Essays on Common Ownership and Corporate Culture

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Abstract

A growing literature in economics and finance suggests that common institutional investors between same-industry firms and corporate culture play significant roles in various corporate policies and outcomes. Motivated by this strand of research, this thesis studies the implications of common ownership and corporate culture in different contexts.

Recent studies show that common ownership improves firm performance, yet little is known about the mechanism underlying such change. Using both firm- and establishment-level data, Chapter 2 investigates how common ownership among same-industry firms improves production efficiency and generates value. The results show that firms with common ownership are significantly more productive than those without this structure. Common owners are more likely to induce employment reduction at unproductive and peripheral establishments. Common ownership also negatively affects the number of establishments at diversified firms. The findings suggest that common ownership encourages managers to deploy resources more efficiently and concentrate on the firm's main business activities.

Chapter 3 examines the pairwise comovement in stock returns among commonly owned firms. Comovement in stock returns is an important determinant of market risk and stability. The empirical analysis reveals that increased common ownership between same-industry firms leads to greater comovement in their stock returns. The results are robust after controlling for time trends and various empirical specifications. The effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their products. These findings are consistent with previous studies, which suggest that comovement at the market level is due to blurred firm boundaries (Bertrand, Mehta, & Mullainathan, 2002; Khanna & Thomas, 2009). Common ownership serves as a mechanism for joint control across firms as it allows for coordination in firm activities, efficient resource allocation, and cross-monitoring (He & Huang, 2017; Morck, Yeung, & Yu, 2000). Thus, the market considers firms with common ownership relevant and correlated in fundamentals.

Chapter 4 studies whether corporate culture explains the difference in bond yield spreads of US public firms. The literature shows that strong corporate culture encourages managers and employees to make consistent decisions, focus on long-term results, and improve productivity (Li, Liu, Mai, & Zhang, 2021). Besides, strong culture firms can have higher accounting integrity where employees are more likely to report fraud and managers are less likely to participate in private benefit extraction (Jiang, Wintoki, & Xi, 2021). Using data from 2002 to 2017, I find a strong and robust positive relation between strong corporate culture and bond yield spreads. In addition, corporate culture affects yield spreads through at least two channels: improving creditworthiness and reducing information asymmetry. The study contributes to the cost of debt literature by identifying a new determinant of bond yield spread, the so-called cultural incentive.

Declaration of Authorship

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signature: ……………………

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Date: 20 April 2023

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List of Abbreviations

C/O	Common Ownership
CEO	Chief Executive Officer
CRSP	Center for Research in Security Prices
CUSIP	Committee on Uniform Securities Identification Procedures
CV	Cultural Value
DiD	Difference-in-Differences
EDGAR	Electronic Data Gathering, Analysis, and Retrieval system
FE	Fixed Effect
FISD	Fixed Income Securities Database
GDP	Gross Domestic Product
GGL	Gilje, Gormley, Levit
HHI	Herfindahl-Hirschman Index
Ind	Industry
LIBOR	London Interbank Offered Rate
MHHI	Modified Herfindahl-Hirschman Index
MV	Market Value
NETS	National Establishment Time-Series
NAICS	North American Industry Classfication System
OLS	Ordinary Least Squares
PPE	Property, Plant, and Equipment
R&D	Research & Development
ROA	Return on Assets
S&P	Standard & Poor's
SEC	Securities and Exchange Commission
SIC	Standard Industrial Classification
TFP	Total Factor Productivity
U.S.	United States
VIF	Variance Inflation Factor
WRDS	Wharton Research Data Service

Chapter 1

Introduction

1.1. Background and motivation

Large institutional investors have significantly increased ownership in public U.S. firms over the past three decades (Choi, Fedenia, Skiba, & Sokolyk, 2017; Grullon, Larkin, & Michaely, 2019). Highly diversified mutual fund families now hold up to 75 percent equity in publicly traded companies (Ben-David, Franzoni, Moussawi, & Sedunov, 2021). The ownership has become even more concentrated in the hands of a few very large financial institutions. The three enormous American asset management funds have ownership stakes in more than 90 percent of U.S. companies, which is tremendous (Davis, 2013). BlackRock manages nearly $10 trillion assets under management as of 2021. Vanguard has nearly $8 trillion, while State Street has $4 trillion. The combined $22 trillion in managed assets is more than half of the total value of all S&P 500 company shares (about $38 trillion). Their control is anticipated to grow (Hirst & Bebchuk, 2022).

As a result, natural competitors in an industry increasingly share the same institutional owner, i.e., have common ownership. Nearly 60% of listed firms in the US had at least one common institutional blockholder with their competitors in 2014 (He & Huang, 2017). What occurs when few institutions control so many firms, especially in the same industry? An incredible benefit – for example, when an institutional passive-investing index fund invests in numerous firms – is to reduce costs and increase returns for millions of individual investors. In contrast, the concern when such ownership is concentrated in one industry is the lack of competition incentives among competing firms. Considering that Vanguard is the largest shareholder in both Ford and General Motors, how would competition between the two companies help Vanguard? Why compete so intensely on prices, innovations, and investments if each company is owned by the same small number of owners? The American economy is stifled by monopoly and oligopoly (Kovacic & Shapiro, 2000). In several areas, including airlines (Goetz, 2002), banking (Foster, 2010), health care (Dafny, 2010), and mobile phone service providers (Khan & Vaheesan, 2017), Americans can conduct business with a small number of firms. Common ownership among such few companies may amplify the oligopolistic effects as it enables these common owners to exert excessive control over the economy.

A vast number of studies show evidence on weakened competition among competing firms after sharing common owners. Bae, Bailey, & Kang (2021) show that common ownership diminishes consumer choice, hikes costs, and likely damages employees. Common ownership leads to higher ticket prices and lower outputs in airline industry (Azar, Schmalz, & Tecu, 2018), and higher interest rates in banking industry (Azar, Raina, & Schmalz, 2022). Bindal & Nordlund (2022) extend the research to entire U.S. markets and find that the effects are more pronounced in industries with similar products where firms must compete to gain market share. After sharing common owners, firms compete less on quality and features, and thus become less innovative with lower research and development (R&D) expenditure (Semov, 2017).

Given the growing popularity of common ownership is unlikely to diminish, recent studies also attempt to research the beneficial sides of common ownership structure. He & Huang (2017) investigate the effects of common ownership on product market performance and find that commonly owned firms experience a significantly higher market share growth. There is a substantial increase in the number of explicit collaborations (strategic alliances, joint venture, or even entire acquisitions) among same industry firms after they have common institutional investors. Moreover, these firms also obtain higher innovation productivity and operating profit margin. Edmans, Levit, &Reilly (2019) prove that common institutional investors can create firm value by strengthening corporate governance via both exit and voice channels. Empirical studies show that common ownership is positively associated with forced CEO turnover-performance sensitivity (Kang, Luo, & Na, 2018) and close-call votes on shareholder-sponsored governance proposals (He, Huang, & Zhao, 2019). Commonly owned firms also have higher Tobin-Q than non-commonly owned firms. These findings demonstrate that common owners effectively monitored firm managers, resulting in increased firm value (Boyson & Mooradian, 2012; Hirshleifer & Thakor, 1994; Shleifer & Vishny, 1986).

However, it is still not clear what are the specific mechanisms underlying those changes in firm performance. Firm-level indicators, such as ROA, do not indicate underlying improvement channels because they cannot track the performance of underlying assets after ownership changes. Thus, the first essay which is presented in Chapter 2 attempts to fill this gap by investigating the impact of common ownership on firm productivity and the possible channels behind such effect. Understanding the specific mechanism through which common ownership improves firm performance would make a significant contribution to our understanding of the bright side of common ownership.

In addition, common ownership allows blockholders to influence a group of firms' corporate choices, potentially tying their performance together and decreasing firm-specific price information. Common ownership can reduce information asymmetry and facilitate coordination, thereby tying firms' potential revenues together (He & Huang, 2017). Common ownership influences how a corporation reveals earnings information in connection to other firms with the same common owners, potentially establishing performance correlations (Massa & Žaldokas, 2017; Park, Sani, Shroff, & White, 2019). Edmans, Levit, & Reilly (2014) prove that common ownership between two firms allows blockholders to choose which firm to be sold when faced with liquidity shocks, affecting both retained and sold firm stock prices. High systematic fluctuation or poor firm-specific information in stock prices can lead to high return comovement among firms (Roll, 1988). Thus, the third chapter examines whether common ownership amongst same-industry firms increases their stock return comovement. Studying the effect of common ownership on stock return comovement is important as it can impact market risk and stability. Comovement affects systemic risk by how markets transfer shocks, and thus also affecting firm cost of capital.

While common ownership is a system of ownership, corporate culture refers to a shared set of values and practices that shape the way a company operates and the way its employees behave. Corporate culture impacts corporate performance indirectly by providing a framework for making decisions and resolving problems, shaping the corporate's ethical standards and social responsibility, and motivating the participation and engagement of all company members (Denison, 1984). More than half of senior executives at 1,348 North American firms say that corporate culture is one of the top three determinants of firm value, and 92% agree that strengthening their firm culture would increase its worth (Graham, Grennan, Harvey, & Rajgopal, 2016).

Differences in corporate culture can explain why a firm succeeds while the other comparable firms fail. Satisfied employees are more driven and likely to stay with a firm over time (Edmans, 2011). While culture may appear ethereal, it can define the difference between success and failure, and fostering human capital is critical for establishing a firm with long-term viability. Strong cultural values can translate directly into higher productivity, lower turnover, and greater customer loyalty. Boyce, Nieminen, Gillespie, Ryan, & Denison (2015) investigate the sales and service divisions of 95 different vehicle dealerships that sold the same items but differed in four key cultural traits: engagement, consistency, flexibility, and mission. The data show that if culture is prioritized, performance levels will follow. An engaged culture characterized by high levels of participation, stability, adaptability, and a clear objective boosts sales and customer satisfaction. Li, Liu, Mai, & Zhang (2021) demonstrates that strong culture firms outperform their rivals with weak culture despite the significant detrimental impact of COVID-19. Furthermore, firms with strong culture are also more likely to assist their community, apply new technology and develop new products. In short, corporate culture is an intangible asset developed to help firms deal with unanticipated events as they occur.

Strong corporate culture encourages executives and staff to focus on the long term. These firms are more resilient than weak cultural firms by keeping existing workforces and adopting new technologies to generate different products (Li, Liu, et al., 2021). Firms that emphasize innovation and quality might reduce information risk by emphasizing the quality of their inventions (Bhattacharya & Ritter, 1983). Bushman, Piotroski, and Smith (2004) show that strong culture firms have fewer lawsuit risks and higher disclosure transparency. In organizations that emphasize integrity and respect, CEOs are less likely to profit from private knowledge (Jiang et al., 2021), and employees are more likely to report fraud (Sengupta, 1998). An upgraded information environment with high-integrity accounting reports decreases default risks and allows creditors to monitor debt agreement violations effectively (Francis, LaFond, Olsson, & Schipper, 2005). Motivated by these studies, the third essay (Chapter 4) investigates whether debt holders incorporate corporate culture in their lending evaluation process.

1.2. Overview of the thesis

This thesis is a comprehensive study that investigates implications of common ownership and corporate culture. The thesis has three empirical chapters, presented in Chapters 2 to 4. Each chapter is a stand-alone study that has its own literature review and empirical results and addresses specific research questions. The chapters are linked and cross-referenced throughout to the purpose of the thesis.

Chapter 2 examines how common ownership improves production efficiency and generates value. It sheds light on the mechanism underlying the improved performance among commonly owned firms. Chapter 3 investigates the comovement in stock return among same-industry firms with common ownership. It demonstrates that common ownership affects return comovement and price efficiency. Chapter 4 studies whether corporate culture explains the difference in bond yield spreads of US public firms and finds a negative association.

The following subsections provide an overview of each empirical chapter and discuss their results and academic contributions. Finally, Chapter 5 of this thesis provides a conclusion and discusses directions for future research.

1.2.1. Common ownership and productivity

Extant literature demonstrates that common ownership improves corporate governance and firm performance with higher Tobin-Q and stock returns (He et al., 2019; Kang et al., 2018). However, existing studies do not attempt to identify the specific mechanisms underlying those changes in firm performance, which is critical to understanding the actual effects of common ownership and how it creates shareholder value. Thus Chapter 2 fills this gap by investigating the impact of common ownership on firm productivity and the possible channels behind such changes.

Using firm-level data for U.S public firms from 1990 to 2015, I first identify whether common ownership affects firm productivity. I estimate productivity using the Cobb-Douglas production function by Olley & Pakes (1996) and apply a semi-parametric procedure to control for multiple endogeneity issues. To quantify the effect of common ownership, I use newly developed GGL measure of Gilje, Gormley, & Levit (2020) which accounts for the attention of common owners on managerial performance sensitivity. Next, I investigate channels through which common owners improve productivity – increasing the efficiency of existing assets, reallocating capitals, and closing establishments – using the establishment-level data from the National Establishment Time-Series (NETS) database for U.S. firms.

I confirm that firms with common ownership are significantly more productive than those without this structure, consistent with existing literature on beneficial impacts of common ownership on firm performance. To address the potential endogeneity issues, I first use firm fixed effects in my panel regressions to remove potential bias arising from time-invariant omitted firm characteristics. Second, to overcome the reverse causality issue, I implement a difference-in-differences (DiD) analysis around the first year that firms have common ownership by employing the propensity score matching technique. My results are robust to controlling for these endogeneity problems.

Second, I find that there is no reduction in the total number of a firm's employee and establishments due to common ownership. However, common owners are likely to induce employment reduction at unproductive and peripheral establishments. To control for the possibility that firms may reallocate resources before the common ownership inclusion, I employ the same DiD setting as above and examine these possibilities in the first-year firms have common ownership, at the establishment level. The results show that common owners are more likely to induce employment layoff across all establishments in the first year, suggesting a widespread approach of employee reduction from common owners. The findings indicate that common owners shift management attention and resources to where they can deliver the most value to the firm. These findings align with prior studies that employee reduction can diminish management slack, reduce redundant investments, and improve the internal capital market (Davis et al., 2014; Li, 2013). Common ownership also negatively affects the number of establishments at diversified firms that operate across multiple industry segments, suggesting that common owners tend to concentrate managerial efforts on large segments to optimize the comparative advantage of organizational skill (Maksimovic & Phillips, 2002).

This study contributes to the burgeoning literature on common ownership by tracing the sources of value creation to the fundamental production process. My establishment-level analysis deepens our understanding of the role of common ownership in improving firm performance. The finding has linkages to the literature investigating the effects of ownership changes on firm performance on mergers and acquisitions, hedge fund activism, and asset sales (Maksimovic & Phillips, 2001, 2002; Warusawitharana, 2008). This study also adds to the stream of literature examining the real effects of monitoring by informed outside shareholders such as large concentrated institutional investors (Becker, Cronqvist, & Fahlenbrach, 2011; Clifford & Lindsey, 2016), mutual funds (Appel, Gormley, & Keim, 2016), and activist hedge funds (Brav, Jiang, & Kim, 2015; Brav, Jiang, Partnoy, & Thomas, 2008). Common owners with high monitoring incentives and industry knowledge are also expectedly effective monitoring shareholders.

1.2.2. Common ownership and stock return comovement

Comovement in stock returns results from high systematic fluctuation or poor firm-specific information in stock prices, affecting market risk and stability (Roll, 1988). Common ownership may affect stock return comovement for various reasons. Common ownership can alleviate information asymmetries and promote collaboration, bringing together potential profits for commonly owned firms (He & Huang, 2017). Common ownership impacts the way in which a firm annouces its earnings information in respect to other firms with the same common owners, potentially establishing performance correlations. (Massa & Žaldokas, 2017; Park et al., 2019).

Edmans et al. (2014) prove that when faced with liquidity shocks, common ownership allows blockholders to choose between a balanced or unbalanced exit, affecting the stock prices of both retained and sold firm. Motivated by these studies, Chapter 3 analyzes whether common ownership can affect stock comovement in the absence of liquidity shocks and agency concerns.

The results show that firm pairs with common ownership experience significantly higher comovement in returns than firm pairs without common ownership. The result is robust to alternative empirical specifications after removing the trends in the data of the pairs and controlling for unobserved variables that may affect the pair's comovement. It is consistent with the idea that the market views common ownership as a mechanism for common owners exercise joint control across firms. A firm pair with common ownership is predicted to move in the same direction 3.5% more often than a pair without common ownership. In addition, when firm pairs share common ownership, their returns are 7% more correlated than when they do not.

Several mechanisms could contribute to the increase in return comovement. I find that the effect of common ownership on pairwise comovement is stronger for firms with less product similarity. While common ownership may help in product space, it may hinder innovation. Commonly owned firms selling similar products are less willing to invest in innovation for the fear that their advanced products will negatively impact the business of other firms with common owners. This innovation incentive may well be in the interest of undiversified shareholders (and consumers) but costly for common owners. Common ownership may thus create more strategic alliances between firms with different products or firms close in the technology space, resulting in the increase in their return comovement. On the other hand, firms with similar products generate less value from innovation collaboration; thus, their stock prices may be less correlated.

My findings are important for both market participants and policymakers. The finding that common ownership increases comovement in returns may deepen the U.S. government's current concerns on the market impacts of common ownership. The increasing likelihood of shocks spreading across stocks due to common ownership may impact systemic risk and the propensity for flash crashes. This chapter also adds to the literature on pairwise comovement in stock returns. My study is consistent with previous research, which suggests that comovement at the market level is caused by correlated fundamentals and blurred firm boundaries.

1.2.3. Corporate culture and the cost of debt

Debt is the primary source of long-term financing for US firms. Thus, a little adjustment in lending rates could substantially alter capital allocation and have significant economic repercussions (Bai, Bali, & Wen, 2019). Two primary determinants of the interest rate that lenders charge borrowers are default risk and protection to lenders in the event of default, such as bond covenants and third-party guarantees. The default risk depends on various factors, such as information environment and agency costs between the firm and its debtholders.

Prior studies show that national culture may affect how much lenders charge borrowers for debt. More cultural distance between lenders leads to harsher criteria for international syndicated bank loan borrowers, such as smaller loans, higher interest rates, and third-party guarantees. Chui, Kwok, & Zhou (2016) find a considerable variation in debt costs between collective and individualistic enterprises. Collective societies have lower corporate debt ratios, according to Chui, Lloyd, & Kwok (2002). These studies focus on national culture and debt burden. However, no study has examined if an individual firm's culture affects its interest rate. Thus, the third essay presented in Chapter 4 examines whether corporate culture impacts bond yield spread.

Corporate culture is a set of common beliefs and norms that determine proper attitudes and behaviors (CrÉMer, 1993; Van den Steen, 2010b). Li, Mai, Shen, & Yan (2021) define company culture as integrity, respect, teamwork, innovation, and quality. A high-integrity firm, for example, prioritizes integrity in its financial performance discussions. Human-focused culture emphasizes honesty, respect, and teamwork; technology-focused culture emphasizes innovation and quality.

Using culture data from 2002 to 2017, I show that strong culture enterprises have lower yield spreads. It's robust to firm and bond characteristics and controls. Strong cultural firms have on average 19 bps lower yield spreads than identical firms with weak corporate culture. I identify two possible channels through which corporate culture affects bond yield spread: enhanced bond creditworthiness and lower information asymmetry. Strong cultural firms have stronger credit ratings and information environments. I also find that corporate culture has more significant impact on riskier firms with high leverage ratios and historical stock return variability.

This research makes two contributions. First, it adds to the expanding literature on how corporate culture affects firm policy and performance by showing how it affects default risk and information environment. Second, this study adds to prior research showing that corporate culture affects debt pricing with narrower bond yield gaps.

Chapter 2

Common Ownership and Firm Productivity[1]

2.1. Introduction

Large institutional investors have increasingly owned shares in multiple firms in the same industry (henceforth, common ownership), partly due to the institutional mergers (Azar et al., 2018) and index investing (Harford, Jenter, & Li, 2011). In 2014, nearly 60% of U.S. public firms had a common ownership structure (He & Huang, 2017). The growing popularity of this structure raises concerns about its impact on the value of commonly owned firms. Edmans et al. (2019) theoretically prove that common institutional investors (common owners) can create firm value by strengthening corporate governance via both exit and voice channels. Empirical studies show that the market reacts favorably to the announcements of forced CEO turnover to performance (Kang et al., 2018) and close-call votes on shareholder-sponsored governance proposals (He et al., 2019) of commonly owned firms. Commonly owned firms also have higher Tobin-Q than non-commonly owned firms. These findings demonstrate that common owners effectively monitored firm managers, resulting in increased firm value (Boyson & Mooradian, 2012; Hirshleifer & Thakor, 1994; Shleifer & Vishny, 1986).

However, existing studies do not attempt to identify the specific mechanisms underlying those changes in firm performance. Firm-level metrics like ROA do not reveal the underlying improvement channels due to its unable to trace the performance of the underlying assets after ownership change. Thus, efficiency benefits from existing assets cannot be distinguished from capital reallocation gains from underperforming assets. In addition, no empirical evidence exists on the direct relation between common ownership and productivity changes. That means the existing literature treats firms as a black box, and it remains unknown how common ownership improves production efficiency. Yet identifying these mechanisms is critical to understand the

[1] This chapter is co-authored with my main supervisor Prof. Yulia Merkoulova and co-supervisor A/Prof. Thanh Huynh

actual effects of common ownership and how it creates shareholder value. This study attempts to fill this gap by investigating the impact of common ownership on firm productivity and the possible channels behind such changes.

To quantify the effect of common ownership, I use newly developed GGL measure of Gilje et al. (2020). The measure considers three factors: the monitoring incentives of common owners towards a firm's performance, their knowledge of the industry in which the firm operates, and the firm manager's attention towards common owners' preferences. The primary advantage of this measure over the measures of He & Huang (2017) and Lewellen & Lowry (2021) is that it relaxes the assumption that all investors are fully attentive to managers' actions. Thus, common owners are expected to pay attention to manager performance in proportion to the importance of the firm in the common owners' portfolios.

Using firm-level data for U.S public firms from 1990 to 2015, I first identify whether common ownership affects firm productivity. I use Olley & Pakes (1996)'s method that estimates the Cobb-Douglas production function using a semi-parametric procedure to measure firm productivity. The procedure provides better estimation than the ordinary OLS regression by controlling for multiple endogeneity issues: simultaneity biases between input and productivity, selection bias when unproductive firms exit and get excluded from the sample, and within-firm serial correlation in productivity. Overall, I find a positive relation between common ownership and firm productivity.

I consider different empirical specifications to study the effect of common ownership on productivity. First, the GGL measure is positively skewed. Among firm-year observations with common ownership, one-fifth have significantly higher GGL (4.366) than the rest (with a mean of 0.158). It indicates that common ownership may trigger a significant shift in firm performance only when the common ownership is strategically important, and the GGL measure therefore crosses a certain threshold. Thus, I redefine commonly owned firms as those in the top fifth quintile of the sample based on the GGL measure. Second, institutional investors may form common ownership based on corporate characteristics, which at the same time determine production efficiency for commonly owned firms. To account for this possibility, I employ the propensity score technique to create a control group with very comparable corporate characteristics for the redefined commonly owned firms. The findings remain statistically significant. The magnitude of the effect is also economically meaningful. Firms with common ownership are approximately 5.338 percent more productive than firms without common ownership. Additionally, the effect is homogeneous across different common owners, as the GGL measure already accounts for differences in attention levels among types of common owners.

In the second part of the chapter, I investigate channels through which common owners improve productivity: increasing the efficiency of existing assets, reallocating capitals, and closing establishments. First, I consider whether firms increase asset efficiency by firing employees. Managers can hire more employees than necessary to entrench themselves. Being unable to evaluate the appropriate level of inputs for specific jobs could also result in redundant employees. Thus, employee reduction can diminish management slack, reduce redundant investments, and improve the internal capital market (Davis et al., 2014; Li, 2013).

Second, I investigate whether common owners improve productivity by reallocating employment within the firm. I first consider the industry focus of establishments within a firm. While most of the main activities and resources are concentrated in core establishments, peripheral establishments – operations outside the main business of the firm – may emerge to serve managers' obscure purposes such as managerial entrenchment and empire building (Gompers, 1996; Williamson, 1964). Unnecessary peripheral units may also result from the shortage of managers' experience (Scharfstein & Stein, 2000). Similarly, I examine the importance of establishment productivity. Unmonitored managers may be slow to fire employees at underperforming establishments at the expense of firm value, while not providing sufficient employees to achieve profit optimization at productive establishments (Bertrand & Mullainathan, 2003). Thus, reducing unnecessary employees in peripheral and unproductive establishments can reduce production expenses. On the other hand, providing more employees at the core and productive establishments push the productions to achieve the profitability optimization level (Maksimovic & Phillips, 2002).

