difference model estimates demonstrate that by reducing managerial incentives, common ownership ultimately reduces productivity and markups by about 1%. These findings contribute relevant and novel evidence to the discussion on potential anti-competitive effects of common ownership. Due to the limitations of our measure of productivity, which confounds actual quantity productivity and market power variation, further analysis of the link between common ownership and actual productivity is needed before a policy response is formulated. Although the effect cannot be quantified, Chapter 2 ascertains a negative association between common ownership and productivity that is larger for lower starting levels of common ownership, and which should raise policy maker attention due to the welfare ramifications of productivity reductions.

Chapter 3 expands the analysis of hedge fund activists' portfolio incentives and their effects on financial returns and economic externalities of campaigns. In contrast to public perception, I find that activists are diversified across target firms' competitors (who are never themselves targeted) during a campaign, and the investments in competitors vary strategically before and after campaign start. Financially, the holdings in competing firms provide a hedge against deteriorating returns of the targeted firm pre-campaign start, resulting in significantly positive abnormal portfolio returns for the diversified activist. The combined target and competitor portfolio also outperforms the market and the target-only holdings after campaign start, suggesting that activist commonly owned competitors may benefit from specific positive spillovers of the campaign. A staggered event study of the campaigns with activist common ownership (where the activist holds both targeted and competing firms at campaign start) finds that activist commonly owned competitors indeed outperform matched, non-activist owned competitors in markups, sales shares and profitability. At the same time, the differentiation between the target's products and the activist commonly owned competitors' products decreases relative to other competitors, and the target significantly reduces its market share. The positive spillovers to activist commonly owned competitors seem to inflict a cost on the target, which the activist is willing to bear as the joint target and competitor portfolio yields sufficient excess returns. The implications for market structure and concentration, as well as consumer welfare remain ambiguous and require further investigation in future research. The findings of Chapter 3 nevertheless indicate that hedge fund activism and its effects on targeted firms, competitors and market structure should be analyzed taking into account the diversified portfolio incentives of activists. With more evidence on the consequences of activist common ownership, it may be necessary to review the liberal regulation of this sector to enhance safe guards for both targeted and non-targeted firms and markets.

Beyond its analytical contributions, this dissertation makes a novel data set available for future academic research. The data set comprises common stock holdings of corporate insiders (Form 3/4/5), blockholders (Form SC 13-D / SC 13-G) and institutional investment managers (Form 13-F), consolidated such that duplication across different file types or filing parties are removed, while reports by multiple sub-funds belonging to one family are aggregated. The holdings data is complemented by a hand-collected list of corporations with multiple classes of common stock, including the number of votes attributed to each class, and the number of shares outstanding for all untraded classes of common stock. Combining the ownership and voting data yields an accurate account of differences in the cash flow ownership and voting control structures of publicly traded U.S. corporations. Sharing this data set with the profession for future academic research into corporate ownership and investors' portfolio structures, I hope that my analysis has shown that a complete picture of varying investor incentives matters for the analysis of corporate governance.

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