Third, I investigate whether common owners accelerate shutting down unnecessary peripheral and unproductive establishments to increase firm aggregate productivity. Maksimovic, Phillips, and Prabhala (2011) study firm boundaries after acquisitions and find that acquirers implement an extensive restructuring by selling nearly one-third and close 20% of the target's plants within three years after transferring ownership. Maksimovic and Phillips (2002) show that firms focus on their core business and sell out peripheral units when the prospects of their core business improve significantly. They also can selectively shut down underperforming plants (Brav et al., 2015; Davis et al., 2014; Kaplan, 1989; Muscarella & Vetsuypens, 1990). Thus, common owners can force managers to shut down establishments.

To investigate these channels, I merge the matched firm-level sample with establishment-level data from the National Establishment Time-Series (NETS) database for U.S. firms. Overall, I find no significant employment changes at the aggregate firm-level after firms have a common ownership structure. Common owners also do not force managers to shut down unproductive and peripheral establishments. However, common owners are likely to induce the employment layoff at peripheral and unproductive establishments while hiring more employees in the core and productive units. These results indicate that common owners shift management attention and resources to where they can deliver the most value to the firm. I also find that common ownership negatively affects the number of establishments in diversified firms – operate across multiple industry segments, suggesting that common owners tend to concentrate managerial efforts on large segments to optimize the comparative advantage of organizational skill (Maksimovic & Phillips, 2002).

Although I am interested in the effect of common ownership on productivity, firms with high production efficiency could also attract more institutional investors. Particularly, highly productive firms in the previous year are more likely to be productive in this year again as experience allows producers to identify opportunities for process improvement (Benkard, 2000). Institutional investors who target high-performance firms thus could acquire blocks of shares in all productive firms within the same industry, raising the reverse causality concerns. In addition, unobservable firm characteristics such as investment opportunities in improving general labor and capital inputs could affect the likelihood of common ownership and, at the same time, determine production efficiency for commonly owned firms, resulting in a spurious correlation between the two.

To address these potential endogeneity biases, I first use firm fixed effects in my panel regressions to remove potential bias arising from time-invariant omitted firm characteristics. Second, to overcome the reverse causality issue, I implement a difference-in-differences (DiD) analysis around the first year that firms have common ownership (included in the fifth quintile) by employing the propensity score matching technique. A short window (two years) reduces concerns relating to reverse causality and allows better control for the impact of unobserved variables as significant changes in those variables are less likely to happen during a short window. My results are robust to controlling for these endogeneity problems. To control for the possibility that firms may reallocate resources before the common ownership inclusion, I employ the same DiD setting and examine these possibilities in the first year that firms have common ownership at the establishment level. The results show that common owners are more likely to induce employment layoff across all establishments in the first year, suggesting a widespread approach of employee reduction from common owners.

This study is the first in the burgeoning literature on common ownership to trace the sources of value creation to the fundamental production process. My establishment-level analysis deepens our understanding of the role of common ownership in improving firm performance. The finding has linkages to the literature investigating the effects of ownership changes on firm performance. For instance, studies on asset sales show that acquirers improve asset productivity using their specific skills to explore the value of acquired resources (Maksimovic & Phillips, 2001, 2002; Warusawitharana, 2008). Empirical studies on takeovers also emphasize the important role of the acquirer by showing that target firms experience a significant improvement in productivity immediately after the acquisitions (Devos, Kadapakkam, & Krishnamurthy, 2009; Li, 2013; Maksimovic et al., 2011). Consistently, research on private equity transactions records an increase in productivity mainly through closing less productive establishments and building more productive units.

This study also adds to the stream of literature examining the real effects of monitoring by informed outside shareholders such as large concentrated institutional investors (Becker et al., 2011; Clifford & Lindsey, 2016), mutual funds (Appel et al., 2016), and activist hedge funds (Brav et al., 2015; Brav et al., 2008). Common owners with high monitoring incentives and industry knowledge are also expectedly effective monitoring shareholders. Further study could study on the spillover effect of common ownership on non-commonly owned firms in the same industry. Specifically, the improvement in performance and market share of commonly owned firms may take the business away from other industry peers, thus suggesting a possibility that non-commonly owned firms will push productivity to catch up with their existing performance level.

2.2. Literature review

In this study, I attempt to address two questions: (1) Does common ownership improve production efficiency? (2) If yes, how does common ownership create such productivity gains? This section reviews the prior literature on these two questions and develops hypotheses to guide the empirical analysis.

2.2.1. Common ownership

Large institutional investors have substantially increased shares in public U.S. firms over the past three decades (Choi et al., 2017; Grullon et al., 2019). Highly diversified mutual fund families and other institutional investors now hold up to 75% equity in publicly traded firms (Ben-David et al., 2021). The ownership has become even more concentrated in the hands of a few very large financial institutions (Davis, 2013).[2] As a result, natural competitors in an industry are increasingly (partial) owned by the same large institution, i.e., common ownership. According to (He & Huang, 2017), nearly 60% of U.S. public firms have the same institutional blockholders with their industry competitors.

Besides the substantial capital growth, there exist other reasons why institutional investors concentrate more ownership in some specific industries. First, common ownership offers institutional investors benefits from the information advantage by simultaneously holding many same-industry firms (Kacperczyk, Sialm, & Zheng, 2005) and combined portfolio profits (to be discussed in following subsections). The benefits expectedly exceed the costs of reduced portfolio diversification caused by the ownership concentration (Demsetz & Lehn, 1985; Zingales, 1994). Further, institutional investors likely invest in competing firms based on their stock-picking skill. (Kacperczyk et al., 2005) investigate the industry concentration of mutual fund and show that funds with more skilled managers are highly associated with a concentrated portfolio. The managers also make decisions based on the belief that some industries will outperform the overall market (Moskowitz & Grinblatt, 1999) or based on the superior information of specific stocks in specific industries (Merton, 1987; Van Nieuwerburgh & Veldkamp, 2009, 2010). However, other investors may invest in two firms within an industry simply because they are in the same index such as the S&P 500 or the Russell 1000 and 2000 indexes (Gilje et al., 2020).

Given the substantial increase of common ownership structure over the past few decades, abundant of studies have investigated its effects on (i) product market competition, (ii) firm activities, and (iii) monitoring role of common institutional investors.

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[2] For example, (Davis, 2013) shows that BlackRock, one of the world's largest asset management companies, are blockholders of more than 1,800 US corporations in 2011. The number accounts for more than 40% of the total nearly 4,300 listed firms in the United States. In one fifth of the cases, Blackrock was the "single largest shareholder" of the firms, frequently consisting of the largest competitors within an industry (also see in (Fichtner, Heemskerk, & Garcia-Bernardo, 2017). Similar results are found for top asset management funds such as Fidelity, Vanguard, and Dimensional Fund Advisors.

2.2.1.1. Product market competition

The impacts of partial common ownership on product market outcome have been rooted to the rich literature on imperfect competition (Bresnahan & Salop, 1986; Hart & Moore, 1990) and shareholder preference aggregation (Azar, 2012, 2017). It suggests that partial common ownership reduces competition among commonly owned firms in the same industry. The aggressive competition allows a firm to acquire more benefits from the market; however, it creates proportional losses to peer firms within an industry in return. Therefore, to maximize joint portfolio profits, institutional investors with multiple block holdings attempt to optimize outcomes of all firms in their portfolios by alleviating such competition (Hansen & Lott, 1996).

Azar et al. (2018) investigate the effect of common ownership concentration, measured by modified Herfindahl-Hirschman Index (MHHI) in O'brien & Salop (1999), on product price in the airline industry. They find that firms with more concentration offer higher ticket prices and lower outputs, creating a decrease in economic efficiency. Azar et al. (2022) also apply the MHHI measure and find a consistent result for the banking industry. However, O'Brien & Waehrer (2016) and Dennis, Gerardi, & Schenone (2022) argue that the MHHI is an endogenous measure of concentration that depends on both common ownership and market shares. There exists another factor which impacts both ticket price and the MHHI. Therefore, it is unable to conclude the effect of the MHHI on flight ticket prices. In line with O'Brien & Waehrer (2016) and Dennis et al. (2022), Gramlich & Grundl (2017) examine the effect of common ownership for the banking industry by directly analyzing the weights that firms place on each other's profits. The results are mixed and economically quite small, contrasting to the findings by (Azar et al., 2022).

Bindal & Nordlund (2022) extends the research to entire U.S. markets and finds that the effects are found only in industries with similar products.[3] The findings are based on the arguments that firms with well-differentiated products do not engage in the competition even before being common owned thanks to their own monopoly profits. In contrast, firms with similar products must compete to gain market share. Therefore, common owners are more likely to eliminate the competitiveness among firms with similar products (Semov, 2017). Firms also compete less on quality and feature, thus become less innovative with lower research and development (R&D) expenditure. However, Koch, Panayides, & Thomas (2021) implement very comprehensive research to re-exam the effects of common ownership to product market competition. They find no anticompetitive effects on both price and non-price measures regardless of industry

[3] The product similarity is measured based on the total similarity score developed by Hoberg and Phillips (2016).

classification choice, common ownership and profitability measures, non-price competition proxy, or model specification.

In short, the existing studies show little support to the convention wisdom that common ownership may reduce the competition among portfolio firms within an industry to maximize the combined portfolio profits.

2.2.1.2. Firm strategic alliances and innovation

In the broad context of common ownership, recent studies also research the influence of common institutional investors on management decisions and corporate activities of portfolio firms within an industry, such as mutual-firm collaboration (Chemmanur, Shen, & Xie, 2016; He & Huang, 2017), investment decisions (Brooks, Chen, & Zeng, 2018; Matvos & Ostrovsky, 2008), financial policies (Massa & Žaldokas, 2017),[4] and voluntary disclosure (Park et al., 2019). For this chapter, I will provide a review of firm collaboration and innovation in this part.

In the case of firm collaboration, He & Huang (2017) study the effects of common ownership on product market performance and find that commonly owned firms experience a significantly higher market share growth, measured by firm sales divided by the same four-digit SIC industry's total sales in a year than do non-commonly owned firms. They attribute the growth in firm market shares mainly to the potential coordination among common owned firms. There is a substantial increase in the number of explicit collaborations (strategic alliances, joint venture, or even entire acquisitions) among same industry firms after they have common institutional investors. Moreover, these firms also obtain higher innovation productivity and operating profit margin. The findings suggest that common owned firms may coordinate on their innovation activities (sharing technologies and R&D resources) and product market strategies implicitly (collective bargaining against suppliers to reduce production and distribution costs or cutting marketing plans against each other).

They provide two fundamental reasons for the possible collaborations. First, common owners reduce the risk of being expropriated from incomplete collaboration contract (Asker & Ljungqvist, 2010; Klein, Crawford, & Alchian, 1978; Williamson, 1985). To maximize the combined value, institutional investors may align the incentives of contracting parties and eliminate the frictions related to incomplete contracts. Second, firms naturally intend to conceal their proprietary information from their competitors (Easterbrook & Fischel, 1981; Hansen & Lott,

[4] Also by Semov (2017), Ni & Yin (2021).

1996; Rubin, 2006), reducing the optimization of collaborations. By seating on the board of both contracting parties, common institutional investors can moderate information asymmetry among them and promote a profitable collaboration.

Consistently, Chemmanur et al. (2016) study the role of common ownership in forming strategic alliances and find that firms participate in more strategic alliances when they share common institutional owners with other industry peers. More important, R&D related alliances formed among common owned firms are positively associated with higher qualitative patents filed.[5] The enhanced innovation mainly derives from the efficient reallocation of human capital (inventors) among alliance partners. Further, common owned firms likely share patent rights through alliance partnership. In particular, the number of new co-patenting patents among common owned firms are strongly associated with the number of R&D-related strategic alliances they form with each other. Consistently, Kostovetsky & Manconi (2018) find a high degree of cross patent citations among common owned firms. By ex-ante being aware of other's research, common owned firms can avoid overlapping innovation and collaborate in co-patenting more efficiently.[6] Aslan (2019) studies the effect of common ownership at product level in consumer goods industry and shows that common owned firms introduce new products at a faster pace and discontinue existing products at a similar rate as non-common owned firms, suggesting innovation benefits from common ownership through information sharing and effective R&D related strategic alliances, in line with Kostovetsky & Manconi (2018) and Chemmanur et al. (2016).

A variety of other research also directly investigates the impact of common ownership on firm innovation itself. For instance, Anton, Ederer, Gine, & Schmalz (2022) investigate how common ownership affects innovation of portfolio firms and find that common ownership stimulates innovation when co-owned firms are close in technology space and the technological spill-over effects can benefit numerous firms. However, when co-owned firms are closer in product space, innovation is distorted, because the innovation of one firm will take business away from other firms. This result is consistent with Bindal & Nordlund (2022) and Semov (2017) that common owners reduce the competitiveness among firms with similar products by discouraging innovation. Aghion, Van Reenen, & Zingales (2013) find that common ownership encourages managers to innovate by reducing the career risk from risky projects. Geng, Hau, & Lai (2016) show that common ownership alleviates holdup problems when one firm afraid of giving another

[5] Other common forms of strategic alliances include marketing, manufacturing, and license alliances.

[6] Kostovetsky & Manconi (2018) indicate that common owners transfer information of new innovation from firm to firm in the shareholder meetings, through their equity analysts who cover both firms, and through portfolio managers in informal communications with firm managements Goldstein (2011).

firm more bargaining power which reduce their own profits (Hart & Moore, 1990). By easing bargaining among industry peers, firm focus on developing its own innovation. Eventually, it generates higher margins of patent production.

In sum, common ownership fosters the coordination among industry peers with more strategic alliances. R&D related alliances formed among common owned firms are associated with higher innovation outcomes and innovation diffusion through co-patenting and cross patent citations. Besides, common ownership can impact firm innovation directly through other channels.

2.2.1.3. Effects of common ownership on governance

Prior studies have shown that common ownership strengthens governance through both exit and voice channels. Under voice channel, common ownership increases common owners' incentive to monitor for numerous reasons. First, holding multiple firms allows common owners to retain monitored firms upon their small liquidity shocks because they can sell less monitored firms (Edmans et al., 2019), mitigating loss if they cut and run – assume that firm value ties with investor's monitoring decision. Second, by simultaneously monitoring multiple same-industry firms, common owners gradually gain valuable governance experience and industry knowledge, allowing them to make more effective governance interventions (He et al., 2019; Kang et al., 2018). Third, concurrently monitoring multiple firms reduces monitoring costs compared to monitoring a single firm (He et al., 2019). Strengthening governance in one firm reduces job externalities for managers in other commonly owned firms, thus inducing them to work harder to maintain current jobs. This market-based mechanism ensures that managers will not move from firms with strong governance to firms with weak governance to reap private benefits (Acharya & Volpin, 2010).

Common owners can induce managers' effort through the threat of exit. Edmans et al. (2019) theoretically prove that common owners sell bad firms first upon their small private liquidity shocks – rather than scaling down their existing portfolio in proportion (consistent with (Berndt & Gupta, 2009; Huang, Ringgenberg, & Zhang, 2017; Maksimovic & Phillips, 2001). Like blockholders, common owners are considered better informed about firm performance than other types of investors (Wermers, 1999, 2000). In addition, holding multiple firms gives them a choice of which stocks to sell upon their shocks. Thus, stock selling by common owners is not purely driven by the shocks but also reflects the firm future returns (Brown & Brooke, 1993; Sias, Starks, & Titman, 2001). These stock sales consequently affect firm stock price and corporate decisions by conveying negative information (Hotchkiss & Strickland, 2003; Scholes, 1972). Managers – in concerns with short-term security price, firm's reputation in debt markets, and his or her interests associated with the firm – will pay more attention to common owners' preferences and induce effort ex-ante (Admati & Pfleiderer, 2009; Edmans, 2009).

2.2.2. Changes in ownership structure and firm productivity

Ownership structure has significant impacts on firm activities. This part will review the effect of change in ownership structure on productivity gains. Existing studies on this effect includes research about asset sales, mergers and acquisitions, private equity (PE) transactions, and hedge fund activism.

2.2.2.1. Asset sales

According to Warusawitharana (2008), almost $100 billion worth of assets were traded in 2004. The business creates the net gains of approximately $162 billion for both sellers and buyers from 1985 to 2008, suggesting an efficiency improvement in capital allocation for the economy. Warusawitharana (2008) investigates the determinants of asset sales and how they improve production efficiency. The results indicate that firms participate in asset sales, such as product lines, plants, subsidiaries, etc., to achieve its optimal size which varies with profitability, consistent with Maksimovic & Phillips (2002). Highly profitable firms engage in asset purchases to increase profitability up to an optimal size. Contrastingly, less profitable firms find it optimal to reduce sizes and sell existing assets. However, the number of assets bought or sold depends on the asset transaction costs. Specifically, the marginal benefits (costs) of the transactions must equal to a firm's marginal value of inside capital (Gomes & Livdan, 2004; Hennessy & Whited, 2007).

Maksimovic & Phillips (2001) investigate the productivity gains from selling partial-firm assets, plants, and divisions, using U.S plant-level data for manufacturing firms. They find that most of the asset sale transaction create productivity gains, which mainly derive from the acquirers' high initial productivity, suggesting that the buying firms can employ their skills to increase the capability of acquired assets. Consistently, Jovanovic & Rousseau (2002) research firm decisions in asset sales and find that firms are more likely to sell less productive plants and divisions (Harford, 2005; Rhodes–Kropf, Robinson, & Viswanathan, 2005).

On the other hand, Maksimovic & Phillips (2002) develop a specific model to predict the time and direction of the sale. They show that firms focus on their core business and sell out peripheral units when the prospects of their core business improve significantly. Besides, assets in peripheral plants are sold more often than ones in main functions when the market experiences positive demand shocks. Yang (2008) employs the neoclassical model to observe the effects of productivity changes by shock on asset sales. The findings indicate that firms are likely to invest in new assets when the improvement in productivity results from market aggregate shock. Whereas firms buy assets from other firms if the rise of productivity comes from firm-specific shocks (Mitchell & Mulherin, 1996). Besides, Eisfeldt & Rampini (2006) shows that firms make decisions based on the investment needs of not only itself but also of all other firms in the industry, in line with Gort (1969) and Maksimovic & Phillips (2002).

In short, assets sales are mainly derived by firm value-maximizing investment decision and market demand shock. Most of the asset sale transaction create productivity gains which mainly derive from the acquirers' high initial productivity, suggesting that the buying firms can employ their skills to increase the capability of acquired assets. Moreover, firms are more likely to sell less productive and peripheral plants, especially during market shock. It indicates that the market for asset sales facilitates the reallocations of assets from low to highly capable firms.

2.2.2.2. Mergers and acquisitions

Mergers and acquisitions are other types of assets sells in which target firms experience a change in management and shareholder ownership. Literature documents a series of actions taken after the takeovers, which may affect productivity. Maksimovic et al. (2011) study how firms redraw their boundaries after acquisitions. They find that acquirers implement an extensive restructuring in a short period of time following the entire acquisitions. Acquirers sell nearly one third and close 20% of the target's plants within three years after transferring ownership. Acquirers retain peripheral plants on which they have experience and successfully turn it into productivity. Whereas Devos et al. (2009) show that acquirers create value from the operating synergies by cutting investment expenditures rather than by increasing operating profits. In short, they suggest that takeovers generate gains by efficiently reallocating resource in acquired firms.

In term of productivity, Maksimovic, Phillips, & Yang (2013) compare the productivity gains of takeovers by public and private firms around the merger wave. They find that public firms are more likely to participate in merger waves and create higher gains in productivity thanks to better access to the capital market. Maksimovic & Phillips (2001), on the other hand, show that acquirers improve target's productivity after the acquisitions when they are more productive than the target. Consistently, Schoar (2002) shows that acquired plants increase productivity when the acquisition is more diversifying and productive. However, while the acquired plants increase productivity, the incumbent plants suffer.

Li (2013) investigates the precise mechanism by which takeovers create value at the establishment level and find that acquirers improve targets' productivity (measured by total factor productivity, TFP) through improving the efficiency of capital and labor employments. They reduce the inputs including capital expenditures, wages, and employment in target plants while keeping outputs constant. Besides, non-productive workers are more likely to be laid off, supporting the hypothesis that acquirers employ their own knowledge to improve targets' governance through diminishing management slack. Moreover, conglomerate acquirers with existing active internal capital market appear to be an effective buyer in improving targets' investment efficiency. The targets' capital is reallocated to industries with better investment opportunities after the acquisitions, consistent with Stein (1997) and Maksimovic & Phillips (2007, 2008).

2.2.2.3. Private equity transactions

Private equity transactions cause changes in corporate ownership, happening at late development stage before firms go publicly. Few studies have been done in concentration on the effects of private equity transactions on firm productivity. The most comprehensive research was done by (Davis et al., 2014). They find that employment and wage decrease sharply after the buyouts. The findings reflect a higher rate of job destruction at shrinking and exiting establishments. However, targets create a significant number of employments at expanding establishments. Productivity also records an increase mainly through closing less productive establishments and building more productive units. The results are consistent with Kaplan (1989) and Muscarella & Vetsuypens (1990) who track the effects of private equity transactions in a small sample of 26 firms.

2.2.2.4. Hedge fund activism

Hedge fund activism is a form of governance intervention from outside shareholders. Different from mutual funds and pension funds, hedge funds can hold a large, concentrated ownership in a small number of firms since they are less restricted by the regulation. Thus, hedge funds are observed to be more effective monitors and have an active intervention to targeted firms. Hedge funds typically target value firms with low market value but relatively strong business fundamentals, potentially subject to agency problems of free cash flows. After the acquisition of a significant number of shares, hedge funds propose new business strategies such as refocusing and spinning-off noncore assets, which raises firm operating performance. Brav et al. (2008) find that the market reacts positively to the announcements of hedge fund activism, indicating the ability to create values of hedge funds when they see large allocative inefficiencies. Brav et al. (2015) further investigate the long-term effect of hedge fund activism at plant-level productivity. They find that firms improve productivity by selling unproductive plants and reducing employees' wages and work hours. The results are consistent with prior findings that hedge fund activists add value by offering effective business strategies, especially on capital redeployment. However, there is limited evidence on the effects from other intervention purposes of hedge fund activism such as capital structure or governance-related activism.

2.3. Hypothesis development

2.3.1. Effects of common ownership on productivity

As discussed above, common ownership increases the monitoring incentive of common owners by providing them with fertile industry knowledge and abilities to retain monitored firms upon their shocks. Managers also consider common owners' preferences in proportion to their ownership stakes in the firm and other industry peers. Empirical studies show that common owners indeed perform shareholder governance activities such as forced CEO turnover decisions based on performance (Kang et al., 2018) and close-call votes on shareholder-sponsored governance proposals (He et al., 2019). The market reacts favorably around the announcement of these interventions. Additionally, commonly owned firms have higher Tobin-Q than non-commonly owned firms (Kang et al., 2018). These findings suggest that common owners effectively monitor firm managers, which possibly results in higher firm value (Boyson & Mooradian, 2012; Hirshleifer & Thakor, 1994; Shleifer & Vishny, 1986).

Improved firm performance, on the other hand, is positively associated with higher productivity. Palia & Lichtenberg (1999) find a positive relationship between increased firm value (measured by Tobin-Q) and firm productivity. In addition, the market rewards firms with increases in firm value when they increase their productivity level. Given that prior literature has established a link between common ownership and increased firm value and market valuation, one might expect that common ownership would also positively affect the underlying determinant of firm value, namely, productivity. Thus, the first hypothesis examines whether common ownership is associated with higher productivity:

H1: Common ownership positively affects firm productivity.

2.3.2. Sources of efficiency gains

I further investigate potential mechanisms underlying the efficiency gains in commonly owned firms. Productivity can improve by increasing the efficiency of existing assets, capital reallocation, and establishment closure.

2.3.2.1. Increasing efficiency of existing assets

Firms can increase productivity by improving the efficiency of existing assets in two ways. First, firms increase asset capacity, thus producing more output given the same level of input. To do so, firms must increase labor skills (measured by higher wages) or upgrade machines, which is costly as it requires significant investment and skills from common owners (Maksimovic & Phillips, 2001).

On the other hand, firms can increase asset efficiency by reducing the input needed to produce a given output. In the absence of shareholder oversight, managers can allocate resources inefficiently (Jensen & Meckling, 1976; Shleifer & Vishny, 1997; Stein, 2003). Suppose that managers cannot directly expropriate resources but can choose not to pay dividends to investors. If no profitable project exists, managers will make suboptimal investments (opportunism), gaining some private benefits but wasting resources (Jensen, 1986). Increasing firm employment is one of the easy suboptimal investments that managers can make to distract shareholders. It is possible for managers to hire more employees than necessary to perform a job. Unable to evaluate the appropriate level of inputs for specific jobs could result in redundant employees. Thus, employment reductions can reduce redundant investments and improve the internal capital market. Li (2013) finds that acquirers increase targets' productivity by reducing capital expenditures, wages, and employment while maintaining outputs. Payroll reductions account for 70% of productivity gains, while capital expenditures and material costs account for 30%. Davis et al. (2014) find that employment and wages fall sharply after buyouts. The findings reflect a higher rate of job destruction at shrinking and closing establishments. So, I hypothesize that common institutional owners will boost productivity by requiring managers to reduce unproductive employees.

H2: Common ownership negatively affects the number of employees.

2.3.2.2. Reallocating capital resources

Firms can also improve productivity by reallocating capital resources among establishments. I first consider the industry focus of establishments within a firm, so-called core establishments, and peripheral establishments – operating units outside the firm's main scope. While most of the main business and resources are concentrated in core establishments, peripheral establishments are established to serve obscure purposes. Gompers (1996) studies discretionary management behavior and shows that management entrenchment and empire-building can lead to more peripheral establishments (in line with Williamson (1964)). In addition, inexperienced managers may open and manage inefficient non-core units (Scharfstein & Stein, 2000). Thus, better monitoring should reduce bad management practices. Common ownership also provides common owners with industry expertise, which may help managers allocate business resources more efficiently. For example, conglomerate acquirers with active internal capital markets appear to be efficient buyers. Following the acquisitions, the targets' capital is reallocated to industries with better investment opportunities (Maksimovic & Phillips, 2007, 2008; Stein, 1997). Thus, it is conjectured that firms will redeploy their resources (employment) after sharing the same institutional owners with other industry peers. In line with this reasoning, I hypothesize that:

H3: Common ownership reduces the number of employees at peripheral establishments and increases the number of employees at core establishments.

Second, I examine the capital reallocation among productive and non-productive establishments after firms have a common ownership structure. Studies on management behavior indicate that managers may be slow to fire employees at underperforming establishments at the expense of firm value (Bertrand & Mullainathan, 2003). Therefore, intensive monitoring from common owners may force managers to pay more attention to employee recruitment and termination. Besides, non-productive workers are more likely to be laid off, supporting the hypothesis that acquirers employ their knowledge to improve targets' governance through diminishing management slack. Based on this argument, I hypothesize that:

H4: Common ownership reduces the number of employees at unproductive establishments and increases the number of employees at productive establishments.

2.3.2.3. Establishment closure

Firms can improve productivity through aggressive plant closures. Maksimovic & Phillips (2001) found that three years after acquiring a target, acquirers sell nearly one-third of the target's plants and close 20% of them. Acquirers keep peripheral plants they know well and turn them into productive assets. Maksimovic & Phillips (2002) create a model to predict sale timing and direction. They show firms focusing on core business and selling off peripheral units when core business prospects improve. They can also disable underperforming plants. Davis et al. (2014) found that firms gain significant productivity after a private equity transaction by closing less productive units and establishing more highly productive ones. The results are consistent with Kaplan (1989) and Muscarella & Vetsuypens (1990), who track the effects of private equity transactions in a small sample of 26 firms. By selling unproductive plants and reducing employee wages and hours, Brav et al. (2015) find that hedge funds increase target productivity. Thus, I hypothesize that:

H5: Common ownership leads to peripheral and unproductive establishment closure.

2.4. Sample selection and variable construction

I examine the effects of common ownership on productivity by constructing my sample from several databases for U.S. firms during the period 1990 – 2015[7]: (i) firm-level data and financial statement items from CRSP and Compustat; (ii) establishment-level data from the National Establishment Time-Series (NETS) database; (iii) quarterly institutional holding data from Thomson Financial's 13F database; (iv) investor activism data from Schedule 13D filings to the U.S. Securities and Exchange Commission (SEC).

2.4.1. Establishment data

I collect the data to compute productivity for each establishment of U.S. firms from the NETS micro-level database, provided by Dun and Bradstreet (D&B) credit rating agency and maintained by Walls Associates (see Walls (2008)). D&B collects comprehensive information of more than 44 million unique U.S. businesses, non-profit and governance establishments, and sole proprietors on various economic aspects such as business establishment, annual sales growth performance, employment, reallocation information. D&B also obtains information directly from independent sources, including secretaries of state, phone calls for credit inquiries, legal and bankruptcy filings, press reports, and court records (Addoum, Ng, & Ortiz-Bobea, 2020; Ljungqvist, Zhang, & Zuo, 2017).

[7] My sample period is constrained by the availability of the NETS database

The NETS database assigns a unique identifier for each establishment that is constant over time regardless of its reallocation or ownership status. It enables me to trace the information on the number of employees and annual sales of each establishment from the foundation year's latest active year during the testing period. The database also offers industry classification based on both primary and secondary SIC codes, which allows me to identify a particular establishment's business concentration, i.e., to classify an establishment as a core or peripheral unit. I match establishment data from the NETS database with firm-level data from Compustat and the Center for Research in Security Prices (CRSP) by carefully matching their historical legal names following Huynh & Xia (2021). To obtain the final sample, I exclude financial firms with SIC codes in 6000-6999 and include only common stocks with CRSP share codes of 10 and 11 as standard in the literature.

2.4.2. Common ownership data

I obtain the data on institutional holdings mainly from Refinitiv (formerly known as Thomson Reuters). For the period from 1990 to March 2013, I collect data from the Refinitiv 13F Institutional Holdings dataset and supplement missing information with raw data from EDGAR's 13F filings. Since 2010, Refinitiv's legacy systems, which generate Mutual Fund and 13F ownership data, began losing and corrupting data.[8] WRDS worked with Refinitiv to correct the data deficiencies and incorporate them into the WRDS SEC Analytics Suite – 13F Holding's dataset. Therefore, I rely on this data source for the June 2013 – 2015 period.

I clean the data following several criteria. First, I filter out cases where a manager reports multiple positions in the same stock on the same report date and use only the holdings with the latest filing date. Second, I identify the ten largest institutions each year using the 13F data on total assets under management. Refinitiv records institutional holdings at the institution level.[9] For each of these institutions, I check for missing quarters – quarters in which the institution should own shares, but Refinitiv does not show it – and supplement them using the raw 13F data provided on EDGAR.[10] Additionally, I confirm that the holdings of these ten largest institutions are consistent between the Refinitiv Institutional 13F Holdings dataset and the WRDS SEC Analytics Suite –

[8] See information on the WRDS website regarding problems of this data in the recent years: https://wrds-www.wharton.upenn.edu/pages/support/research-wrds/research-guides/research-note-regarding-thomson-reuters-ownership-data-issues/.

[9] Refinitiv reports the ownership for the holdings typically above 10,000 shares or $200,000 and excludes cases which are potential confidentiality issues, unmatched to a master security file, and have more than one manager share control.

[10] As discussed in Lowry, Rossi, & Zhu (2019), EDGAR only contains 13F filings for 1999 and later, thus restricting this process to this period. This step led to the data supplement of Barclay in 2003Q4, AXA in 2003Q4, Mellon in 2008Q4, JP Morgan in 2008Q3, and Blackrock in 2010Q1 and Q2.

13F Holdings dataset for the matching year of 2013. This step ensures that no significant change in holdings occurs between the end of the Thomson data and the start of the WRDS data. For institutions not included in the top ten largest, holdings are carried forward one quarter in cases where the institution misses a reporting period to make up for reporting gaps (Griffin & Xu, 2009).

Third, I aggregate institutional holdings at the fund-family level to match the institutional feature of voting and governance among member funds following Azar et al. (2018). The aggregation ensures that the incentives of all members in a fund family are consistent and align with their investors' incentives.[11] Forth, I compute each manager's holdings in a firm by aggregating holdings of that manager in all stocks with the same six-digit CUSIP. Last, institutional investors are defined as block-holders if they hold at least 5% of firm outstanding shares. An institutional investor is considered as a common owner when it simultaneously holds blocks of shares in more than one firm in the same three-digit SIC codes from CRSP (following Lewellen & Lowry (2021) at a given point in time (as defined by He & Huang (2017)).

2.4.3. Common ownership measure

To quantify the effects of common ownership on managerial incentives and firm performance, I employ the newly developed common ownership measure of Gilje et al. (2020). The measurement begins at the firm-pair level, i.e., between each pair of rival firms. I form a product of three components: a firm's proportion in a common owner's portfolio, that common owner's stakes in that firm and in a rival firm. Then, I aggregate the products across all common owners between two firms. In the second step, I construct a firm-level measure by aggregating the firm-pair measures across all rivals of a firm. In particular, the firm-level common ownership measure, GGL, is measured using the following equation:

$$GGL_j = \sum_{k=1}^{K} \sum_{i=1}^{N} \beta_{i,j} * \alpha_{i,j} * \alpha_{i,k} \quad (2.1)$$

where $\beta_{i,j}$ represents the proportion of firm j in common owner i's portfolio, and $\alpha_{i,j}$ and $\alpha_{i,k}$ represent owner i's ownership percentages in each firm. I compute the ownership percentages using blockholdings only since blockholders have feasible channels to affect managers' utility (via voting, stock selling, or negative public statements). The proportion of firm j in common owner i's portfolio is computed as $\alpha_{i,j}\bar{\upsilon}_j/(Y_i + \sum_{m=1}^{M} \alpha_{i,m}\bar{\upsilon}_m)$, where M is the number of firms in common owner i's portfolio; $\bar{\upsilon}$ is firm market value; and $Y_i \geq 0$ captures non-traded assets, T-bills, or any

[11] These family funds include Fidelity, Invesco, Capital Research, Merrilyn, and Blackrock

other assets of common owner i. Thus, $\beta_{i,j}$ measures the weight of firm j in the portfolio of investor i. GGL is first computed using quarterly data and then averaged across four quarters in a fiscal year to get the annual measure.

This measure accounts for three factors. The first factor, common owners' stake in a firm, accounts for the extent to which the firm's managers care about those common owners' preferences. The managers' attention increases or decreases proportionally to the common owner's stake in the firm. The second factor, common owner's stakes in rival firms, captures common owners' knowledge gained by owning other firms in the same industry. The last factor measures how attentive common owners allocate across their portfolio firms. A firm representing a large (small) share in the portfolio gets proportionally more (less) attention from those common owners.

A key feature of this measure is the relaxation of the assumption that all common owners are fully attentive to managers' actions or assuming $\beta = 1$ when constructing the GGL measure. By relaxing this assumption, common owners' attention towards managers' incentive to improve firm value is proportional to the weight of that firm in the common owners' portfolio. Thus, less attentive investors will not shift managerial efforts toward better firm performance. This construction also accounts for the possibility that common owners formed through institution mergers and index investing are less attentive to manager performance in some specific firms. The less importance in common owners' portfolio, small β, can explain the insignificant effects of common ownership formed through mergers and index investing on firm performance in prior studies. For example, Lewellen & Lowry (2021) find no evidence on improved firm performance following exogenous shocks to common ownership: institution mergers, index additions and reconstitutions. Their findings could result from the fact that they did not control the relative importance of these firms in the common owner's portfolio after these events.

The primary advantage of this measure over He & Huang's (2017) and Lewellen & Lowry's (2021) measures is that it is not predicated on the assumption that all investors are fully attentive to managers' actions. Thus, common owners pay attention to manager performance in proportion to the firm's importance in the portfolio of common owners. Moreover, combining three factors facilitate the comparison of common ownership effects across firms.

2.4.4. Productivity measure

To measure firm productivity, I consider the Cobb-Douglas production function:

$$Y_{it} = A_{it}(\tau)L_{it}^{\beta_l}K_{it}^{\beta_k} \qquad (2.2)$$

where output in firm i at time t, Y_{it}, is a function of labor, L_{it}, and capital, K_{it}. I am interested in assessing whether the productivity of firm i is a function of common ownership, denoted by τ. In the first step, I estimate firm-level productivity, and in the second step, I specify how common ownership can affect productivity.

Taking the natural logs of Equation 2.2, which I denote by small letters, I estimate

$$y_{it} = \beta_o + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \, (2.3)$$

The dependent variable, y_{it}, is the log of value-added for firm i in period t; l_{it} and k_{it} are log values of labor and capital of the firm, respectively; ω_{it} is the productivity; and η_{it} is an error term, which is not known by both firm and econometrician, thus not affecting the firm's decision making. I employ the semiparametric procedure developed by Olley & Pakes (1996) to estimate Equation 2.3. The procedure is conducted following İmrohoroğlu & Tüzel (2014). The major advantage of this approach over more traditional estimation techniques such as ordinary least squares (OLS) is its ability to control for simultaneity between input choices and productivity shocks, as well as selection bias. The detail of variable construction and parameter estimation is explained in Appendix 2. Using these estimates, I define the log of measured productivity for firm i at time t, denoted by ω_{it}, as

$$\omega_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \qquad (2.4)$$

In the estimation, I use industry-specific time dummies to control for the effect of industry and aggregate productivity in any given year. To avoid a potential look-ahead bias in the productivity estimates, the production function parameters are estimated every year using all available data up until that year. I compute productivity for each year between 1990 and 2015 using that year's data and the corresponding production function estimates for that year. The estimates for $\hat{\beta}_l$ and $\hat{\beta}_k$ are relatively stable over the years: $\hat{\beta}_l$ ranges from 0.678 to 0.743, and $\hat{\beta}_k$ ranges from 0.297 to 0.356, comparable with those of İmrohoroğlu & Tüzel (2014). The productivity ω_{it} captures variations in output not explained by shifts in the observable inputs (like labour and capital). In this case, I want to measure whether productivity ω_{it} is driven by unmeasured input variations, namely common ownership.

In the second stage, I specify the possible link between common ownership and firm-level productivity by estimating the model:

$$\omega_{it} = \gamma_o + \alpha_i + \alpha_t + \gamma_1 CommonOwnership_{it} + \gamma OtherFactors_{it} + \varepsilon_{it} \qquad (2.5)$$

using the OLS with firm fixed effects, α_i, to control for unobserved firm-level heterogeneity. I also include year fixed effects, α_t, to control for shocks that may vary over time. Given that the dependent variable, productivity, is already controlled for industry fixed effects, I do not include it into the model again to avoid the over-specification.

2.4.5. Control variables

The Equation 2.5 also includes other unmeasured input factors that may affect productivity at the firm level, as specified in Syverson (2011), including innovation, R&D, and industry competition. Innovation in product quality may raise product prices, increasing revenue per unit of output. I measure innovation following Kogan, Papanikolaou, Seru, & Stoffman (2017). They develop an innovation measure by first calculating the total dollar value of innovation for a firm at a given time by simply adding the values of all patents granted to that firm. After that, the measure is scaled by firm size (book assets). R&D investments can trigger significant productivity growth but create a greater unstable outcome than investment in physical capital. Thus, engaging in R&D potentially causes more uncertainty in firm productivity. R&D data are obtained from Compustat.

Finally, competitive pressures can affect an industry's productivity. Competition shifts market share to more efficient producers (i.e., lower-cost and thus lower prices); shrink relatively high-cost firms and plants; sometimes force them to exit and make room for more efficient producers. Market competition is measured using ownership concentration – Herfindahl-Hirschman Index (HHI) from Refinitiv Institutional Ownership data. Lower HHI indicates a less concentrated market and increased competition among industry peers. I also include other control variables that determine the formation of common ownership, including index inclusion (for three indexes S&P 500, S&P 400, S&P600), firm size measure by the log of total assets, dividend distribution, market to book value, institutional ownership, and block ownership.

2.4.6. Summary statistics

Table 2.1 reports summary statistics for key variables at firm-level in Panel A and establishment-level in Panel B. The final sample contains 78,000 firm-year observations covering approximately

3,000,000 establishment years spanning 1990–2015. About 55.19% of the firm-year observations in the sample are held by at least one common investor, which is consistent with that of He and Huang (2017). Nearly 45% of the sample observations has no common owners, indicating no managerial incentives derived from common ownership to shift firm performance at these firm year observations. To minimize the effects of outliers, I winsorize all continuous variables at the top first and 99th percentiles. I rescale the GGL measure for all commonly owned firms by its sample average to facilitate the interpretation of the GGL as a relative measure. Thus, an average commonly owned firm has GGL equal to 1.000. The statistics show that the distribution of GGL has a significant skewness. An average firm-year observation in the sample has a GGL of 0.552, whereas a median commonly owned firm has a GGL of only 0.117. Managers of firms with GGL in the 99th percentile have 14 times higher incentives to improve firm performance than managers of firms with mean GGL. The TFP is also rescaled to have a mean of one for entire firms in the sample.

Firms with large firm size, large market to book value, high institutional ownership, paying dividends, and being added in indexes are more likely to have a common ownership structure. Consistently, the univariate comparisons show that commonly owned firms had larger total assets, greater institutional ownership, more activist investors, and higher institutional blockholder's ownership on average. Besides, these firms also smaller market capitalization with higher productivity, more employees and R&D capital expenditures.

In Panel B, an average plant exists for 8.9 years. Approximately 75.5% of the establishment in the sample operates in the main business sector of the firm. 82.3% of the establishments in each firm perform better than the average productivity of all establishments.

Table 2. 1: Summary Statistics

This table provides sample summary statistics for key variables in Chapter 1 based on U.S. public firms' sample from 1990 to 2015. Panel A provides firm-level statistics, while Panel B provides establishment-level statistics. The unit of observation in Panel A and B, respectively, is a firm-year and establishment-year. Panel C reports the correlation matrix of dependent and independent variables. All variables are defined in Appendix 1.

	Full sample			Common Ownership			Non-common Ownership		
	N	Mean	Std.	N	Mean	Std.	N	Mean	Std.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Firm-level									
GGL	78,422	0.552	1.953	43,281	1.000	2.542	35,141	0.000*	0.000
Productivity	78,422	1.000	0.678	43,281	1.021	0.682	35,141	0.974*	0.673
Assets (billions)	78,422	1933.7	5639.0	43,281	1941.8	5218.1	35,141	1923.7	6117.8
MktCap (billions)	78,372	2231.8	7185.1	43,275	2147.3	6333.7	35,097	2335.9*	8111.8
Age	78,422	17.970	14.291	43,281	18.585	14.339	35,141	17.213*	14.195
Market to Book ratio	78,422	1.861	1.323	43,281	1.862	1.307	35,141	1.860	1.343
Dividend Dummy	78,422	0.000	0.009	43,281	0.000	0.013	35,141	0.000*	0.000
S&P 500 Dummy	78,422	0.115	0.318	43,281	0.112	0.315	35,141	0.118*	0.322
S&P 400 Dummy	78,422	0.090	0.286	43,281	0.113	0.317	35,141	0.061*	0.240
S&P 600 Dummy	78,422	0.128	0.334	43,281	0.184	0.387	35,141	0.060*	0.238
Innovation	67,862	0.034	0.109	35,993	0.040	0.116	31,869	0.026*	0.098
R&D (billions)	78,422	0.033	0.060	43,281	0.039	0.063	35,141	0.027*	0.055
Industry Competition	56,645	0.169	0.201	33,585	0.119	0.131	23,060	0.242*	0.256
Employees (thousand)	78,422	8.156	20.553	43,281	8.067	19.213	35,141	8.266*	22.091
Institutional ownership	78,422	0.450	0.297	43,281	0.583	0.253	35,141	0.287*	0.265
Block Ownership	78,422	0.144	0.136	43,281	0.208	0.123	35,141	0.066*	0.108
Block Dummy	78,422	0.743	0.437	43,281	1.000	0.000	35,141	0.427*	0.495
Panel B: Establishment-level									
LnGGL	4,783,100	0.235	0.505	2,732,247	0.411	0.611	2,050,853	0.000*	0.000
Log(Emp)	4,757,500	2.854	1.411	2,719,575	2.812	1.339	2,037,925	2.909*	1.501
Change in Log(Emp)	4,393,300	0.012	0.146	2,460,650	0.011	0.142	1,932,650	0.014*	0.150
Core_25	4,757,500	0.823	0.382	2,719,575	0.839	0.367	2,037,925	0.802*	0.399
Core_50	4,757,500	0.726	0.446	2,719,575	0.745	0.436	2,037,925	0.701*	0.458
Productive_firm	4,757,500	0.294	0.456	2,719,575	0.298	0.457	2,037,925	0.289*	0.453
Productive_segment	4,757,500	0.383	0.486	2,719,575	0.380	0.485	2,037,925	0.386*	0.487
Establishment Age	4,757,500	8.867	6.301	2,719,575	9.323	6.393	2,037,925	8.257*	6.124
Ln(Establishment/firm)	52,786	2.709	1.455	30,418	5.641	1.363	22,368	5.914*	1.338
Ln(Establishment/segment)	52,786	5.798	1.355	30,418	5.303	1.610	22,368	5.660*	1.583
Establishment Age	4,757,500	8.867	6.301	2,719,575	9.323	6.393	2,037,925	8.257*	6.124

2.5. Relation between common ownership and firm productivity

2.5.1. OLS analysis

I examine the effect of common ownership on firms' productivity (Hypothesis 1) using the OLS estimation as specified in Equation 2.6:

$$Productivity_{it} = \gamma_o + \gamma_1 CommonOwnership_{it} + \gamma OtherFactors_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \quad (2.6)$$

where i and t index for firm and year, respectively. The unit of observation is a firm-year. The dependent variable is the natural logarithm of a firm's productivity, as specified in Section 2.4.4. The main explanatory variable, $CommonOwnership_{i,t}$, is the GGL measure. Since the GGL is highly skewed, I use the natural logarithm of one plus this measure in the regressions. $OtherFactors_{it}$ are control variables which are explained in Section 2.4.5. The α_{i} and α_{t} denote firm and year fixed effects, respectively. I include firm fixed effects to mitigate the concern for time-invariant omitted variables correlated with productivity and common ownership. Standard errors are clustered at the firm level.

The coefficient of interest, γ_1, measures how common ownership affects firms' productivity. If firms with common ownership have higher productivity than ones without this structure, γ_1 will be positive. The null hypothesis that common ownership is irrelevant conditional on firm performance corresponds to a γ_1 equal to zero. Table 2.2 reports the OLS regression results estimating Equation 2.6. Column 1 shows the linear relationship between common ownership and productivity. Column 2 adds control variables that may affect the level of common ownership in each firm, and Column 3 includes factors that may affect firm productivity. The coefficient estimates of common ownership in all three specifications are positive and significant at the 5% level, suggesting that common ownership is associated with higher productivity. In terms of economic significance, Column 3 implies that a 100% increase in GGL (i.e., GGL increases from one to two) will lead to a 1.115%[12] increase in productivity. In addition, one standard deviation changes in LnGGL (that is equivalent to exp(0.506) or 1.659 unit increase in GGL) could lead to a 0.014[13] standard deviation increase in log productivity (1.014 unit increase in productivity)[14]. Thus, the magnitude of this effect is economically meaningful.

[12] That equals to (2^0.016-1)*100

[13] That equals to 0.016*std(LnGGL)/std(Log_productivity) = 0.016*0.506/0.561

[14] In an unreported summary statistics table for the regression in Column 3, the Log(firm productivity) has mean of -0.155 and standard deviation of 0.561, whereas the LnGGL has mean of 0.227 and standard deviation of 0.506.

In addition, the results show a negative relationship between productivity and R&D, consistent with the literature that high R&D investments may create a greater unstable outcome and potentially causes more uncertainty in firm productivity. Similarly, a high HHI index (a more concentrated market and less competition among industry peers) is associated with less productivity[15]. Surprisingly, innovation is negatively related to productivity, inconsistent with the prior studies where highly innovative firms have better productivity.

Table 2. 2: Common Ownership and Productivity

Panel A examines the effect of common ownership on firm productivity. The dependent variable is the logarithm of productivity. CommonOwnership is the log of GGL measure. Firm Size is the logarithm of total assets. Market to book ratio is the ratio of firm market value to its book value. Dividend Dummy equals one for firms paying dividends and zero otherwise. S&P (500, 400, 600) Dummy equals one for firms added in the index and zeroes otherwise. Innovation value is patent value divided by total assets as computed by Kogan et al. (2017). R&D is research and development expense over total assets. Block Ownership is the percentage of block ownership. Institutional Ownership is the percentage of institutional ownership. Industry Competition is ownership concentration – Herfindahl-Hirschman Index. T-statistics (in parentheses) with standard errors clustered at the firm level. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Log(Firm Productivity)		
	(1)	(2)	(3)
LnGGL	0.031***	0.017**	0.016**
	(4.406)	(2.512)	(2.186)
Firm Size		0.111***	0.077***
		(16.211)	(9.505)
Market to Book ratio		0.101***	0.103***
		(30.911)	(28.612)
Dividend Dummy		0.276***	-0.075***
		(32.240)	(-7.115)
S&P 500 Dummy		-0.110***	-0.048**
		(-5.801)	(-2.127)
S&P 400 Dummy		-0.086***	-0.077***
		(-6.927)	(-5.491)
S&P 600 Dummy		-0.091***	-0.076***
		(-9.234)	(-7.164)
Block Ownership		-0.442***	-0.445***
		(-16.795)	(-15.705)
Institutional Ownership		0.287***	0.308***
		(16.461)	(14.195)
R&D			-3.049***
			(-18.259)
Innovation Value			-0.148***
			(-3.252)
Industry Competition			-0.061***
			(-2.993)
Firm FE & Year FE	Y	Y	Y
Observations	77,411	77,411	61,544
Adjusted/Pseudo R^2	0.531	0.572	0.618

[15] Market competition is measured using ownership concentration – Herfindahl-Hirschman Index (HHI). A low HHI index indicates a less concentrated market and more competition among industry peers.

2.5.2. Identifying treatment and control firms

Since the GGL measure is highly right-skewed, it is likely that its effect on performance is nonlinear and is concentrated in the firms with very high common ownership. To investigate this possibility, I divide all commonly owned firms into five quintiles based on their GGL measures; then compute the statistics of GGL measure and productivity for each quintile, as shown in Table 2.3. Columns 1 and 2 show that the GGL measure is much higher in quintile five than in other quintiles. Particularly, firms in quintile five have a mean GGL of 4.366 and a median of 2.456. Whereas an average firm in adjacent quintile four has a GGL of 0.472 and a median of 0.429. Firms in quintile five make up a larger share of their common owner's portfolio and have a higher percentage of common owner ownership. Thus, common ownership level may trigger a significant shift in firm performance only when GGL measure crosses a particular threshold, i.e., from quintile four to quintile five. As a result, I redefine commonly owned firms as those firms that belong to quintile five. To verify a significant difference in GGL measure between quintile five and previous quintiles, I test whether the level of GGL measure is significantly different from zero in each quintile. The result shows that the GGL in quintiles one through four is not significantly different from zero, whereas the GGL in quintile five is. Consequently, I redefine common ownership as a dummy variable that equals one if the firm belongs to quintile five and zero if the firm belongs to another quintile or does not have common ownership. Unless otherwise stated, this definition of common ownership applies throughout this chapter.

Table 2. 3: Productivity by GGL-sorted Quintiles

This table shows the mean, median, and standard deviation of common ownership and productivity based on five common ownership quintiles, where the GGL is smallest in the first quintile and largest in the fifth quintile.

	GGL			Productivity			N
	Mean	Median	STD	Mean	Median	STD	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GGL1	0.005	0.004	0.004	0.924	0.795	0.564	8,764
GGL2	0.033	0.031	0.014	0.946	0.799	0.589	8,764
GGL3	0.124	0.117	0.045	0.993	0.828	0.645	8,765
GGL4	0.472	0.429	0.188	1.074	0.875	0.731	8,764
GGL5	4.366	2.456	4.278	1.174	0.957	0.822	8,765

Another issue to consider while building the sample is the potential self-selection bias. Institutional investors may form common ownership based on corporate characteristics, which at the same time determine production efficiency for commonly owned firms. I employ the propensity score technique to address this concern. I match firm-year observations from the treatment group with those of the control group using the data from the previous year. The treatment group comprises commonly owned firms (firms in quintile five), whereas the control group consists of firms that are not commonly owned and firms in quantiles one through four. I estimate a logit model in which the dependent variable GGL_Dummy is set to one if firms in the treatment group and zero otherwise. The control set contains all control variables (except for the dividend dummy) in the last column of Table 2.4, which reports the primary effect of common ownership on productivity. These are major factors affecting the likelihood that a firm has a common ownership structure, as shown in Gilje et al. (2020). I exclude the dividend dummy variable from the control set since it is a categorical variable and relatively few firms in the treatment sample pay dividends, resulting in less meaningful matching. I also account for the difference in productivity between firms in the treatment and control groups in the previous year to ensure that increased productivity after adopting common ownership is not due to prior firm performance. This procedure enables me to control for the differences in corporate characteristics between firms with high and low common ownership.

I utilize the predicted probabilities (propensity scores) from the logit regression to match firm-year observations in the treatment group with those in the control group based on the nearest neighbor matching procedure. Each observation in the treatment group is matched with one observation in the control group without replacement. Overall, this yields 5,161 firm-year observations in the treatment group and 5,161 firm-year observations in the matched control group with very comparable features but differing common ownership.

Panel A, Column 1 of Table 2.4 shows the logit regression results between the treatment and control group in the previous year. Firm size, market to book ratio, S&P index, block ownership, institutional ownership, R&D, and industry competition contribute significantly to a firm's likelihood of having common institutional investors before the matching procedure is implemented. The logit model generates a Pseudo R-squared of 0.244 and a chi-square p-value less than 0.0001, suggesting that the model specification adequately captures variation in the dependent variable.

The analysis for the matched sample is reported in Panel A, Column 2. Except for the R&D ratio, which is only statistically significant at the ten percent level, none of the independent variables is statistically different from zero. The post-match coefficient estimates are smaller in magnitude than the pre-match coefficient estimates are and no longer statistically significant, showing that the matching procedure succeeded in removing the differences in firm characteristics the treatment and the control groups. Moreover, Pseudo R-squared drops from 0.244 before matching to 0.001. The p-value of Chi-squared jumps from 0.000 in the pre-match analysis to 0.847 in the matched sample, indicating that the logit regression model cannot capture a significant amount of variation in the dependent variables. Panel B reports the distribution and differences in the propensity scores for both groups. The propensity scores of the two groups are almost identical. The average distance in propensity scores between the treatment and control groups is less than 0.005, with a maximum (minimum) of -0.023 (0.271). Panel C displays the post-match summary statistics. Again, except for the market to book ratio and R&D, the independent variables in the matched sample are not significantly different between commonly and not commonly owned firms. Overall, the results across Panel A to Panel C indicate that the propensity score matching process creates reasonable matches.

Panel D reports the difference in productivity between commonly owned firms and their non-commonly owned peers. There is a statistically significant difference in productivity between firms with and without common ownership. Finally, in Panels E and F, Column 1, we present the regression results for the effects of common ownership on firm productivity using the post-match sample. I include the firm fixed effects and year fixed effects in Column 2 to account for any omitted and unobservable firm characteristic variables that were not included in the model and may vary over time. I leave out the industry fixed effects because they were already controlled for in the model to estimate productivity. The dependent variables are the GGL dummy variable and the natural logarithm of GGL, respectively. As reported, common ownership has a statistically significant effect on productivity at the 1% level. Panel E demonstrates that firms with common ownership have about 5.866% (in Column 1 and 5.338% in Column 2) higher productivity than those without common ownership.

I then use this sample to match with establishment-level data and perform further tests in Section 2.6.

Table 2. 4: Common Ownership and Productivity - Matched Sample

The table presents the effects of common ownership on productivity using the matched sample between firms with and without common ownership. Panel A, Column 1, reports the results of a logit model based on the pre-matched firms in the treatment and the control groups. The dependent variable of the logit model equals one if the firm belongs to the treatment group (has common ownership) and zero if the firm comes from the control group (do not have common ownership). The independent variables of the logit model are the control variables used in the regression Equation 2.5 measured in the pre-common ownership. Panel A, Column 2, reports the results of the same logit model based on the post-matched firms in the treatment and the control groups. Panel B reports statistical distributions of the propensity scores of the treatment and control groups and their differences. Panel C reports pre-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding *t* -statistics. Panel D reports post-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding *t* -statistics. Panel E reports the results for the regression based on the matched sample. The main independent variable is a GGL dummy variable if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise. Standard errors are clustered by firm. T-statistics are shown in parentheses. * **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Logit regressions with pre- and post-matched samples

	Dependent variable: GGL_Dummy	
	Pre-match (1)	Post-match (2)
Productivity	0.423***	0.047
	(5.128)	(0.599)
Firm Size	0.300***	-0.024
	(6.473)	(-0.479)
Market to Book ratio	0.243***	0.016
	(8.300)	(0.568)
S&P 500 Dummy	0.026	0.066
	(0.150)	(0.354)
S&P 400 Dummy	0.240*	0.071
	(1.771)	(0.498)
S&P 600 Dummy	-0.133	-0.016
	(-1.216)	(-0.134)
Block Ownership	4.555***	-0.304
	(13.905)	(-0.783)
Institutional Ownership	1.512***	0.348
	(6.027)	(1.203)
Innovation Value	-0.115	-0.114
	(-0.371)	(-0.372)
R&D	13.884***	1.148
	(19.574)	(1.549)
Industry Competition	-0.609*	0.073
	(-1.718)	(0.143)
Establishment per firm	-0.127***	0.011
	(-4.196)	(0.316)
Constant	-6.118***	-0.164
	(-21.708)	(-0.502)
Observations	26,952	6,960
p-value of χ^2	0.000	0.8960
Pseudo R^2	0.2573	0.0021
Log likelihood	-7924.7485	-4813.978

Panel B: Propensity scores distribution

Group	N	Mean	Minimum	Maximum	Std. dev
Treatment	3,480	0.026	-3.277	3.657	0.799
Control	3,480	0.011	-3.277	3.794	0.786
Difference	3,480	0.015	0.000	-0.137	0.013

Table 2.4: continued

Panel C: Differences in variables in pre-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.036	-0.055	0.018	1.36	0.173
Firm Size	6.382	6.416	-0.035	-0.84	0.403
Market to Book ratio	2.432	2.337	0.095	2.38	0.017
S&P 500 Dummy	0.195	0.194	0.001	0.06	0.952
S&P 400 Dummy	0.160	0.152	0.008	0.89	0.372
S&P 600 Dummy	0.180	0.182	-0.002	-0.22	0.828
Block Ownership	0.222	0.227	-0.005	-1.34	0.179
Institutional Ownership	0.666	0.663	0.003	0.63	0.532
Innovation Value	0.092	0.089	0.003	0.70	0.487
R&D	0.068	0.063	0.005	3.08	0.002
Industry Competition	0.091	0.093	-0.002	-0.81	0.419
Establishment per firm	2.241	2.264	-0.023	-0.58	0.563

Panel D: Differences in variables in post-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.028	-0.065	0.037	2.71	0.007
Firm Size	6.509	6.519	-0.010	-0.23	0.815
Market to Book ratio	2.351	2.171	0.181	4.85	0.000
S&P 500 Dummy	0.205	0.199	0.006	0.63	0.531
S&P 400 Dummy	0.173	0.161	0.012	1.32	0.188
S&P 600 Dummy	0.195	0.202	-0.006	-0.66	0.509
Block Ownership	0.246	0.221	0.025	7.61	0.000
Institutional Ownership	0.693	0.664	0.030	5.91	0.000
Innovation Value	0.096	0.092	0.004	0.85	0.394
R&D	0.069	0.060	0.009	5.08	0.000
Industry Competition	0.087	0.089	-0.002	-0.90	0.368
Establishment per firm	2.269	2.295	-0.026	-0.64	0.523

Panel E: Regression

Variable	Dependent variable: Log of Productivity	
	(1)	(2)
GGL_Dummy	0.057***	0.052***
	(2.657)	(2.739)
Firm Size		0.081***
		(3.243)
Market to Book ratio		0.098***
		(15.119)
S&P 500 Dummy		-0.070
		(-1.312)
S&P 400 Dummy		-0.114***
		(-2.774)
S&P 600 Dummy		-0.095***
		(-3.091)
Block Ownership		-0.526***
		(-6.508)
Institutional Ownership		0.352***
		(5.378)
Innovation Value		-2.885***
		(-8.441)
R&D		-0.053
		(-0.806)
Industry Competition		-0.173
		(-1.039)
Establishment per firm		-0.056**
		(-2.501)
Firm FE & Year FE	Y	Y
Observations	6,300	5,805
Adjusted/Pseudo R^2	0.610	0.685

2.6. Within-firm effects of common ownership: New insights from the NETs data

The key innovation of this paper is to exploit establishment-level data to better understand how common ownership affects firm productivity. To investigate this effect, I first test hypothesis 2 on how common ownership affects firm employment at the firm level using the equation:

$$\Delta Log(Employment)_{i,t+1} = \beta_0 + \beta_1 CommonOwnership_{i,t} +$$
$$\gamma Control_{i,t} + \alpha_i + \alpha_k \times \alpha_t + \varepsilon_{i,t} \quad (2.7)$$

where *i, k, t* index for firms, industries, and years, respectively. The unit of observation is a firm-year. The dependent variable, $\Delta Log(Employment)_{i,t+1}$, captures employment allocation measured by the within-firm annual change in the natural logarithm of the employment. The number of firm employees is computed using data from both Compustat and the NETS databases. The main independent variable and other control variables are described in Section 2.5.1. I avoid adding extra control variables to the model because firm employment growth, according to Gibrat's Law (Gibrat, 1931), is a stochastic process that is randomly distributed across firms and independent of firm-specific characteristics such as size, age, R&D, innovation, and capital. This law is consistent with most literature on firm employment growth and supported by Sutton (1997) and Caves' (1998) survey articles. The coefficient β_1 measures how a firm's employment allocation decisions respond to the introduction of common ownership compared with observationally similar non-commonly owned firms. If the firm reduces employment after the formation of common ownership, then β_1 will be negative.

Table 2.5 shows the estimation results using the matched sample between firms with and without common ownership in Section 4.2. The dependent variable in all columns is the change in the log number of employees. I obtain firm employment data in Columns 1 and 3 from Compustat. I compute firm employment in Columns 2 and 4 by aggregating employees from all firm establishments obtained from the NETS database. The results show that common ownership does not affect aggregate firm employment. However, it does not rule out a possibility that equal employment changes occur across establishments within the same firm but in opposite directions. The following sections will conduct additional research into this possibility.

Table 2. 5: Common Ownership and Firm Employment

This table shows estimates for the impact of common ownership on change in firm employment. The dependent variables are changes in the log number of firm employees. Employment data are obtained from Compustat in Columns 1 and 3 or from the NETS database in Columns 2 and 4 by aggregating employees from a firm's all establishments. The main independent variable is a GGL dummy variable if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise. Other variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors clustered at the firm level. ***, **, and * denote statistical statistical significance at 1%, 5%, and 10% levels, respectively.

	ΔLnEmp_ Compustat	ΔLnEmp_ NETS	ΔLnEmp_ Compustat	ΔLnEmp_ NETS
	(1)	(2)	(3)	(4)
GGL_Dummy	0.003	-0.016	-0.003	-0.013
	(0.264)	(-0.993)	(-0.285)	(-0.693)
Firm Size			-0.091***	0.014
			(-5.074)	(0.665)
Market to Book ratio			0.027***	0.006
			(7.474)	(0.885)
S&P 500 Dummy			-0.048	-0.029
			(-1.171)	(-0.684)
S&P 400 Dummy			-0.016	-0.010
			(-0.628)	(-0.342)
S&P 600 Dummy			-0.038**	-0.029
			(-2.170)	(-0.977)
Block Ownership			-0.037	-0.162*
			(-0.717)	(-1.721)
Institutional Ownership			0.047	0.127*
			(1.128)	(1.658)
R&D			0.054	-0.023
			(1.468)	(-0.353)
Innovation Value			-1.048***	0.048
			(-6.993)	(0.203)
Industry Competition			0.026	0.378**
			(0.198)	(2.403)
Firm FE	Y	Y	Y	Y
Industry X Year FE	Y	Y	Y	Y
Observations	4,744	4,971	4,421	4,637
Adjusted/Pseudo R^2	0.236	0.100	0.303	0.089

2.6.1. Establishments operating in core and peripheral business lines

To determine whether firms redeploy employment internally, I first estimate Equation 2.6 to examine if firms reallocate employees between core and peripheral establishments after sharing common owners with other industry peers (Hypothesis 3):

$$\Delta Log(Employment)_{ij,t+1} = \beta_0 + \beta_1 CommonOwnership_{i,t} + \beta_2 Core_{ij,t}$$

$$+\beta_3 CommonOwnership_{i,t} \times Core_{ij,t} + \gamma Control_{ij,t} + \alpha_i + \alpha_k \times \alpha_t + \varepsilon_{ij,t} \quad (2.8)$$

where *i, j, k, t* index for firms, establishments, industries, and years, respectively. The unit of observation is an establishment-year. The dependent variable, $\Delta Log(Employment)_{ij,t}$, captures employment allocation as measured by the annual change in the natural logarithm of employment within an establishment. The indicator variable, $Core_{ij,t}(Peripheral_{ij,t})$, equals one (zero) if the establishment operates (does not operate) in its parent firm's core industry at the beginning of year t. An establishment is considered to operating in the firm's core industry if the aggregated sales of all establishments with the same six-digit NAICS code with that establishment exceed 25% of the firm's total sales (Maksimovic & Phillips, 2002; Giroud & Mueller, 2015; Ersahin, Irani & Le, 2020). Each establishment within a firm is sorted on a year-to-year basis to characterize as a core or peripheral unit based on its industry classification and sales in the previous year.

$Control_{ij,t}$ is a set of control variables at the establishment and firm level. Establishment-level controls include establishment age, defined as the number of years since an establishment was founded; firm size, defined as the log number of establishments owned by a given firm; and segment size, defined as the log number of establishments owned by a given firm in each industry segment (based on six-digit NAICS industries). This set of control variables is used consistently in research on establishment-level performance (see (Giroud, 2013; Schoar, 2002)). The control variable at the firm level is identical to that in Equation 2.6. The estimation considers firm and industry × year fixed effects (α_i and $\alpha_{k,t}$) avoid biases in coefficient estimates (Gormley & Matsa, 2014). The standard errors are clustered at the firm level.

Common ownership has the effect of β_1 on peripheral establishments and $\beta_1 + \beta_3$ on core establishments. The interaction coefficient, β_3, reflects the distinct effects of common ownership between core and peripheral establishments within the same firm. If commonly owned firms withdraw employment uniformly across establishments, the coefficients β_1 should be negative and statistically significant, while the coefficient β_3 should be insignificant. On the other hand, if common ownership is irrelevant to employment allocation decisions at the establishment level with different business focus (null hypothesis), then both β_1 and β_3 are equal to zero. Last, the direct coefficient β_2 observes potential differences in resource allocation at core establishments of non-commonly owned firms.

Table 2. 6: Resource Allocation by Establishment Industry Focus

This table presents estimates for the within-firm impact of common ownership on employment change among establishments within the firm's core and peripheral industry focus. The unit of observation in each regression is establishment-year. The dependent variables are the change in the log number of establishment employees. Core (peripheral) establishments are establishments operating in six-digit NAICS industries that account for more than (less than) 25% of the firm's total sales in Columns 1 and 2, and 50% in Columns 3 and 4. The main independent variable is a GGL dummy variable equal to one if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with a Core dummy variable. Establishment Age is the number of years since the foundations of that establishment. Establishment per firm is the natural logarithm of the total number of establishments of the parent firm. Establishment per Segment is the natural logarithm of the total number of establishments of the parent firm in the same six-digit NAICS industry segment with that establishment. Other firm control variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Change in Log of Establishment Employment			
	(1)	(2)	(3)	(4)
GGL_Dummy	-0.011***	-0.012***	-0.008**	-0.009**
	(-2.747)	(-2.696)	(-2.488)	(-2.474)
Core	-0.021***	-0.021***	-0.015***	-0.013***
	(-4.703)	(-4.094)	(-4.130)	(-3.392)
GGL_Dummy x Core	0.010**	0.010*	0.007*	0.005
	(2.181)	(1.943)	(1.754)	(1.243)
Establishment Age	-0.012***	-0.014***	-0.013***	-0.014***
	(-7.956)	(-7.639)	(-7.938)	(-7.590)
Establishment per Firm	-0.023***	-0.017***	-0.023***	-0.017***
	(-3.276)	(-2.816)	(-3.270)	(-2.935)
Establishment per Segment	-0.001	-0.001	0.001	0.001
	(-0.180)	(-0.282)	(0.260)	(0.132)
Firm Controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Industry X Year FE	Y	Y	Y	Y
Observations	473,589	427,992	473,589	427,992
Adjusted/Pseudo R^2	0.057	0.055	0.057	0.055

Table 2.6 reports the regression results. Columns 1 and 2 classify an establishment as core or peripheral if the aggregated sales of all establishments in a firm with the same six-digit NAICS code as that establishment exceed 25% of that firm's total sales. Columns 3 and 4 instead use a 50% cut-off. Columns 1 and 3 include variables for establishment controls, whereas Columns 2 and 4 include both establishment and firm controls. The GGL dummy variable coefficient estimates are negative and statistically significant, indicating that common ownership does indeed induce employment layoff at peripheral establishments. The significant estimates of the interaction term between common ownership and core variable imply that common ownership has a different impact on employment at the core and peripheral establishments. Common ownership is associated with a statistically significant change in the number of employees at peripheral

establishments (in Column 4). The effects of common ownership on core units, however, are relatively small and statistically insignificant with the F-value on the combined coefficients of GGL_dummy and GGL_dummy x Core in Column 4 equal to 0.05 and p-value of 0.826.

2.6.2. Establishment productivity

Similarly, I modify Equation 2.7 to examine how firms reallocate their employment between productive and unproductive establishments after the formation of a common ownership structure (hypothesis 4):

$$\Delta Log(Employment)_{ij,t+1} = \beta_0 + \beta_1 CommonOwnership_{i,t} + \beta_2 Productive_{ij,t}$$

$$+\beta_3 CommonOwnership_{i,t} \times Productive_{ij,t} + \gamma Control_{ij,t} + \alpha_i + \alpha_k \times \alpha_t + \varepsilon_{ij,t} \quad (2.9)$$

where *i, j, k, t* index for firms, establishments, industries, and years, respectively. The unit of observation is an establishment-year. The indicator variable, $Productive_{ij,t}(Unproductive_{ij,t})$, equals one if the establishment is classified as productive (unproductive) in year t. I define an establishment as productive if its productivity (as measured by the sales-to-employee ratio) exceeds the median of all establishments' productivities belonging to the same firm and unproductive otherwise. Establishments are classified at the beginning of each year based on their performance in the previous year. The other variables are the same as in Equation 2.7.

Like Equation 2.8, the effect of common ownership is β_1 for unproductive establishments and $\beta_1 + \beta_3$ for productive establishments. The interaction term coefficient, β_3, captures different effects of common ownership between productive and unproductive establishments within the same firm. If commonly owned firms withdraw employment uniformly across establishments, then the coefficients β_1 are negative and statistically significant, whereas the coefficient β_3 should be insignificant. On the other hand, if common ownership is irrelevant to employment allocation decisions between productive and unproductive establishment (null hypothesis), then both β_1 and β_3 equal zero. Last, coefficient β_2 measures the potential differences in resource allocation at productive establishments of non-commonly owned firms.

Table 2.7 reports the regression results. Columns 1 and 2 classify an establishment into productive and unproductive based on the establishment parent's total productivity as defined above. The operation of different establishments within the same firm could be heterogeneous and depends on their industry characteristics. Thus, Columns 3 and 4 compare an establishment's productivity with the median of all other establishments with the same 6-digit NAICS industry in the sample in a year. Columns 1 and 3 include establishment control variables, whereas Columns 2 and 4 add both establishment and firm controls. The coefficient estimates of the GGL dummy variable are negative and statistically significant, indicating that common ownership negatively affects employment at unproductive establishments. The significant estimates of the interaction term between common ownership and productive variable suggest that common ownership creates different effects on productive and unproductive establishments. However, the effects of common ownership on productive units are relatively small and statistically insignificant with the F-value on the combined coefficients of GGL_dummy and GGL_dummy x Prroductive in Column 4 equal to 0.62 and p-value of 0.430.

Table 2. 7: Resource Allocation by Establishment Productivity

This table presents estimates for the within-firm impact of common ownership on employment change among productive and unproductive establishments. The unit of observation in each regression is establishment-year. The dependent variables are the change in the log number of establishment employees. In Columns 1 and 2, an establishment is considered productive (unproductive) if its corresponding productivity rank is above (below) the median productivity of the establishments belonging to the firm each year. Columns 3 and 4 use the within-industry productivity to rank establishments. The main independent variable is a GGL dummy variable equal to one if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with Productive dummy variable. Establishment Age is the number of years since the foundations of that establishment. Establishment per Firm is the natural logarithm of the total number of establishments of the parent firm. Establishment per Segment is the natural logarithm of the total number of establishments of the parent firm in the same six-digit NAICS industry segment with that establishment. Other firm control variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Change in Log of Establishment Employment			
	(1)	(2)	(3)	(4)
GGL_Dummy	-0.006**	-0.008**	-0.008**	-0.010***
	(-2.232)	(-2.523)	(-2.417)	(-2.738)
Productive	-0.001	-0.002	-0.001	-0.002
	(-0.352)	(-0.705)	(-0.390)	(-0.683)
GGL_Dummy x Productive	0.005*	0.006**	0.006*	0.007**
	(1.841)	(2.052)	(1.856)	(2.063)
Establishment Age	-0.013***	-0.014***	-0.013***	-0.014***
	(-7.914)	(-7.595)	(-7.938)	(-7.620)
Establishment per firm	-0.022***	-0.016***	-0.022***	-0.016***
	(-3.133)	(-2.717)	(-3.084)	(-2.638)
Establishment p segment	0.002	0.001	0.001	0.001
	(0.364)	(0.313)	(0.280)	(0.181)
Firm Controls	N	Y	N	Y
Establishment FE	N	N	N	N
Firm FE	Y	Y	Y	Y
Industry X Year FE	Y	Y	Y	Y
Observations	473,589	427,992	473,589	427,992
Adjusted/Pseudo R^2	0.057	0.055	0.057	0.055

So far, the results show that there are significant employee reductions at peripheral establishments and unproductive establishments. However, it is unclear whether the effects occur evenly between productive peripheral and unproductive peripheral units, or between unproductive core units and unproductive peripheral units. Therefore, I further examine whether commonly owned firms are more likely to withdraw employment at peripheral establishments, which are unproductive. To do so, I divide the sample into two groups of core establishments and peripheral establishments and re-examine Equation 2.9 for productive and unproductive units. I use the 25% cut-off to classify core and peripheral only since the common ownership effects are not robust with firm control variables in Column 4 of Table 2.6. The results are reported in Table 2.8.

Table 2. 8: Interaction between Establishment Industry Focus and Productivity

This table presents estimates for the within-firm impact of common ownership on employment change among establishments within the firm's core and peripheral industry focus interacts with establishment productivity. The unit of observation in each regression is establishment-year. The dependent variables are the change in the log number of establishment employees. Columns 1 and 3 show the testing results on the core establishments sample, whereas Columns 2 and 4 show the results on the peripheral establishments. Core (peripheral) establishments are establishments operating in six-digit NAICS industries that account for more than (less than) 25% of the firm's total sales. In Columns 1 and 2, an establishment is considered productive (unproductive) if its corresponding productivity rank is above (below) the median productivity of the establishments belonging to the firm in a given year. Columns 3 and 4 use the within-industry productivity to rank establishments. The main independent variable is a GGL dummy variable equal to one if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with Productive dummy variable. Other establishment and firm control variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Change in Log of Establishment Employment			
	Core	Peripheral	Core	Peripheral
	(1)	(2)	(3)	(4)
GGL_Dummy	-0.003	-0.013***	-0.005	-0.015***
	(-0.722)	(-2.586)	(-1.077)	(-2.776)
Productive_firm	-0.003	0.004		
	(-1.063)	(1.410)		
GGL_Dummy x Productive_firm	0.006*	0.004		
	(1.786)	(1.019)		
Productive_industry			-0.004	0.003
			(-1.016)	(0.992)
GGL_Dummy x Productive_industry			0.007*	0.006
			(1.664)	(1.576)
Establishment Age	-0.012***	-0.018***	-0.012***	-0.018***
	(-6.508)	(-7.116)	(-6.525)	(-7.054)
Establishment per firm	-0.020**	-0.009	-0.020**	-0.009
	(-2.395)	(-1.260)	(-2.322)	(-1.323)
Establishment p segment	-0.015	-0.003	-0.016*	-0.003
	(-1.645)	(-0.384)	(-1.730)	(-0.402)
Firm Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry x year FE	Y	Y	Y	Y
Observations	343,401	83,504	343,401	83,504
Adjusted/Pseudo R^2	0.046	0.085	0.046	0.085

Columns 1 and 3 show the effects of common ownership on core establishments. The positive estimate of interaction term in Column 1 indicates that common ownership increases employees only at the core and productive establishments. The results are statistically significant at the 10% level. In terms of economic significance, commonly owned firms are likely to have a 0.300% (in Column 1) positive change in the number of employees at the core and productive units. Given that more than 70% of establishments in a firm are operating in the main business line, this effect is relatively economically significant. On the other hand, commonly owned firms are more likely to reduce the employees at unproductive peripheral establishments with the effects varying from -1.308% (in Column 2) to -1.511% (in Column 4).

2.6.3. Establishment closure

Alongside employment, I further examine the likelihood of establishment closures. Such closures reflect an extreme form of resource withdrawal that may not happen without outside pressure (Bertrand & Mullainathan, 2003). Table 2.9 reports the results.

In this case, the dependent variable is equal to one if the establishment is closed in the subsequent year and zero otherwise. Columns 1 and 2 investigate the closure effects at the core and peripheral establishments using both 25% and 50% cut-off, whereas Columns 3 and 4 examine the effects at productive and unproductive establishments classified by both firm and industry productivity. Overall, I do not find the closure effects across all types of establishments.

To summarize, the establishment-level results indicate the significant resources movement among establishments within the same firm. Firms with common ownership are more likely to withdraw their employees at unproductive and peripheral establishments and move them to more productive core units. Although the effects are statistically significant at the establishment level, no change can be observed at the aggregate firm level.

Table 2. 9: Establishment Closure

This table presents the effects of common ownership on establishment closure. The unit of observation in each regression is establishment-year. The dependent variable is establishment closure equal to one if the establishment closes in the subsequent year and zero otherwise. Core (peripheral) establishments are establishments operating in six-digit NAICS industries that account for more than (less than) 25% of the firm's total sales in Column 1 and 50% in Column 2. In Column 3, an establishment is considered productive (unproductive) if its corresponding productivity rank is above (below) the median productivity of the establishments belonging to the firm in a given year. Column 4 uses the within-industry productivity to rank establishments. The main independent variable is a GGL dummy variable equal to one if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with Core or Productive dummy variable. Establishment Age is the number of years since the foundations of that establishment. Establishment per firm is the natural logarithm of the total number of establishments of the parent firm. Establishment per Segment is the natural logarithm of the total number of establishments of the parent firm in the same six-digit NAICS industry segment with that establishment. Other firm control variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Establishment Closure			
	(1)	(2)	(3)	(4)
GGL_Dummy	0.008	0.010	0.010	0.007
	(1.318)	(1.554)	(1.467)	(1.061)
Core	0.002	0.004		
	(0.475)	(0.989)		
GGL_Dummy x Core	-0.000	-0.004		
	(-0.027)	(-0.699)		
Productive			-0.002	-0.004*
			(-1.356)	(-1.916)
GGL_Dummy x Productive			-0.004	0.002
			(-1.112)	(0.555)
Establishment Age	-0.000	-0.000	0.000	0.000
	(-0.009)	(-0.007)	(0.159)	(0.066)
Establishment per firm	-0.041*	-0.041*	-0.041*	-0.042*
	(-1.692)	(-1.693)	(-1.691)	(-1.701)
Establishment p segment	-0.010	-0.010	-0.010	-0.010
	(-0.956)	(-0.947)	(-0.982)	(-0.964)
Firm Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry x year FE	Y	Y	Y	Y
Observations	447,782	447,782	447,782	447,782
Adjusted/Pseudo R^2	0.134	0.134	0.134	0.134

2.6.4. Firm diversification

Finally, I investigate whether common ownership has a different effect on diversified and undiversified firms. Literature on multiple-segment firms claims that conglomerate business destroys firm value and inefficiently invests across industry segments (Berger & Ofek, 1995; Lang & Stulz, 1994). They attribute the underperformance of conglomerate firms mainly to the imperfection in firm corporate governance and segment valuation caused by diversification. Maksimovic & Phillips (2002) revisit the production gains in single and multiple segment firms and find that establishments in larger segments of highly diversified firms are particularly more efficient than those in smaller sectors. Besides, conglomerate firms allocate more resources and expand faster in segments where their establishments are productive and receive more positive demand shocks. Let's suppose such efficiency gains come from firm skill in producing within an industry, all else equal. In that case, single-segment firms will generate higher returns than multiple-segment firms with the same total size. This comparative advantage on organizational skills also implies that establishments in small segments are more likely to be less efficient and receive less attention from management. Thus, common owners can improve production efficiency by concentrating managerial efforts on large segments and reducing resources at small segments. To investigate this possibility, I argue that commonly owned firms will reduce the number of establishments in more diversified firms.

As shown in Table 2.1, an average firm operates across 4.6 industries, whereas half of the sample run business in less than three industries. Thus, I classified a firm to be undiversified if it operates in one to three industries; and to be diversified if its business spreads over three industries. I then test the equation:

$$Log(No\_Establishment)_{i,t} = \beta_0 + \beta_1 CommonOwnership_{i,t} + \beta_2 Diversified_{i,t}$$

$$+\beta_3 CommonOwnership_{i,t} \times Diversified_{i,t} + \gamma Control_{i,t} + \alpha_i + \alpha_k \times \alpha_t + \varepsilon_{i,t} \quad (2.10)$$

where *i, k, t* index for firms, industries, and years, respectively. The dependent variable is the natural log number of establishments per firm. Diversified is a dummy variable that equals one if firms operate in more than three industries and zero otherwise. The number of firm industries is identified based on the establishment's six-digit NAICS industry code. Other variables are the same as Equation 2.7. The results are shown in Table 2.10.

Common ownership has no effect on the number of firm establishments at an aggregate level, as indicated in Column 1. However, the results change when considering the effects for different types of firms. Column 3 shows that common owners are more likely to reduce the number of establishments in diversified firms with a 2.761% (or exp(0.055-0.083)-1) higher than in undiversified firms. The combined coefficients of Diversified and GGL_Dummy x Diversify, reflecting the different effect of common ownership on diversified and undiversified firms, are statistically significant with F-value of 38.90 and p-value of 0. The reduction suggests that common owners may shut down the unproductive establishments in small segments of diversified firms to improve the aggregate productivity and refocus resources to the main business segments.

Table 2. 10: Establishment Numbers

This table presents the effects of common ownership on the number of firm establishments. The unit of observation in each regression is a firm-year. The dependent variable is the natural log number of establishments per firm. The main independent variable is a GGL dummy equal to one if a firm has GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with Diversified. Diversified is an indicator equal to one if firms run their business across more than three industries and zero otherwise. Other firm control variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log Number of Establishments		
	(1)	(2)	(3)
GGL_Dummy	-0.000	0.046	0.055
	(-0.018)	(1.329)	(1.560)
Diversified		0.406***	0.364***
		(8.370)	(7.517)
GGL_Dummy x Diversified		-0.094**	-0.083**
		(-2.268)	(-2.063)
Firm Size			0.138***
			(2.928)
Market to Book ratio			-0.018**
			(-2.406)
S&P 500 Dummy			0.259**
			(2.530)
S&P 400 Dummy			0.054
			(0.867)
S&P 600 Dummy			-0.016
			(-0.409)
Block Ownership			-0.103
			(-0.996)
Institutional Ownership			-0.045
			(-0.561)
R&D			0.899***
			(3.166)
Innovation Value			0.241***
			(2.875)
Industry Competition			-0.100
			(-0.597)
Firm FE	Y	Y	Y
Industry x Year FE	Y	Y	Y
Observations	5,064	5,064	4,722
Adjusted/Pseudo R^2	0.962	0.965	0.966

2.7. Additional tests

2.7.1. Types of common owners

Activist investors are considered to have strong motives and abilities to influence corporate decision-making. Brav et al. (2008) show that hedge funds are effective monitors and actively intervene in the operating activities of their invested firms. Further, Brav et al. (2015) find that hedge funds improve target firm's productivity. Targets experience a comprehensive capital redeployment within three years of the activism by selling unproductive establishments and reducing employees' wages and work hours based on hedge funds' business strategies proposal. Thus, common ownership effects on firm productivity can be more pronounced when common owners include activist investors.

To ascertain if the impact of common owners on firm performance depends on specific types of institutions, I analyze whether common ownership of activist investors is associated with higher firm productivity than common ownership of nonactivist investors. Activist data are obtained from Schedule 13D filings to the U.S. Securities and Exchange Commission (SEC). The Schedule requires mandatory filings from any shareholder who owns at least 5% of any share class and intentionally interferes firm's corporate control. I match the 13D filers with the 13F institutions in my sample and identify those common institutional owners who are activist investors (filed at least one 13D in the past three years) and those who are not. Last, I required the activist investors to file at least one 13D form for firms in the same 3-digit SIC industry as the given commonly owned firm. I examine the effect of activist investors by employing an interaction term between $\mathsf{CommonOwnership}$ and $\mathsf{Activists}$ which is a dummy variable equal to one if commonly owned firms have hedge funds as common owners and zero otherwise.

$$Productivity_{it} = \beta_1 CommonOwnership_{i,t} + \beta_2 Activists_{i,t}$$

$$+\beta_3 CommonOwnership_{i,t} \times Activists_{i,t} + \gamma Control_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \quad (2.11)$$

where i indexes firm and t indexes year, respectively. The unit of observation is a firm-year. If hedge funds enhance the effects of common ownership on firm productivity as compared to other common institutional owners, β_3 will be positive and statistically significant.

Overall, Table 2.11 shows that the effects of activist and non-activist common owners on firm performance are identical. The GGL measure already accounts for managerial incentives by considering the proportion of firms in the common owner's portfolio. Higher GGL indicates that common owners value firm performance more, although such common owners can be passive.

For instance, Appel et al. (2016) show that large voting blocks of passive mutual funds positively impact firm performance. Thus, rather than investor type, the effect of common owners is more likely to be determined by investor attention. Another factor to consider is that firms with a high level of common ownership are likely to be large. In contrast, activist investors, such as hedge funds, are more likely to target small but potentially profitable firms, rendering the number and effect of activist investors insignificant compared to other types of common owners.

Table 2. 11: Activist Common Institutional Owners

This table shows the effects of activist common institutional owners on firm productivity and employment change. The dependent variables are the log of productivity in Columns 1 and 2 and the change in log number of employees (from Compustat) in Columns 3 and 4. The main independent variable is a GGL dummy variable if firms have GGL in quintile 5 of Table 2.2 and zero otherwise and its interaction term with an Activist dummy variable. Other variables are defined in Table 2.3. T-statistics (in parentheses) with standard errors clustered at the firm level. ***, **, and * denote statistical statistical significance at 1%, 5%, and 10% levels, respectively.

\	Log of Productivity		ΔLnEmp_Compustat	
	(1)	(2)	(3)	(4)
GGL_Dummy	0.058**	0.049**	-0.006	-0.008
	(2.432)	(2.295)	(-0.675)	(-0.852)
Activist	-0.055	-0.032	-0.010	-0.006
	(-1.218)	(-0.959)	(-0.733)	(-0.460)
GGL_Dummy x Activist	0.058	0.043	0.000	0.002
	(1.092)	(0.987)	(0.006)	(0.109)
Firm Size		0.089***		-0.097***
		(3.417)		(-6.901)
Market to Book ratio		0.104***		0.027***
		(15.349)		(7.983)
S&P 500 Dummy		-0.093*		-0.041
		(-1.666)		(-1.410)
S&P 400 Dummy		-0.115***		-0.021
		(-2.743)		(-1.117)
S&P 600 Dummy		-0.089***		-0.027*
		(-2.877)		(-1.956)
Block Ownership		-0.500***		-0.039
		(-5.857)		(-0.884)
Institutional Ownership		0.329***		0.040
		(4.892)		(1.102)
Innovation Value		-2.839***		-0.962***
		(-8.075)		(-7.631)
R&D		-0.016		0.022
		(-0.244)		(0.686)
Industry Competition		-0.216		-0.049
		(-1.206)		(-0.412)
Establishment per firm		-0.065***		-0.000
		(-2.868)		(-0.042)
Firm FE & Year FE	Y	Y	Y	Y
Observations	5,945	5,476	5,596	5,177
Adjusted/Pseudo R^2	0.606	0.684	0.194	0.266

2.7.2. Endogeneity: DiD analysis

Although I attempted to overcome issues of selection bias, endogeneity problems could bias the results. Unobservable firm characteristics such as investment opportunities may affect both likelihood of common ownership and productivity, resulting in a spurious correlation between the two. Firms with higher production efficiency may also attract more common owners, resulting in reverse causality. This section addresses these potential issues using a DiD approach based on a quasi-natural experiment where firms have common ownership for the first time.

2.7.2.1. Productivity

First, I create a treatment group by focusing on the year before and the year after a firm has common ownership (which is included in quintile 5, as defined in Section 2.5.2). Then, I use the propensity score matching to create a control group by matching treatment firms to firms without common ownership in the year before introducing common ownership. A short window (two years) alleviates concerns about reverse causality. It also allows better control for the impact of unobserved variables, as significant changes in those variables are less likely to occur during that period. In this setting, the treatment group excludes any firms with common ownership within three years of their initial public offering (the first year that they appear in Compustat). In addition, I exclude three years after common owners leave firms to avoid any persistent effects. Thus, if a firm has common ownership for ten consecutive years following its initial public offerings, all these years are excluded from the treatment group. I also exclude firms with common ownership in the first year if those firms have GGL in quintile four in the preceding year to ensure a meaningful difference in GGL between the treatment and control groups. The firm-year observations excluded from the treatment group are also not included in the control group to ensure the quality of the quasi-natural experiment. The control group also excludes any firm-year observations whose GGL is in quintile four to ensure a significant distinction between treatment and control firms.

The advantage of this experiment is that it allows observing the significant change in the level of common ownership in each firm over the years. In comparison, the method in prior studies such as He & Huang (2017) considers all of the events when a firm has new common owners even though the change in common ownership level in these events is small and insignificant.

Each treatment and control group contains 1,588 firm-year observations before and following a firm's first inclusion in quintile 5. Table A.2.2 of the Appendices show the DiD procedure. The results are highly consistent with those in Table 2.4. Again, productivity differences between treatment and control groups are statistically insignificant in the pre-common ownership year, as shown in Panel C, but significant in the post-common ownership year, as shown in Panels D and E.

Table 2. 12: DiD Analysis of Common Ownership Effects on Productivity

The table presents a difference-in-differences analysis of common ownership effects on firm performance on the first-year firm with common ownership based on the matched sample. Treat is a dummy variable equal to one if a firm is in the treatment group and zero in the control group. Post is a dummy variable equal to one for the first-year firm with common ownership and zeroes for the previous year before common ownership. Treat*Post is the interaction between these two variables. Standard errors are clustered by firm. T-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Log of Productivity	
	(1)	(2)
Treat*After	0.078***	0.076***
	(3.034)	(2.958)
Treat	-0.032	-0.031
	(-0.493)	(-0.548)
After	-0.021	-0.022
	(-1.317)	(-1.448)
Firm Size		0.096***
		(2.667)
Market to Book ratio		0.063***
		(4.913)
S&P 500 Dummy		-0.136
		(-1.317)
S&P 400 Dummy		-0.035
		(-0.306)
S&P 600 Dummy		-0.176**
		(-2.115)
Block Ownership		-0.355***
		(-2.636)
Institutional Ownership		0.193
		(1.595)
R&D		-2.563***
		(-3.426)
Innovation Value		0.291**
		(2.308)
Industry Competition		-0.053
		(-0.390)
Establishment per firm		-0.064
		(-1.356)
Firm FE & Year FE	Y	Y
Observations	1,796	1,796
Adjusted/Pseudo R^2	0.729	0.762

Table 2.12 displays the DiD analysis results. The coefficient estimate Treat*Post is positive and statistically significant in all specifications, indicating that treatment firms experience a greater increase in productivity than control firms. In terms of economic significance, the coefficient estimates for Treat* Post across the two columns indicate that treatment firms experience around a 8.112% increase in productivity during the first year following common ownership, as compared to control firms (in Column 2).

2.7.2.2. Efficiency channels

In this subsection, I examine whether common owners induce employment changes at establishments around the inclusion of common ownership. Managers may foster employment layoffs before the introduction of common ownership. To test this conjecture, I perform a DiD analysis on the establishment's employments applying the same setting as in the previous section. I compare the number of employees between firms in the treatment group with firms in a matched control groups during the year before and after a firm has common ownership. In addition, I compare whether there is a change in employees at the establishment based on their main business activities and productivity. An establishment is classified as a core (peripheral) unit if the establishment operates (does not operate) in its parent firm's core industry in the year before its parent firms have common ownership, i.e., if the aggregated sales of all establishments with the same six-digit NAICS code with that establishment exceed 25% of the firm's total sales. Similarly, an establishment is classified as productive if its productivity (as measured by the sales-to-employee ratio) exceeds the median of all establishments' productivities belonging to the same firm in the year before firms have common ownership and unproductive otherwise.

Table 2.13 presents the results. The dependent variable is the natural logarithm of establishment employees. All the regressions include the same set of control variables (the log of establishment age, the natural log number of establishments per firm, and the log number of establishments per segment). Errors are clustered at the firm level. As we can see, the coefficient estimates before Treat*Post are all negative and significant, suggesting that common owners induce employment layoff across all types of establishments. However, commonly owned firms are more likely to lay off employees at peripheral establishments and unproductive establishments. Moreover, the DiD estimates of -0.090 to -0.223 are economically significant, given the mean of 3.101 and standard deviation of 1.537 for the log number of employees in the DiD sample. The above DiD analysis suggests that inducing employment layoff might be one possible economic channel through which common ownership increases firm productivity significantly in the first-year firms have this structure.

Table 2. 13: DiD Analysis of Common Ownership Effects on Employments Change

The table presents a difference-in-differences analysis of common ownership effects on establishment employees on the first-year firms have common ownership (with GGL belong to quintile 5). The dependent variable in all regressions is the natural log number of establishment employment. Columns 1 to 4 report the change in the log of establishment employees at the core and peripheral establishments. Core (peripheral) establishments are establishments operating in six-digit NAICS industries that account for more than (less than) 25% of the firm's total sales in Columns 1 and 2; and for more than (less than) 50% of the firm's total sales in Columns 3 and 4. Columns 5 to 8 report the change in the log number of establishment employees at productive and unproductive establishments. An establishment is considered productive (unproductive) if its corresponding productivity rank is above (below) the median productivity of the establishments belonging to the firm each year in Columns 5 and 6; and above (below) the median productivity of the establishments belonging to the industry segment each year in Columns 7 and 8. Columns 3 and 4 use the within-industry productivity to rank establishments. Treat is a dummy variable equal to one if an establishment's parent firm is in the treatment group and zero in the control group. Post is a dummy variable equal to one for the first-year firm with common ownership (GGL belongs to quintile 5) and zeroes for the previous year before common ownership. Treat*Post is the interaction between these two variables. Establishment Age is the number of years since the foundations of that establishment. Establishment per firm is the natural logarithm of the total number of establishments of the parent firm, while Establishment per Segment is the natural logarithm of the total number of establishments of the parent firm in the same six-digit NAICS industry segment with that establishment. Standard errors are clustered by firm. T-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log of Establishment Employment							
[-1,1]	Core_25	Peri_25	Core_50	Peri_50	Prod_ firm	Unprod_ firm	Prod_ naics	Unprod_ naics
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat*Post	-0.096**	-0.172**	-0.078**	-0.223*	-0.161***	-0.090**	-0.111***	-0.111*
	(-2.104)	(-2.564)	(-2.040)	(-1.896)	(-2.682)	(-2.161)	(-3.149)	(-1.733)
Treat	0.434	-0.150	0.367	0.240	0.154	0.391	0.072	0.467*
	(1.503)	(-0.720)	(1.203)	(0.836)	(0.693)	(1.245)	(0.219)	(1.886)
Post	0.038	0.081	0.047*	0.048	0.096**	0.015	0.020	0.041
	(1.538)	(1.073)	(1.878)	(0.717)	(2.014)	(0.748)	(0.634)	(1.421)
Est. Age	0.134*	0.261***	0.106	0.302***	0.125	0.182**	0.210***	0.126*
	(1.719)	(3.360)	(1.332)	(3.565)	(1.324)	(2.152)	(3.043)	(1.663)
Est. per firm	-0.207	-0.106	-0.219*	-0.083	-0.321***	-0.128	-0.097	-0.223**
	(-1.638)	(-1.145)	(-1.663)	(-0.524)	(-2.619)	(-0.909)	(-0.626)	(-1.982)
Est. per segment	0.166	-0.078	0.179	-0.047	0.209	0.113	0.094	0.164
	(1.108)	(-0.797)	(1.144)	(-0.277)	(1.485)	(0.770)	(0.709)	(1.133)
Constant	2.851***	3.635***	2.904***	3.171***	3.391***	2.552***	2.936***	2.708***
	(4.418)	(7.657)	(4.036)	(5.804)	(7.358)	(4.344)	(4.835)	(5.257)
Observations	180,117	42,730	160,762	64,109	66,963	158,119	87,610	137,458
Adjusted R2	0.035	0.050	0.033	0.039	0.052	0.025	0.013	0.045

2.7.3. Persistent effects of common ownership

Table 2.14 investigates the change in productivity following a firm's return to a non-common ownership position. In this DiD setting, the treatment group includes only the last year of a firm's common ownership (year t-1) and the first year after common owners exit (year t). This group includes only a two-year window in which all observations in the first-year t-1 are commonly owned firms, and all observations in the second-year t are still those firms but without common ownership. The control sample includes firms with common ownership in year t-1 and continued to have it in year t. Like the setting in Table 2.12, the treatment and control groups exclude any firm-year observations where firms have common ownership within three years of their initial public offering. If a firm has had common ownership for ten years in a row since its initial public offering, all those years will be excluded from the treatment group.

Each treatment and control group contains 1,386 firm-year observations before quintile-five exclusion and 1,386 firm-year observations after quintile-five exclusion. Table A.2.3 in the Appendices shows the DiD procedures like those in Table 2.4. The results in Panels C, D, and E demonstrate no significant differences in productivity between treatment and control groups before and after the common owners leave the firms. Table 2.14 confirms the results by the different-in-different regression.

Table 2. 14: Permanent Effects of Common Ownership on Productivity

The table presents a difference-in-differences analysis of common ownership effects on firm performance on the first-year common institutional owners' exit from the firm. Panel F reports the results for the diff-in-diffs regression based on the matched sample. Treat is a dummy variable equal to one if a firm is in the treatment group and zero if in the control group. Post is a dummy variable equal to one for the first-year common institutional owners exit from the firm (GGL steps down from quintile 5) and zero for the last year firms have common ownership. Treat*Post is the interaction between these two variables. Standard errors are clustered by firm. T-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: Log of Productivity	
	(1)	(2)
Treat*After	0.003	0.002
	(0.170)	(0.071)
Treat	-0.015	-0.006
	(-0.623)	(-0.279)
After	-0.025*	-0.018
	(-1.847)	(-1.326)
Firm Size		0.126***
		(3.060)
Market to Book ratio		0.101***
		(8.172)
S&P 500 Dummy		-0.173**
		(-1.983)
S&P 400 Dummy		-0.187***
		(-2.633)
S&P 600 Dummy		-0.060
		(-1.108)
Block Ownership		-0.208
		(-1.432)
Institutional Ownership		0.244**
		(2.516)
Innovation Value		-2.862***
		(-4.273)
R&D		0.009
		(0.075)
Industry Competition		-0.579**
		(-2.120)
Establishment per firm		-0.024
		(-0.590)
Firm FE & Year FE	Y	Y
Observations	2,772	2,620
Adjusted/Pseudo R^2	0.709	0.746

2.8. Conclusion

This chapter investigates the impact of common ownership on firm productivity and the possible channels behind that. Using the firm-level data for U.S. publicly listed firms, I confirm that firms with common ownership experience significantly higher productivity than firms without this structure. I have established causality using a difference-in-differences approach based on the quasi-natural experiment. Further, I trace out the source of efficiency gains by exploiting the establishment-level data from the NETS database. I find that common owners are likely to induce the employment layoff at unproductive and peripheral establishments. In addition, common owners also reduce the number of establishments in firms operating across multiple industry segments. These results are similar across different types of common owners, given that my common ownership measure has already controlled for the diverse attention among institutional investors.

This study is the first in the emerging literature on common ownership to trace value creation sources to the fundamental production process. It complements concurrent studies on the real effects of ownership structure changes on firm performance, and at the same time, distinguishes common owners from other blockholders.

2.9. Appendices

2.9.1. Measuring TFP

Productivity measures the efficiency in the production process by estimating the variation in output produced from a given set of inputs and is often estimated by Cobb-Douglas production function using ordinary least squares (OLS). The production equation is:

$$y_{it} = \beta_o + \beta_l l_{it} + \beta_k k_{it} + u_{it} \quad (2.12)$$

where y_{it} is the log of value added for firm i in period t; l_{it} and k_{it} are log values of labor and capital of the firm, respectively; $u_{it} = \omega_{it} + \varepsilon_{it}$ where ω_{it} is the productivity; and ε_{it} is an error term which is unknown by both firm and econometricians, thus not affecting the firm's decision making.

However, estimations of this model may suffer from both simultaneity and selection bias. Simultaneity happens as more efficient firms are, all else equal, likely to employ more inputs to maximize profitability (Marschak & Andrews, 1944). Particularly, the gain in production efficiency is unknown to econometricians but seen by the firm, thus affecting the firm decision on the input quantity. If the OLS regression does not account for this effect, the estimates for these inputs will be biased upward. On the other hand, selection bias arises as inefficient firms are more likely to exit from the sample, mechanically increasing the average efficiency of the remaining sample. This happens as firms with more capital stocks k_{it} can generate higher future profits, thus being able to maintain operation with even low productivity and forcing small firms to exit the market. The negative relationship between capital stock and likelihood of exit for a given efficiency level will bias the capital coefficient downward unless it is controlled for. Thus, this study employs the semiparametric procedure suggested by Olley & Pakes (1996) to control for these biases, following (İmrohoroğlu & Tüzel, 2014). The production is estimated in two steps to control for the simultaneity bias first and selection bias in the second stage.

Olley and Pakes (1996) assume that firms decide to remain the operation or shut down the business based on its state variables: the productivity ω_{it} and capital k_{it} at the beginning of each period. The firm will receive a certain liquidity value if it chooses to exit or will decide the level of variable input l_{it} and investment I_{it} if it chooses to stay in the market. The further investment I_{it} is conditional on the productivity ω_{it} and capital k_{it}:

$$I_{it} = I(\omega_{it}, k_{it}) \quad (2.13)$$

Given I_{it} is strictly positive, the inverse function for the unobserved productivity ω_{it} can be written as:

$$\omega_{it} = I^{-1}(I_{it}, k_{it}) = h(I_{it}, k_{it}) \ (2.14)$$

where h is strictly increasing in I_{it}. Using this function to control for the simultaneity problem by substituting (3) into (1):

$$y_{it} = \beta_l l_{it} + \emptyset_{it}(i_{it}, k_{it}) + \varepsilon_{it} \ (2.15)$$

where

$$\emptyset_{it}(i_{it}, k_{it}) = \beta_o + \beta_k k_{it} + h\ (i_{it}, k_{it}) \ (2.16)$$

$\emptyset_{it}$ is approximated with a second order polynomial series in capital and investment. Equation (2.15) can be estimated by OLS and produces a consistent estimate for l_{it} because the function $\emptyset_{it}$ controls for unobserved productivity, and the error term is no longer correlated with the inputs.

In the second stage, I then estimate survival probabilities to control for selection bias. The probability that a firm will stay in year t depends on its productivity in year t-1, which in turn depends on capital and investment in year t-1. From Equations 2.15 and 2.16, I fit the following equation by nonlinear least squares:

$$y_{i,t} - \hat{\beta}_l l_{i,t} = \beta_k k_{i,t} + g\left(\hat{\emptyset}_{t-1} - \beta_k k_{i,t-1}, \hat{P}_{survival,t}\right) + \xi_{i,t} + \varepsilon_{i,t} (2.17)$$

where $\hat{P}_{survival,t}$ denotes the probability of firm survival from time $t-1$ to time t and is estimated using a Probit with a survival indicator variable on a polynomial expression containing capital and investment. The entire estimation process applies clustered bootstrap to treat all observations of a firm as one cluster to generate proper standard errors. At the end of this stage, $\hat{\beta}_l$ and $\hat{\beta}_k$ are estimated.

Finally, productivity is measured by:

$$P_{i,t} = exp\ (y_t - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{i,t}) (2.18)$$

I estimate Equation 2.15 with industry-specific time dummies to control for any effects caused by different industries or aggregate TFP in any given year.

2.9.2. Constructing TFP

I use annual fundamental data from Compustat from 1987 to 2015 to calculate firm productivity, excluding financial firms (SIC classification between 6000 and 6999) and regulated firms (SIC classification between 4900 and 4999). I require positive sales, employees, total assets, gross property, plant, and equipment, depreciation, accumulated depreciation, and capital expenditures for the remaining observations. The sample is an unbalanced panel of approximately 13,900 distinct firms with a total of approximately 317,500 firm-year observations.

The value added (y_{it}) equals Net sales – Materials, deflated by the GDP price deflator. Materials are computed as Total expenses minus Labor expenses, where Total expenses are the gap between Sales and Operating income before depreciation and amortization. Labor expenses are calculated by multiplying the number of employees by the national average wage index. The stock of labor (l_{it}) is the number of employees. Subsequently, the value added can be computed as Operating income before depreciation and amortization plus Labor expenses.

Capital stock (k_{it}) is calculated by deflating gross property, plant, and equipment by the price deflator for investment, as described in (Hall, 1990), in order to eliminate the impact of possible embodied technological progress as described in (Greenwood, Hercowitz, & Krusell, 1997). Since the capital investment is made at various times in the past, to deflate it with an appropriate price deflator, I calculate the average age of capital at every year for each company (assuming that investment is made all at once in a year) by dividing accumulated depreciation (Gross PPE - Net PPE) by current depreciation and further smoothing it by taking a 3-year moving average. The capital investment year will equal current year minus average age. Using the resulting capital stock, I calculate the available capital stock at the beginning of each period by delaying it by one time period. Fixed investment to capital ratio (i_{it}) is computed as Capital expenditure deflated by the price deflator for investment for that year and divided by the beginning of the period real capital stock.

I obtain both price indexes for Gross Domestic Product (as a deflator for the value added) and for private fixed investment (as a deflator for investment and capital) from the Bureau of Economic Analysis; national average wage index from the Social Security Administration; and other variables from Compustat.

2.9.3. Tables

Table A.2. 1: Variable Definitions

This appendix presents definitions for the variables used in Chapter 2.

Variable	Definition	Source
Panel A: Firm-level variables		
GGL	Common ownership measure	Refinitiv's 13F
Productivity	Productivity of a given firm	Compustat
ΔLog(Employment)	Within-firm annual change in the natural logarithm of the employment	NETS
Assets (billions)	Firm total assets	Compustat
MktCap (billions)	Market capitalization	Compustat
Market to Book ratio	The ratio of market value to book value of equity	Compustat
Dividend Dummy	Dummy variable which equals one for firms paying dividends, and zero otherwise	Compustat
S&P Dummy	Dummy variable which equals one for firms included in the index, and zero otherwise	Compustat
Innovation	The total dollar value of innovation produced by a given firm i at time t, based on the stock market (sm) (all the values of firm patents) and scaled the total by firm size (book assets).	Kogan et al. (2017)
R&D (billions)	Research and development expenditures (xrd)/total assets (at). It is set to zero for missing firms	Compustat
Industry Competition	Measured by ownership concentration – Herfindahl-Hirschman Index	Compustat
Employees (thousands)	Number of firm employees	Compustat
Institutional Ownership	Total ownership of institutional investors in a firm	Refinitiv's 13F
Block Ownership	Total ownership of blockholder investors in a firm	Refinitiv's 13F
Activist	Dummy variable which equals one if commonly owned firms have at least one common institutional owner submitting the 13D file for the firms within the same industry with that firm in the last three years, and zero otherwise	13D Filings
Panel B: Establishment-level variables		
ΔLog(Employment)	Within-establishment annual change in the natural logarithm of the employment	NETS
Age	Number of years since the foundation of an establishment	NETS
Establishment per firm	Natural logarithm of the total number of establishments of the parent firm	NETS
Establishment per segment	Natural logarithm of the total number of establishments in the three-digit SIC industry segment of the parent firm	NETS
Core (Peripheral)	Establishments belong (does not belong) to the core industry of the parent firm at the beginning of a given year	NETS
Productive (Unproductive)	Establishments have productivity rank above (below) the median productivity of all establishments belonging to the same firm in a given year.	NETS

Table A.2. 2. DiD Analysis of Common Ownership Effects on Productivity

This table presents the difference-in-differences analysis which is discussed in Section 2.7.2.1 and Table 2.12. The results show the effect of common ownership on firm performance on the first year after firms have common ownership structure (with GGL belonging to quintile 5). Panel A, Column 1, reports the results of a logit model based on the pre-matched firms in the treatment and the control groups. The dependent variable of the logit model equals one if the firm belongs to the treatment group (has common ownership) and zero if the firm comes from the control group (without common ownership). The independent variables of the logit model are the control variables used in the regression Equation 2.5 measured in the pre-common ownership year. Panel A, Column 2, reports the results of the same logit model based on the post-matched firms in the treatment and the control groups. Panel B reports statistical distributions of the propensity scores of the treatment and control groups and their differences. Panel C reports pre-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding t-statistics. Panel D reports post-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding t-statistics. Panel E reports the diff-in-diffs estimator based on the matched sample. Panel F reports the results for the diff-in-diffs regression based on the matched sample. Treat is a dummy variable equal to one if a firm is in the treatment group and zero in the control group. Post is a dummy variable equal to one for the first-year firm with common ownership (GGL belongs to quintile 5) and zeroes for the previous year before common ownership. Treat*Post is the interaction between these two variables. Standard errors are clustered by firm. T-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Logit regressions with pre- and post-matched samples

	Dependent variable: GGL_Dummy	
	Pre-match (1)	Post-match (2)
Productivity	0.305**	-0.002
	(2.313)	(-0.013)
Firm Size	0.277***	0.063
	(4.698)	(0.874)
Market to Book ratio	0.029	0.036
	(0.589)	(0.609)
S&P 500 Dummy	-0.297	-0.276
	(-1.368)	(-0.947)
S&P 400 Dummy	-0.031	-0.152
	(-0.164)	(-0.579)
S&P 600 Dummy	-0.054	0.054
	(-0.333)	(0.248)
Block Ownership	-0.806	-0.306
	(-1.300)	(-0.423)
Institutional Ownership	1.456***	0.021
	(3.894)	(0.047)
R&D	12.365***	-0.763
	(14.534)	(-0.707)
Innovation Value	0.631	0.313
	(1.493)	(0.631)
Industry Competition	-0.368	0.266
	(-0.768)	(0.450)
Establishment per firm	-0.002	-0.020
	(-0.056)	(-0.360)
Constant	-6.702***	-0.335
	(-18.287)	(-0.719)
Observations	25,059	898
p-value of χ^2	0.000	0.9950
Pseudo R^2	0.1054	0.0029
Log likelihood	-2013.518	-620.66957

Table A.2. 2: continued

Panel B: Propensity scores distribution

Group	N	Mean	Minimum	Maximum	Std. dev
Treatment	449	0.051	-2.805	2.757	0.756
Control	449	0.133	-2.805	3.010	0.718
Difference	449	-0.083	0.000	-0.253	0.038

Panel C: Differences in variables in pre-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.102	-0.122	0.020	0.53	0.598
Firm Size	6.647	6.562	0.084	0.61	0.543
Market to Book ratio	2.100	2.038	0.062	0.65	0.517
S&P 500 Dummy	0.245	0.247	-0.002	-0.08	0.938
S&P 400 Dummy	0.122	0.127	-0.004	-0.2	0.840
S&P 600 Dummy	0.160	0.147	0.013	0.55	0.579
Block Ownership	0.135	0.138	-0.004	-0.44	0.662
Institutional Ownership	0.564	0.562	0.002	0.14	0.889
R&D	0.059	0.063	-0.004	-0.65	0.518
Innovation Value	0.090	0.081	0.010	0.8	0.424
Industry Competition	0.104	0.105	-0.001	-0.1	0.920
Establishment per firm	2.657	2.643	0.014	0.11	0.909

Panel D: Differences in variables in post-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.054	-0.142	0.088	2.46**	0.014
Firm Size	6.769	6.650	0.119	0.87	0.383
Market to Book ratio	2.163	1.984	0.178	1.98**	0.048
S&P 500 Dummy	0.252	0.254	-0.002	-0.08	0.939
S&P 400 Dummy	0.138	0.125	0.013	0.59	0.554
S&P 600 Dummy	0.176	0.160	0.016	0.62	0.533
Block Ownership	0.216	0.144	0.072	8.29***	0.000
Institutional Ownership	0.657	0.564	0.093	5.96***	0.000
R&D	0.058	0.061	-0.003	-0.57	0.570
Innovation Value	0.104	0.082	0.021	1.71*	0.087
Industry Competition	0.098	0.105	-0.007	-0.79	0.431
Establishment per firm	2.670	2.644	0.026	0.20	0.839

Panel E: Difference-in-differences estimator

Variable	Treatment		Control		Diff-in-diff	t-statistic	p-value
	Before	After	Before	After			
Productivity	-0.102	-0.054	-0.122	-0.142	0.068	2.609***	0.009

Table A.2. 3: Permanent Effects of Common Ownership on Productivity

This table presents the difference-in-differences analysis which is discussed in Section 2.7.2.3 and Table 2.14. The results show the effect of common ownership on firm performance in the first year that common institutional owners exit from the firm. Panel A, Column 1, reports the results of a logit model based on the pre-matched firms in the treatment and the control groups. The dependent variable of the logit model equals one if the firm belongs to the treatment group (has common ownership) and zero if the firm comes from the control group (without common ownership). The independent variables of the logit model are the control variables used in the regression Equation 2.5 measured in the last year firms have common ownership. Panel A, Column 2, reports the results of the same logit model based on the post-matched firms in the treatment and the control groups. Panel B reports statistical distributions of the propensity scores of the treatment and control groups and their differences. Panel C reports pre-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding t-statistics. Panel D reports post-common ownership variable averages for the treatment and control groups, the differences in means of each variable, and the corresponding t-statistics. Panel E reports the diff-in-diffs estimator based on the matched sample. Panel F reports the results for the diff-in-diffs regression based on the matched sample. Treat is a dummy variable equal to one if a firm is in the treatment group and zero if in the control group. Post is a dummy variable equal to one for the first-year common institutional owners exit from the firm (GGL steps down from quintile 5) and zero for the last year firms have common ownership. Treat*Post is the interaction between these two variables. Standard errors are clustered by firm. T-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Logit regressions with pre- and post-matched samples

	Dependent variable: GGL_Dummy	
	Pre-match (1)	Post-match (2)
Productivity	-0.071	-0.035
	(-0.720)	(-0.289)
Firm Size	-0.095*	-0.011
	(-1.659)	(-0.159)
Market to Book ratio	-0.220***	-0.042
	(-4.862)	(-0.837)
S&P 500 Dummy	-0.232	0.038
	(-1.139)	(0.150)
S&P 400 Dummy	-0.207	0.070
	(-1.303)	(0.343)
S&P 600 Dummy	0.015	-0.068
	(0.115)	(-0.420)
Block Ownership	-1.018	0.629
	(-1.644)	(0.922)
Institutional Ownership	-1.275***	-0.220
	(-2.738)	(-0.449)
Innovation Value	1.067***	0.169
	(3.832)	(0.520)
R&D	-5.250***	0.926
	(-5.785)	(0.822)
Industry Competition	-5.081***	-0.465
	(-3.522)	(-0.417)
Establishment per firm	0.041	0.021
	(1.099)	(0.473)
Constant	1.775***	0.076
	(3.660)	(0.148)
Observations	2,748	1,386
p-value of χ^2	0.0000	0.9845
Pseudo R^2	0.0438	0.0021
Log likelihood	-1483.9492	-958.7141

Table A.2. 3: continued

Panel B: Propensity scores distribution

Group	N	Mean	Minimum	Maximum	Std. dev
Treatment	693	-0.016	-2.990	2.143	0.722
Control	693	-0.011	-2.437	2.051	0.698
Difference	693	-0.005	-0.554	0.092	0.025

Panel C: Differences in variables in pre-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.059	-0.033	-0.026	-0.90	0.370
Firm Size	6.843	6.842	0.000	0.00	0.998
Market to Book ratio	2.039	2.094	-0.055	-0.80	0.423
S&P 500 Dummy	0.251	0.250	0.001	0.06	0.951
S&P 400 Dummy	0.175	0.166	0.009	0.43	0.668
S&P 600 Dummy	0.215	0.228	-0.013	-0.58	0.561
Block Ownership	0.234	0.229	0.004	0.70	0.485
Institutional Ownership	0.691	0.692	-0.001	-0.10	0.918
Innovation Value	0.115	0.109	0.006	0.53	0.594
R&D	0.054	0.051	0.003	0.80	0.422
Industry Competition	0.074	0.073	0.000	0.12	0.907
Establishment per firm	2.619	2.596	0.023	0.25	0.802

Panel D: Differences in variables in post-common ownership year

Variable	Treatment	Control	Difference	t-statistic	p-value
Productivity	-0.075	-0.049	-0.026	-0.88	0.380
Firm Size	6.924	6.942	-0.019	-0.21	0.837
Market to Book ratio	1.894	2.036	-0.142	-2.23	0.026
S&P 500 Dummy	0.258	0.268	-0.010	-0.43	0.670
S&P 400 Dummy	0.166	0.163	0.003	0.14	0.885
S&P 600 Dummy	0.237	0.234	0.003	0.13	0.899
Block Ownership	0.194	0.240	-0.046	-6.95	0.000
Institutional Ownership	0.669	0.706	-0.037	-3.69	0.000
Innovation Value	0.113	0.110	0.003	0.23	0.815
R&D	0.054	0.052	0.002	0.50	0.615
Industry Competition	0.071	0.073	-0.002	-0.71	0.479
Establishment per firm	2.637	2.603	0.035	0.38	0.704

Panel E: Difference-in-differences estimator

Variable	Treatment		Control		Diff-in-diff	t-statistic	p-value
	Before	After	Before	After			
Productivity	-0.059	-0.075	-0.033	-0.049	0.000	0.01	0.589

Chapter 3

Common Ownership and Return Comovement[16]

3.1. Introduction

Over the last decades, same-industry firms have progressively shared blockholders, i.e., a common ownership structure. In 2014, more than 60% of publicly listed companies in the United States had this structure (He & Huang, 2017). The growing popularity of common ownership demonstrates that depicting firms as autonomous decision-makers in the product market may no longer adequately represent their strategic interactions. Indeed, prior research indicates that large common blockholders can influence the performance and investment choices of same-industry firms in their portfolios (Koch et al., 2021). While the existing literature focuses almost entirely on the performance of commonly owned firms, there has been little emphasis devoted to the role of common ownership in influencing return comovement. Given the substantial growth in common ownership and that it remains largely unregulated, it is critical for both academics and policymakers to understand the economic consequences of the structure, particularly its implications for return comovement and systematic risk.

Comovement in stock returns is a fundamental component of the market's risk and stability. It is crucial to determine the efficiency of the cross-sectional diversification and management of systematic risk, thus affecting firms' cost of capital. Comovement also impacts the level of systemic risk through the way shocks are transmitted among stocks in the markets. High comovement in returns reflects a high level of systematic variation or a low level of firm-specific information compounded into stock prices (Roll, 1988). Common ownership allows blockholders to exert influence on the corporate decisions of a group of firms potentially binding their performance together and reducing individual firm-specific information incorporated in prices. Can common ownership between same-industry firms increases comovement in stock returns?

[16] This chapter is my solo paper.

There are several reasons why common ownership is likely to impact comovement between stock returns. For example, common ownership can foster fundamental correlation among commonly owned firms by reducing information asymmetry and facilitating coordination, thereby tying their potential earnings together (He & Huang, 2017). Chemmanur et al. (2016) discover a high number of co-patents and mutual citations among same-industry firms with common owners. Moreover, common ownership affects how a firm discloses its earnings information in relation to other firms with the same common owners, potentially creating correlations in news about firm performance (Massa & Žaldokas, 2017; Park et al., 2019). Despite these reasons, research on how common ownership impacts comovement is scarce. Edmans et al. (2014) theoretically prove that common ownership between any two firms in the same or different industries allows blockholders to choose between a balanced or unbalanced exit when faced with liquidity shocks, affecting stock prices of both retained and sold firms in the same or opposite directions. Common owners are more likely to follow imbalanced exit, and thus causing negative return comovement when the agency problem is severe, or liquidity shocks are infrequent.

Motivated by Edmans et al.'s (2014) study, chapter three empirically tests whether common ownership can impact comovement in stock returns even in the absence of liquidity shocks and agency concerns. Moreover, the chapter differs from other studies by solely investigating the effects of common ownership on comovement in returns between same industry firms. I question whether there is excessive comovement in returns between firms in the same industry with and without this structure. I first identify all pairs of firms in the same industry that share no or at least one common owner from 1990 to 2019 for the US public firms. I then follow Gilje et al. (2020) to measure common ownership effects in any firm pairs with common owners, which depends on the importance of each firm in the common owners' portfolio and the proportion of that common owner's ownership in each firm. The measure captures the attention and knowledge of common owners to the firm pairs and how much firm managers care about the common owners' preferences.

I construct two measures for pairwise comovement between two firms with common ownership following Morck et al.'s (2000) method and adjusting for a within-US study. The first measure observes the number of days that stock prices of each pair of firms move in the same direction and divide it by the total number of days in which both firms move in either direction. If the two firms always move in the same (opposite) direction, the measure equals one (zero). The second measure is the correlation coefficient between the returns of two paired firms. While the first comovement measure captures time-period-specific shocks and depends on the number of days where two returns move in the same direction, the second correlation measure reveals both the direction and magnitude of the two returns' movement.

Given that each observation in the sample contains a pair of firms, unobservable firm effects can cause the errors to be correlated across pairs. I address this problem by applying the non-parametric bootstrapping estimation method by Krackhardt (1988) to determine the significance of estimated coefficients. Firms with common ownership are also more likely to share an overall trend caused by unobserved reasons, overestimating the degree of comovement attributable to the effects of common ownership. For example, increased supplier-customer relationships may cause firms' fundamentals to be correlated when common ownership is present. Thus, I do the trend correction for long-run trends by detrending the data on firm-level returns (Chan, Hayya, & Ord, 1977; Khanna & Thomas, 2009). There are other reasons why the returns of two firms could be correlated, whether they share common ownership. For instance, two firms operating in the same industry may be exposed to the same sources of materials and product demands, as well as legal and political risks. These common factors may blur firm boundaries, reducing firm-specific information incorporated in stock returns. Using common industry effects, I attempt to account for the possibility that firms may share fundamentals even if the common ownership between them does not exist.

My multivariate ordinary least-squares (OLS) analysis shows that firm pairs with common ownership experience significantly higher comovement in returns than firm pairs without common ownership. The result is robust to alternative empirical specifications after removing the trends in the data of the pairs and controlling for unobserved variables that may affect the pair's comovement. It is consistent with the idea that the market views common ownership as a mechanism for common owners exercise joint control across firms. A firm pair with common ownership is predicted to move in the same direction 3.562% more often than a pair without common ownership. In addition, when firm pairs share common ownership, their returns are 7.251% more correlated than when they do not.

While I am interested in whether common ownership influences comovement in returns, comovement in returns may also influence the likelihood of common ownership. For instance, institutional investors may target same-industry firms with a high correlation in stock returns to create common ownership. To overcome the reverse causality concerns, I implement a difference-in-differences (DID) analysis around the mergers of large financial institutions as an external shock to firms' common ownership levels (Lewellen & Lowry, 2021). The mergers create a significant shift in the level of common ownership between a firm pair in the same industry – each firm is block-held by one party before the merger. Thus, the treatment sample consists of firms whose ownership linkages with same-industry firms are likely to increase just because of the merger. On the other hand, the control sample consists of other block-held firms in the same institution's portfolio that are unlikely to experience such changes. I find evidence that treatment firms, relative to control firms, experience an approximately five to ten percent larger increase in return comovement surrounding the institution mergers, which rules out the mechanical effect of common ownership.

Several mechanisms could contribute to the increase in return comovement. I find that the effect of common ownership on pairwise comovement is stronger between firms with less product similarity. While common ownership may help in product space, it may hinder innovation. Commonly owned firms selling similar products are less willing to invest in innovation for the fear that their advanced products will negatively impact the business of other firms with common owners. Employing such a tool may well be in the interest of undiversified shareholders (and consumers) but costly for common owners. Common ownership may thus create more binding value between firms with different products or firms close in the technology space, increasing their comovement in returns. On the other hand, firms with similar products generate less value from innovation collaboration; thus, their stock prices may be less correlated.

My findings are important for both market participants and policymakers. The U.S.'s Council of Economic Advisers considered common ownership a rising concern for the economy[17]. Elhauge (2015) states that block-holding multiple firms within the same industry promotes anticompetitive effects and thus should be prohibited. Posner, Scott Morgan, and Weyl (2016) and Schmalz (2018) propose a policy restricting institutions' ownership in a sector to a certain percentage or to a single large stake in only one firm. However, it could be premature to enact such policies as numerous papers find no discernible effect of common ownership on industry competition (Kennedy, O'Brien, Song, & Waehrer, 2017; Koch et al., 2021; Patel, 2018; Rock & Rubinfeld, 2018). My finding that common ownership increases comovement in returns may deepen the U.S. government's current concerns on the market impacts of common ownership. The increasing likelihood of shocks spreading across stocks due to common ownership may impact systemic risk and the propensity for flash crashes. Comovement in returns also affects

[17] https://obamawhitehouse.archives.gov/sites/default/files/page/files/20160414_cea_competition_issue_brief.pdf
http://www.oecd.org/competition/common-ownership-and-its-impact-on-competition.htm

systematic risk and expected return premiums. Comovement between firms with common ownership can raise firm costs of capital and impact the real economy through their investment levels. If all firms are eventually controlled by a single institution, the impact of common ownership on market stability should be obvious.

This chapter also adds to the literature on pairwise comovement in stock returns. My study is consistent with previous research, which suggests that comovement at the market level is caused by correlated fundamentals and blurred firm boundaries (Bertrand et al., 2002; Khanna & Thomas, 2009). Common ownership acts as a mechanism for joint control across firms. Firms with common ownership are considered relevant by the market, possibly because they allow for coordination in firm activities, efficient resource allocation, and cross-monitoring (He & Huang, 2017; Morck et al., 2000). This study also adds to the body of knowledge about the impact of ownership structure on institutional selling. Compared to large separate institutional ownership in a single firm, common owners with selling options between good and bad firms can create incremental effects on stock prices (Edmans et al., 2019). Finally, comovement in returns between commonly owned firms can provide new trading opportunities for individual investors who follow a specific trading style, such as trading by categories, and seek to invest in a small group of firms with similar characteristics (Barberis & Shleifer, 2003; Barberis, Shleifer, & Wurgler, 2005; Wahal & Yavuz, 2013).

3.2. Related literature and hypotheses

There is considerable literature studying the effects of common ownership; see Section 2 of Chapter 1 or Schmalz (2018) for a more detailed summary. Thus, this section only reviews papers directly related to my empirical investigation about the effect of common ownership on comovement, then proceeds to develop hypotheses.

3.2.1. Comovement in returns

The extent to which stock returns comove determines the effectiveness of diversification strategy and portfolio or market risk. Comovement affects asset prices, required returns, and the cost of capital. Thus, its determinants have been widely studied.

Stock returns reflect new market-wide and firm-specific information. High comovement in returns can be attributed to either a high level of market-wide information (systematic variation) or a low level of firm-specific information (firm-specific variation) capitalized into stock prices (Roll, 1988). In frictionless economies with rational investors, stock prices equal rationally forecasted cash flows discounted at an appropriate rate for their risks. Thus, any market-wide return comovement must result from the correlation in the news about fundamental values such as the same cash-flow stream (Barberis et al., 2005) or correlated macro discount factors (Campbell, Polk, & Vuolteenaho, 2010; Li, 2002; Pindyck & Rotemberg, 1993). High fundamentals correlation is common in undiversified low-income economies where listed firms may concentrate in a few industries. An industry event or rumours such as leadership succession within a controlling family can potentially affect the entire economy. An economy depends disproportionately on a few large firms, which are the suppliers and customers of most other listed firms can also ensure a high level of return comovement. Emerging markets experience higher comovement in returns than developed markets due to uncertain protection of private property rights, which reduces firm-specific information incorporated into stock prices (Morck et al., 2000).

Firm fundamentals may also converge due to blurred boundaries between firms, reducing the amount of firm-specific information in prices (Barberis et al., 2005). Blurred boundaries occur when two or more businesses are not entirely segregated. Control pyramids, family holdings, and business groups are all common ways to exercise joint control over business activities (Bertrand et al., 2002; La Porta, Lopez-De-Silanes, & Shleifer, 1999). Weaker protection for public investors may encourage income shifting between controlled firms via non-arm's-length transactions for goods, services, or capital at inflated prices, causing their earnings to be interdependent. Khanna and Thomas (2009) show that firm-specific variation within a country can be attributed to the variance between firms within the same industry and ownership networks through three mechanisms of joint control: equity interlocks, director interlocks, and individual owners. These ties between firms are associated with either decreased transparency at the firm level or increased correlation in firm fundamentals. They allow firms to pool their resources together, create the supplier-customer relationship, or facilitate inter-organizational coordination, enabling firms to share common cash flow rights (Johnson, La Porta, Lopez-de-Silanes, & Shleifer, 2000). These connections enhance ownership network-specific information when pricing individual firms' stocks while simultaneously reducing firm-specific residuals, thereby improving the overall fit of the regression equation.

On the other hand, comovement in returns might simply be the consequence of numerous market frictions, inadequate assimilation of information in prices, or sentiment. These factors cause stock prices to temporarily diverge from fundamentals and impact the degree of comovement. Adding a firm to an index, for example, tends to raise its degree of return comovement even if its fundamentals stay the same (e.g., (Barberis et al., 2005; Claessens & Yafeh, 2013). Investors may group stocks into different categories based on their market capitalization or industry characteristics and allocate funds to specific groups to simplify portfolio decisions (Chan, Lakonishok, & Swaminathan, 2007; Fodor, Jorgensen, & Stowe, 2021). Suppose some of these investors are noise traders with correlated sentiments, and their trading affects prices. As they move funds from one category to another, it will create a demand for all stocks in the new category, resulting in comovement (Barberis & Shleifer, 2003). The comovement can also result from the habitat view when many investors prefer to trade on a specific subset of all available stocks due to transaction costs, insufficient information, or restricted regulation (Wahal & Yavuz, 2013). These investors may create a common factor in stock returns of these subset firms, leading to comovement in returns. Another reason for the comovement could attribute to the information diffusion that certain equities reflect market-wide information more rapidly than others (Chan & Chan, 2014; Chan & Hameed, 2006).

My contribution to this literature is in showing that common ownership has a significant impact on return comovement and that this impact is consistent with correlation in fundamentals or trading demands.

3.2.2. The effect of common ownership on comovement

Much of the prior studies focus on the anti-competitive effects of common ownership. They show that common owners are more likely to reduce competition and motivate coordination among commonly owned firms to increase their combined portfolio value. He & Huang (2017) discover that firms with common ownership grow market share significantly faster and engage in more explicit collaborations through joint ventures, strategic alliances, and acquisitions with other commonly owned firms. Chemmanur et al. (2016) investigate the role of common ownership in forming strategic alliances between industry peers and find a greater number of co-patenting patents among commonly owned firms. Kostovetsky & Manconi (2018) find that firms receive more citations among firms that share common owners around the Russell 1000/2000 index boundary or the mergers of their financial institution, indicating the facilitation of innovation diffusion among their portfolio firms. This chapter examines whether increased coordination among commonly owned firms bides their earnings together, thus increasing their return comovement.

Park et al. (2019) investigate information disclosure among commonly owned firms and find that common ownership can lead to more earnings disclosure, thus higher market liquidity measured by Amihud (2002)'s approach and lower bid-ask spread. Disclosure is higher with the larger proportion of same-industry firms who share common owners. More firm-specific information released to the market can reduce the market return variation. However, Park et al. (2019) also find that firms disclose more when one of the commonly-owned firms experiences temporary (and exogenous) loss of public information from analyst coverage due to, for example, a broker closure or merger. Massa & Žaldokas (2017) show that lenders in commonly owned firms learn common owners' behavior to make decisions. These findings suggest a potential correlation in earning news and thus returns among commonly owned firms. This chapter adds to this literature on common ownership effects by investigating whether more information disclosure and potential correlated news among common ownership impact their comovement in returns.

Prior studies have investigated the institutional-based comovements in stock returns between firms in the same portfolio. For example, AntÓN & Polk (2014) find that price pressure following liquidity shocks of mutual funds during the 2003 trading scandal results in excessive comovement among large firms in the same portfolio, consistent with (Coval & Stafford, 2007; Lou, 2012). Fricke and Savoie (2017) extend AntÓN & Polk's (2014) study to a larger set of funds and small firms and find consistent results. Jotikasthira, Lundblad, & Ramadorai (2012) demonstrate that liquidity shocks to mutual funds cause comovement between the markets they invest in. Gao, Moulton, & Ng (2017) provide empirical evidence of return predictability across firms with the same institutional ownership. According to Bartram, Griffin, Lim, & Ng (2015), a company's stock return is greater when institutional investors have strong returns on overseas stocks. These preceding studies mainly show that correlation in different firms in the same common fund portfolio is primarily due to fund flow shocks. My research differs from the prior studies in that it focuses on the effects of institutional investors on portfolio firms in the same industry. The effects of common ownership on firms in the same industry are expected to result from a deeper understanding of the common owners in that industry, which may cause a correlation in fundamentals between firms. I also examine if common ownership can impact stock prices even when there are no liquidity shocks to fund flows.

Edmans et al. (2014) theoretically prove that common ownership can affect return comovement of commonly owned firms, even when their fundamentals are independent. Assume that liquidity shocks force common owners to sell a portion of their portfolio. If the common owners choose a balanced exit and sell both firms, the prices of both firms will fall. In contrast, if common owners choose an unequal exit, the value of the sold firm decreases while the value of the retained firm increases. In general, the correlation is positive in the case of a balanced exit and negative when the probability of an imbalanced exit is sufficiently high. The direction of comovement depends on the probability of an imbalanced exit determined by the severity of the agency problem. If the blockholder uses a balanced exit strategy, the firm of a working manager is sold if the other manager is slack, lowering the incentive for the first manager to work. If the blockholder uses an imbalanced exit strategy, the firm of a working manager will not be sold in the liquidity shock of the blockholder, but only the other firm, increasing the incentive for the first manager to work. Whether the common owners choose a balanced or imbalanced exit, the comovement of these firms' returns will be affected. Motivated from this study, this chapter empirically tests whether common ownership impacts comovement in returns between same-industry firms.

3.2.3. Hypothesis development

Common ownership is more likely to increase comovement for several reasons. First, common ownership is a mechanism for blockholders to execute joint control across firms, facilitating coordination. By serving on the boards of directors of both firms, common owners can mitigate information asymmetry, lowering the risk of expropriation due to incomplete contracts and aligning the incentives of both parties. Coordination can happen in the form of strategic alliances, intercorporate resource allocation, or research and development (He & Huang, 2017). Such coordination allows commonly owned firms to reduce production and distribution costs, eliminate duplication of research and development efforts, and improve product market competitiveness. These strategic benefits for all contracting parties create a potential correlation in their projected earnings; as a result, increasing comovement in returns of these firms.

Second, firms are likely to issue more earnings and capital expenditure forecasts when one of its commonly owned firms experiences a temporary (and exogenous) loss of public information from analyst coverage due to, for example, a broker closure or merger (Park et al., 2019). It implies that the earnings of one commonly owned firm can have implications on the earnings of other firms with the same common owners. In other words, there is a potential correlation in earnings news among commonly owned firms. Moreover, high earnings announcements resulting from common ownership are associated with increased stock liquidity of all these firms (Park et al., 2019). An increase in liquidity comovement is likely to be followed by an increase in return comovement, and vice versa. The reason is that many determinants of liquidity comovement are also determinants of return comovement. Besides, a loss in market liquidity tends to raise future expected market returns, resulting in a negative concurrent market return. This higher liquidity comovement will lead to high return comovement.

Third, common ownership can affect comovement in stock returns through their exit strategy. The price of both firms will fall if the common owners choose a balanced exit and sell both firms. Moreover, it also pulls down the performance of both commonly owned firms as the firm of a working manager is sold even if he works hard when the other manager is slack, reducing his incentive to work (Edmans et al., 2014). Based on the discussion above, my first hypothesis is as follows.

H1A. Common ownership between pairs of same-industry firms increases comovement in returns of the pairs.

On the other hand, common owners can choose an unbalanced exit. Common owners will sell the firms of slacked managers only and retain the firms of working managers upon their liquidity shocks. This option reduces the value of the sold firm while increasing the value of the retained firm, creating negative relation in their stock returns. Thus, the alternative hypothesis is as follows.

H1B. Common ownership between pairs of same-industry firms reduces comovement in returns of the pairs.

3.3. Data selection and summary statistics

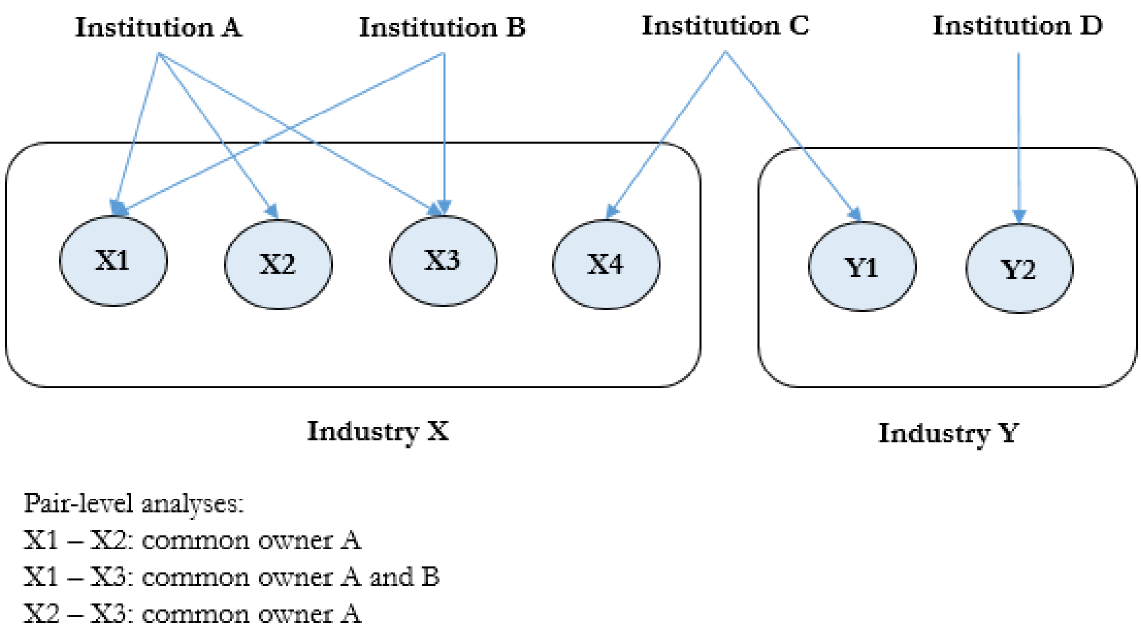
I collect data from several sources and construct a sample for U.S. firms from 1990 to 2019 to investigate the effects of common ownership on pairwise correlation in stock returns. To identify which firm has common ownership each year, I first extract data on institutional blockholders and industry concentration from Thomson Financials 13F database, as I did in the first chapter. The common ownership data is then merged with the stock price data from CRSP to estimate the pairwise correlation.

3.3.1. Pairwise common ownership

Common ownership is formed among same-industry firms with at least one institutional shareholder who holds a minimum of five percent ownership in both firms. Figure 3.1 depicts a common ownership formation scenario. Assume the market has two industries (X and Y) and four institutional investors (A-D). Firms are designated by the letters X1 through X4, as well as Y1 and Y2. An arrow indicates that an institutional investor owns at least 5% of a firm. The lack of an arrow indicates no direct ownership of more than 5% between the institution and a specific firm. Thus, there are three pairs of common ownership in industry X: those between firms X1-X2, X1-X3, and X2-X3, and none in industry Y. Four pairs with non-common ownership are X1-X4, X2-X4, and X3-X4 in industry X, and Y1 – Y2 in industry Y.

Figure 3.1: Sample Construction of Common Ownership

Figure 3.1 illustrates the sample construction for common ownership. Assume the market has two industries (X and Y) and four institutional investors (A-D). Firms are designated by the letters X1 through X4, as well as Y1 and Y2. An arrow indicates that an institutional investor owns at least 5% of a firm. The lack of an arrow indicates no direct ownership of more than 5% between the institution and a specific firm. Thus, there are three pairs of common ownership in industry X: those between firms X1-X2, X1-X3, and X2-X3, and none in industry Y. Four pairs with non-common ownership are X1-X4, X2-X4, and X3-X4 in industry X, and Y1 – Y2 in industry Y.



To measure the effects of common owners on a pair of firms, I apply the measure of Gilje et al. (2020). Assuming there are I common owners between two firms A and B. First, I measure the effect of all common owners on firm A in relation to firm B. I form a product of three components: Firm A's proportion in the portfolio of common owner i, the stakes of common owner i in firm A and in firm B. Then, I aggregate the products across all common owners between two firms to get the measure for firm A.

$$GGl(A,B) = \sum_{i=1}^{I} \beta_{i,A} * \alpha_{i,A} * \alpha_{i,B} \quad (3.1)$$

where $\beta_{i,A}$ represents the proportion of firm A in common owner i's portfolio. $\alpha_{i,A}$ and $\alpha_{i,B}$ represent owner i's ownership percentages in each firm. I compute the ownership percentages using blockholdings only since blockholders have feasible channels to affect managers' utility (via voting, stock selling, or negative public statements). The proportion of firm A in common owner i's portfolio is computed as $\alpha_{i,A}\bar{v}_j/(Y_i + \sum_{m=1}^{M} \alpha_{i,m}\bar{v}_m)$, where M is the number of firms in common owner i's portfolio; $\bar{v}$ is firm market value; and $Y_i \geq 0$ captures non-traded assets, T-bills, or any other assets of common owner i. Thus, $\beta_{i,A}$ measures the weight of firm A in the portfolio of investor i.

Second, I follow the same procedure to compute the effect of all common owners on firm B in relation with firm A as:

$$GGl(B,A) = \sum_{i=1}^{I} \beta_{i,B} * \alpha_{i,A} * \alpha_{i,B} \quad (3.2)$$

Last, the pairwise common ownership is measured as the average effect of all common owners on the pair of firms A and B:

$$\text{PairGGL} = \frac{1}{2}\big(GGl(A,B) + GGl(B,A)\big) = \frac{1}{2}\sum_{i=1}^{I} \alpha_{i,A} * \alpha_{i,B} * (\beta_{i,A} + \beta_{i,B}) \quad (3.3)$$

PairGGL is first computed using quarterly data and then averaged across four quarters in a fiscal year to get the annual measure. I clean the data in institutional ownership from Refinitiv's 13F Institutional Holdings dataset based on several dimensions as described in Section 2.4.2 of Chapter 1.

A high degree of common ownership between firm pairs implies close attention of common owners to the performance of the firms in pairs and great attention of those firms' managers to common owners' references. The measure accounts for comprehensive attention between common owners and firm management. The primary advantage of this measure over He & Huang's (2017) and Lewellen & Lowry's (2021) measures is that it is not predicated on the assumption that investors are fully attentive to managers' actions or $\beta = 1$. Common owners pay more attention to firms representing a large proportion in their portfolios. Less attentive investors will not shift managerial efforts, as so for firm decisions. Similarly, firm managers care more about the preferences of common owners who hold more shares in their firms. The ownership of common owner i in firm B representing the knowledge common owner I can acquire from owning another same-industry firm.

3.3.2. Pairwise comovement

I construct the first measure of pairwise comovement between two firms by following Morck et al.'s (2000) method and adjusting for within-US study. I observe the number of days that stock prices of each pair of firms move in the same direction and divide it by the total number of days in which both firms move in either direction. Considering two firms i and j, the stock comovement is given as

$$f_{i,j} = \frac{\sum_t \left(n_{i,j,t}^{up} + n_{i,j,t}^{down}\right)}{T_{i,j}} \quad (3.4)$$

where $n_{i,j,t}^{up}$ ($n_{i,j,t}^{down}$) is equal to one if both returns are positive (negative) for day t, and 0 otherwise; and $T_{i,j}$ is the number of days in a fiscal year in which both returns move in any direction. Thus, $f_{i,j}$ is equal to one (zero) if the two firms always move in the same (opposite) directions. Besides, I exclude days where either return stays the same to avoid any bias caused by non-trading of illiquid stocks as mentioned in Morck et al. (2000).

The second measure is the correlation coefficient between the returns of two paired firms as:

$$C_{i,j} = \frac{Cov(i,j)}{\sqrt{Var(i).Var(j)}} \quad (3.5)$$

where $Cov(i,j)$ is the covariance between the daily returns of firm i and j for all days in a year. $Var(i)$ and $Var(j)$ is the variances of firm i's and firm j's daily returns. Similarly, I exclude days where either return remains unchanged to make it consistent with the first measure.

The first measure of pairwise comovement, $f_{i,j}$, expectedly captures time-period-specific shocks and depends on the number of days where two returns move alongside. The pairwise correlation coefficient, $C_{i,j}$, reveals both the direction and magnitude of the two returns' movement. As a result, a significant time trend affecting both firms uniformly can exaggerate the overall comovement, causing their prices to move in the same direction over time. To address this concern, I use simple linear regression to detrend the returns data (Khanna & Thomas, 2009). For each firm, I find the value of its average trend over the year and measure the difference between the actual daily return and the predicted daily return using the estimated trend and the previous day's price. The detrend data capture the deviation in daily stock prices of a firm from its own underlying trend. Finally, I use this detrended return to construct two pairwise comovement measures defined above, denoted $f_{i,j}^d$ and $C_{i,j}^d$. The main results with the dependent variable are based on the returns data without detrending, $f_{i,j}$ and $C_{i,j}$, and are robust using detrended data.

3.3.3. Control variables

I control for variables that affect the co-movement between a pair of firms, including product similarity, analyst coverage, market value, industry concentration, industry volatility, and industry size. Industry volatility and industry size are constructed at industry level, while other variables are constructed at pair level.

First, pair product similarity is a continuous variable equal to the similarity in products between two firms. I use the similarity score from (Hoberg & Phillips, 2016) to capture the extent to which a firm produces similar products to their competitor[18]. The pairwise similarity score between firm i and firm j is equal to one minus the cosine distance of vector Vi and Vj, where Vi is the vector of firm i's product description reported in its annual 10-K report. Intuitively, the score is higher when firm i and j use more of the same words. Firms with high product similarity are more likely to be correlated in stock returns because they are more likely to subject to the same source of variation. Second, analysts typically cover similar firms in the same industry to lower their marginal cost of information gathering and the firm's investment opportunity (Bhushan, 1989). Analysts will choose not to cover a company if it has marginal costs and poor growth prospects. These analyst coverages are also expected to provide effective coverage in monitoring managerial behavior and providing adequate information to investors. As a result, firms with a higher number of analysts in common are more likely to have synchronous returns. Third, like An and Zhang (2013), I control for the effects of firm size which is the average market capitalization of two firms. Firms with similar size are likely to have higher comovement.

Forth, pair industry concentration is the Herfindahl-Hirschman Index, proxy for the level of industry concentration. A more concentrated industry faces less competition and higher correlation in stock returns (more likely to correlate in fundamentals). Roll (1992) finds that high industry or firm concentration, as captured by such Herfindahl indices, contributes to the high volatility of certain stock market indices. Fifth, industry volatility is the standard deviation of returns for each 3-digit SIC industry. Industry volatility reflects the return comovement of stocks in that industry with the market. High industry volatility is likely to associate with high pairwise comovement (Chan, Hameed, & Kang, 2013). Sixth, as in Morck et al. (2000), I control for industry size by including the logarithmic number of stocks within a 3-digit SIC industry.

According to Khanna & Thomas (2009), director overlap - the number of directors seating on the boards of both firms divided by the average size of two boards – positively affects their

[18] Product similarity data is available at https://hobergphillips.tuck.dartmouth.edu

pairwise comovement. They suggest that director interlocks facilitate coordination across firms by reducing hold-up problems and fostering growth. However, I do not include this variable in the model because such interlocking directorates are prohibited under the Antitrust laws if firms compete. The pairs of firms in the sample are from the same industry, so mainly subject to these laws. Empirically, the same industry firms in the sample with common directors are less than 1%.

3.3.4. Summary statistics

Table 3.1 shows the summary statistics. The data set contains 2,922,925 pairwise observations where the two firms have at least one common institutional owner from 1990 to 2019. The comovement measure is truncated in [0,1], while the correlation is bounded from -1 to 1. On average, firms are more likely to move in the same direction. A medium pair of firms in the sample moves in the same direction 55.2 percent of the time and has a correlation coefficient of 0.111, comparable with those of Morck et al. (2000). After removing the average trend in stock return of both firms over the year, the comovement and correlation for a median firm in the sample are 0.606 and 0.282, respectively. The sample contains 293 3-digit SIC industries and a total of 10,498 firms. Each year, these firms generate 19,137 firm pairs with common ownership and 78,947 firm pairs without common ownership.

To facilitate the interpretation of PairGGL as a relative measure, I rescale PairGGL to have a mean of 1 (rescale by its sample average) for all pair firms with common ownership. Thus, a value of one indicates the average level of incentives, and a value of two represents twice the average level of incentives. An average firm pair in the sample has a PairGGL measure equal to one with a standard deviation of 4.731, respectively. Pairs of firms in the 99th percentile have a PairGGL of 38.265. Panel B shows that overall, firm pairs with common ownership on average have higher comovement and correlation than firm pairs without common ownership. The average market capitalization, industry concentration and product similarity of an average firm pair are 3,809 million dollars, 0.0165, and 7.7%, respectively. An average firm pair operates in an industry with a volatility of 0.065 and a log number of firms of 5.884. Industry volatility reflects the return comovement of stocks in that industry with the market. High industry volatility is likely to associate with high pairwise comovement (Chan et al., 2013).

Table 3.1: Summary Statistics

Panel A shows the summary statistics of all variables, and Panel B shows the main statistics of comovement measures for firm pairs with and without common ownership. F is the measure of return comovement which is equal to one (zero) if the two firms always move in the same (opposite) directions. C is the measure of correlation in return between pairs of firms. Fd and Cd is the detrended measures of f and C reusing simple linear regression to remove the value of its average trend over the year. F_log, C_log, fd_log, and Cd_log are the logistic transformation of f, fd, C, and Cd respectively. PairGGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry.

Panel A:	N	Mean	Std	Min	P1	P10	P50	P90	P99	**Max**
f	2,922,925	0.561	0.061	0.339	0.448	0.491	0.552	0.643	0.741	0.939
fd	2,922,925	0.575	0.253	0.000	0.063	0.202	0.606	0.890	0.986	1.000
c	2,922,925	0.139	0.147	-0.662	-0.107	-0.017	0.111	0.332	0.618	0.980
cd	2,922,925	0.211	0.485	-0.962	-0.804	-0.509	0.282	0.807	0.929	0.995
f_log	2,922,925	0.249	0.258	-0.668	-0.207	-0.035	0.208	0.589	1.051	2.739
fd_log	2,922,925	0.420	1.509	-16.11	-2.704	-1.371	0.429	2.089	4.272	16.118
c_log	2,922,925	0.289	0.326	-1.594	-0.214	-0.033	0.223	0.691	1.444	4.613
cd_log	2,922,925	0.568	1.275	-3.940	-2.221	-1.124	0.579	2.239	3.303	6.053
PairGGL	2,922,925	1.000	4.731	0.000	0.000	0.000	0.000	0.978	38.265	38.265
Pair_product_ similarity	2,628,433	0.077	0.070	0.000	0.000	0.000	0.062	0.173	0.298	0.955
Pair_ind_ concentration	2,922,925	0.165	0.125	0.010	0.032	0.050	0.124	0.344	0.562	1.000
Pair_MV (mil)	2,821,355	3,809	16,859	1.857	14.599	76.529	547.01	5,480	75,672	1,060,239
Pair_analyst_ coverage	2,922,925	0.083	0.129	0.000	0.000	0.000	0.000	0.267	0.533	1.000
Ind_volatility	2,922,886	0.065	0.041	0.000	0.014	0.027	0.057	0.135	0.179	1.375
Ind_size	2,922,925	5.884	1.060	0.000	2.639	4.489	5.951	7.040	7.153	7.153

Panel B:	Firm pairs with C/O			Firm pairs without C/O		
	N	Mean	Std	N	Mean	Std
f	554,517	0.600	0.065	2,368,408	0.551	0.056
fd	554,517	0.569	0.238	2,368,408	0.577	0.256
c	554,517	0.223	0.164	2,368,408	0.119	0.135
cd	554,517	0.220	0.488	2,368,408	0.209	0.484

Panel C: Correlation coefficients

	f_log	fd_log	c_log	cd_log	Pair GGL	Pair_ Ind_ HHI	Pair_M V	Pair_ analyst_ coverage	Ind_ Volatility
f_log	1								
fd_log	0.099	1							
c_log	0.840	0.107	1						
cd_log	0.203	0.714	0.234	1					
PairGGL	0.175	0.002	0.175	0.026	1				
Pair_ind_HHI	-0.397	0.010	-0.385	-0.037	-0.124	1			
Pair_MV	0.102	-0.025	0.120	-0.010	0.235	-0.11	1		
Pair_analyst_ coverage	0.441	0.029	0.445	0.085	0.199	-0.332	0.124	1	
Ind_Volatility	-0.121	0.055	-0.097	0.094	-0.059	0.101	-0.060	-0.082	1
Ind_size	-0.217	-0.043	-0.249	-0.075	-0.072	0.108	-0.061	-0.151	0.348

All correlation coefficients in the table are significant at 1% level (p<0.01)

There is a high skewness in the distribution of firm pairs across industries. Industries with the highest number of firms, such as computer and data processing services, drugs, and electronic components and accessories, also have the largest number of firm pairs. Table 3.2 provides the list of industries with the greatest number of firm pairs. A typical industry has 36 firms, resulting in 65 firm pairs with common ownership and 269 without common ownership. On average, the ratio of firm pairs with and without common ownership in an industry is one-fourth.

Table 3. 2: Firm Pairs by Industry

This table shows the list of 25 industries with largest number of firm pairs with and without common ownership in the sample.

No.	3-digit SIC	Description	No of firms	No of firm pairs with C/O	No of firm pairs without C/O
1	737	Computer and Data Processing Services	1,175	3,403	24,197
2	283	Drugs	583	2,194	10,130
3	367	Electronic Components and Accessories	395	1,632	6,589
4	384	Medical Instruments and Supplies	381	699	3,534
5	366	Communications Equipment	338	298	2,128
6	357	Computer and Office Equipment	313	314	2,172
7	738	Miscellaneous Business Services	276	227	1,086
8	131	Crude Petroleum and Natural Gas	269	284	1,482
9	481	Telephone Communications	229	99	683
10	382	Measuring and Controlling Devices	189	384	1,106
11	138	Oil and Gas Field Services	171	149	277
12	873	Research and Testing Services	160	166	583
13	581	Eating and Drinking Places	154	210	535
14	809	Health and Allied Services, NEC	131	24	136
15	874	Management and Public Relations	118	56	188
16	371	Motor Vehicles and Equipment	107	152	350
17	491	Electric Services	95	160	263
18	701	Hotels and Motels	77	21	69
19	355	Special Industry Machinery	71	66	194
20	799	Miscellaneous Amusement, Recreation Services	70	14	118
21	483	Radio and Television Broadcasting	69	32	78
22	596	Nonstore Retailers	69	10	53
23	331	Blast Furnace and Basic Steel Products	66	77	101
24	356	General Industrial Machinery	66	67	195
25	369	Miscellaneous Electrical Equipment and Supplies	64	8	68
Total		293 industries	10,498	19,137	78,947
Mean			36	65	269
Median			9	2	3

3.4. Empirical results

3.4.1. Logistic transformation

Since the dependent variables, comovement measures $f_{i,j}$ and $f_{i,j}^{d}$, are truncated on $[0,1]$, I follow Morck et al. (2000) to transform these measures using a logistic transformation, avoiding the econometric issue of data that are potentially censored at the boundaries. I also use the same method to transform the other dependent variables, correlation $C_{i,j}$ and $C_{i,j}^{d}$ that are bounded on [-1,1]. In robustness analyses, I confirm that transforming correlation measures using logistic transformation makes no significant difference from the Fisher transformation applied in Li (2002).

I estimate different specifications of the following equation:

$$PairwiseComovement = \alpha_0 + \alpha_1 CommonOwnership_{i,j} + \alpha_2 Controls_{i,j}$$

$$+IndFE_{i,j} + TimeFE_{i,j} + \varepsilon_{i,j} \quad (3.6)$$

where $PairwiseComovement$ measures are the log transformation of $f_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}$ or $C_{i,j}^{d}$. $CommonOwnership_{i,j}$ is PairGGL measuring common ownership effect on firm managerial incentives between two firms i and j. PairGGL is computed by aggregating the effects of all common institutional owners between two firms who hold at least 5% ownership in each firm. Control variables include pair product similarity, pair industry concentration, pair MV, pair analyst coverage, industry volatility, and industry size, which are explained in the next section. The model also controls for year and industry fixed effects. The standard errors are clustered by industry to control for the possible correlation in residuals between pairs of firms in the same industry.

Because any common owner of this firm-pair could be common owner of other firm-pair as well, the error terms for these firm-pair observations will be correlated and bias the coefficient estimators. Thus, I apply the non-parametric bootstrapping method to determine the significance of estimated coefficients. The method creates a new dataset by sampling with replacement of the original dataset which is then used to obtain another set of estimators. When the sample size gets larger, the distribution of sample means approximates a normal distribution regardless of the population's distribution.

The specific procedure includes creating an empirical distribution for each of the coefficients under a null hypothesis that common ownership does not affect pairwise comovement. I then compare the estimated coefficient from the OLS regression to the empirically generated distribution. The empirical distribution of coefficient estimates under this null is produced as follows. First, I construct a matrix where its rows and columns are the 1st and 2nd firms in each pair. The matrix elements are the dependent variable observations of comovement for each pair. The rows and columns of the matrix are then rearranged with the same permutation. The dependent variable observations are reassigned to the independent variables. This technique preserves any dependency between elements in the same row or column (firm-level effects) but removes the predicted relationship between the dependent and independent variables. Following that, the coefficient for each variable is computed using the new permutation. For each regression (in this chapter, except the regressions in the difference-and-different analysis), I perform 100 permutations. The computed coefficient under the alternative hypothesis of a significant relationship is explained in the following manner. I assert that there is a significant correlation between the two variables given the error structure if the coefficient is located sufficiently far within one tail of the distribution generated by the null, and the independent variable can explain some of the observed variation in the dependent variable.

This approach is conceptually like traditional hypothesis testing, except that instead of imposing a theoretical distribution centered on the estimated coefficient, the actual data are utilized to generate a distribution centered on the null. Rather than asking whether zero is substantially different from the predicted coefficient based on theoretical distribution characteristics, I question if my estimated coefficient is significantly different from the center of the empirical distribution under the null. For evaluating hypotheses in multiple regression analysis utilizing pair-level data, this technique outperforms standard least squares (Krackhardt, 1988). An alternate technique would be to add firm fixed effects, although this would diminish the estimation's efficiency. Another option is to employ a generalized least squares technique, which would entail placing some structure on the covariance matrix. A third option is to assume independence in OLS and cluster the mistakes by company in the pair (Ciarlini & Pavese, 1994).

3.4.2. OLS regression results

Tables 3.3 to 3.5 present the results on the effects of common ownership on pairwise correlation. I first divide the sample into two groups with and without common ownership to observe the difference of common ownership effects between two groups on comovement. Table 3.3 shows that a firm pair with common ownership is predicted to move in the same direction 3.562% more often than a pair without common ownership. In addition, when firm pairs share common ownership, their returns are 7.251% more correlated than when they do not.

Table 3. 3: OLS Regression of Comovement on Common Ownership - Dummy Variable

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, where as C, and C_log is the logistic transformation of correlation C in their stock returns. PairGGL_dummy is the measures of common ownership which equal to one if there is at least one common owner between two firms in the pairs and zero otherwise. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	f_log	fd_log	c_log	cd_log
	(1)	(2)	(3)	(4)
PairGGL_dummy	0.097***	0.035***	0.104***	0.070***
	(19.445)	(3.356)	(11.586)	(3.668)
Pair_product_similarity	0.293***	1.119***	0.312***	0.975***
	(4.774)	(3.745)	(3.019)	(4.666)
Pair_ind_concentration	-0.498***	0.162	-0.605***	-0.164
	(-6.389)	(1.317)	(-6.136)	(-1.189)
Pair_MV	0.000*	-0.000***	0.000***	0.000
	(1.661)	(-4.982)	(2.747)	(-1.372)
Pair_analyst_coverage	0.524***	0.323***	0.675***	0.616***
	(11.365)	(5.676)	(8.253)	(7.063)
Ind_volatility	0.133	1.697*	0.188	1.490*
	(1.208)	(1.947)	(1.198)	(1.655)
Ind_size	-0.007	0.064	-0.012	0.068
	(-0.280)	(0.864)	(-0.278)	(0.954)
Constant	0.280**	-0.203	0.349	-0.032
	(2.092)	(-0.550)	(1.533)	(-0.096)
Observations	2,602,250	2,602,250	2,602,250	2,602,250
Adjusted R-squared	0.426	0.088	0.457	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 3.4 reports the OLS regression results estimating Equation 3.1. Columns 1 and 3 show the linear relationship between common ownership and pairwise comovement measures. Columns 2 and 4 add control variables that may affect the likelihood of common ownership in both firms and the pairwise comovement. All regression models include the industry fixed and year fixed effect to control constant effects across industry and year. The standard errors are clustered by industry and year. The main independent variable, PairGGL, is winsorized at the first and 99th percentiles to reduce the effect of outliers in all tables.

Table 3. 4: OLS Regression of Comovement on Common Ownership

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, whereas C, and C_log is the logistic transformation of correlation C in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	f_log		c_log	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.008***	0.003***	0.010***	0.004***
	(22.941)	(12.291)	(19.931)	(11.060)
Pair_product_similarity		0.295***		0.310***
		(7.369)		(5.243)
Pair_ind_concentration		-0.556***		-0.667***
		(-18.607)		(-17.222)
Pair_MV		0.000***		0.000***
		(2.917)		(7.442)
Pair_analyst_coverage		0.557***		0.706***
		(29.173)		(24.238)
Ind_volatility		0.142		0.197
		(1.468)		(1.243)
Ind_size		-0.009		-0.013
		(-0.745)		(-0.712)
Constant	0.241***	0.311***	0.279***	0.380***
	(25.282)	(4.496)	(20.223)	(3.431)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.215	0.412	0.256	0.448
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

The coefficients of PairGGL across four regression models show that common ownership between a pair of same industry firms is positively associated with both measures of pairwise comovement, supporting hypothesis 1A. In terms of economic magnitude, a one-unit increase in PairGGL (or incentives level) will increase 0.300% comovement and a 0.401% correlation in stock returns of firms in a pair. One standard deviation (4.731) increase in PairGGL leads to 0.941% increase in comovement and 1.484% increase in correlation of pair stock returns. A pair of firms with similar products, large size, and more analyst coverage are more likely to comove in stock return than firms with low product similarity, small size, and less analyst coverage. However, firm pairs in highly concentrated industries are less likely to comove than firm pairs in low industry concentration. Table 3.5 shows that the positive relationship between common ownership and pairwise comovement is robust at a 1% significant level after controlling for the common trend in stock returns between two firms.

Table 3. 5: OLS Regression of Comovement on Common Ownership – Detrended Data

This table shows the effects of PairGGL on two detrended measures of pairwise comovement, comovement fd_log and correlation Cd_log. Fd_log is the logistic transformation of comovement fd in stock returns of firm pair, whereas Cd_log is the logistic transformation of correlation C in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg & Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	fd_log		cd_log	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.004***	0.002***	0.009***	0.005***
	(6.645)	(4.565)	(10.379)	(7.123)
Pair_product_similarity		1.114***		0.964***
		(5.445)		(5.788)
Pair_ind_concentration		0.143		-0.202
		(1.290)		(-1.418)
Pair_MV		-0.000***		-0.000**
		(-4.368)		(-2.537)
Pair_analyst_coverage		0.328***		0.625***
		(5.745)		(13.478)
Ind_volatility		1.700*		1.496
		(1.837)		(1.567)
Ind_size		0.064		0.069
		(0.903)		(1.016)
Constant	0.417***	-0.196	0.559***	-0.019
	(6.101)	(-0.443)	(8.892)	(-0.044)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.082	0.088	0.103	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Consistent with the prior studies, comovement in returns between same industry firms is positively associated with product similarity as they are more likely to be subject to the same source of variation. Return comovement is also more pronounced among firms with more analysts in common. Analysts often cover firms with similar characteristics to lower their marginal cost of information gathering, consistent with Bhushan (1989). In contrast, firm pairs in the more concentrated industry show less correlation in stock returns. However, firm pairs in the highly volatile industry are associated with high pairwise comovement (consistent with Chan, Hameed,

& Kang, 2013). This result aligns with Roll's (1992) findings that high industry concentration contributes to the high volatility of certain stock market indices.

3.4.3. Endogeneity issue

While the results show that common ownership increases comovement in returns, comovement in returns may also influence the likelihood of common ownership, causing reserve causality issue. For instance, institutional investors may proactively target same-industry firms with a high correlation in stock returns to create common ownership. Moreover, unobservable firm characteristics may also affect the likelihood of common ownership that, at the same time, determine the comovement in stock returns for commonly owned firms, resulting in a spurious correlation between the two.

To address these potential endogeneity biases, I implement a difference-in-differences (DiD) analysis around the mergers of large financial institutions as an external shock to firms' common ownership levels (He & Huang, 2017). The mergers between financial institutions often occur for reasons unrelated to the fundamentals of their portfolio firms; thus, it could be used as an external shock to the firm's common ownership level. Although some firms may have common ownership before the merger, Lewellen & Lowry (2021) show that institution mergers cause substantial and lasting increases in the level of common ownership for the pairs of affected firms. New common owners also have new and different effects on managerial incentives compared to current common owners in those firms. It is less likely that other common owners in those firms before the mergers exit the firms during the mergers. Thus, mergers between financial institutions can serve a strong instrument to identify the effect of common ownership on firm performance as well as return comovement.

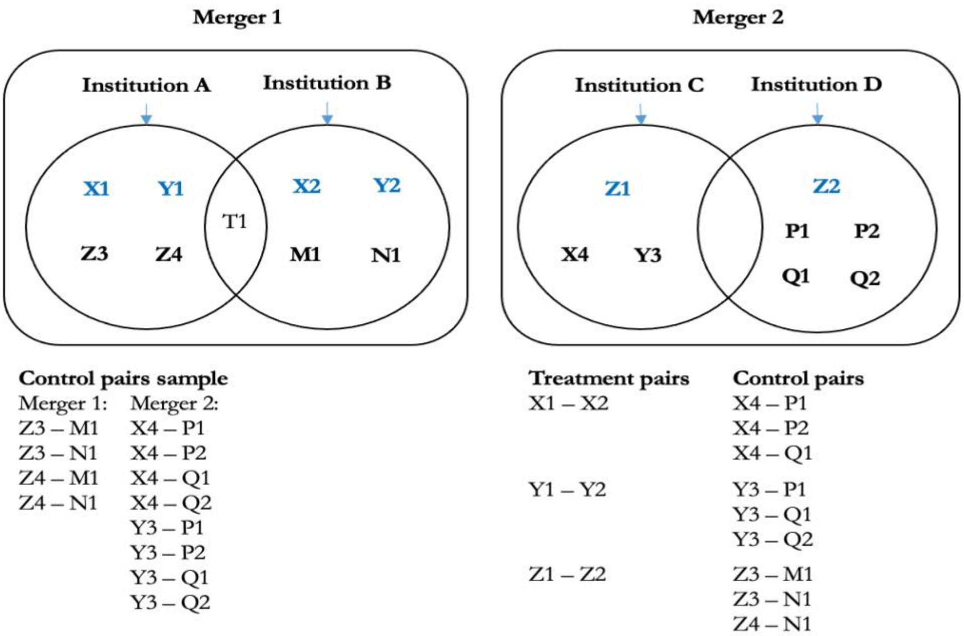
Prior studies also apply three other approaches to address the endogeneity issues, which are the Blackrock/BGI merger, additions to the S&P500 index, and reconstitutions of Russell 1000/2000 indices. However, these approaches are likely not appropriate to use as an exogenous shock to the common ownership level due to obvious concerns about endogenous index inclusion. Moreover, being added to the S&P500 index affects many types of institutional ownership in firms, which is inherently difficult to distinguish. Index additions allow index-tracking institutions to increase their ownership in the added firms, raising the firm's total institutional ownership and common ownership with other portfolio firms but reducing the ownership of other blockholders. On the other hand, Russell index reconstitutions are more transparent and based on market capitalization alone, thus causing fewer endogenous issues about index inclusion. However, Lewellen & Lowry (2021) find that the reconstitutions do not affect the level of common ownership, which disqualifies them as an instrument for this study. Russell reconstitutions are more likely to affect the holdings of mutual funds that track the Russell indices rather than 13F institutions (Schmidt & Fahlenbrach, 2017).

I construct both treatment and control groups around the financial institution mergers. The treatment group contains pairs of firms in the same industry (the same 3-digit SIC industry); each firm is block-held by one institution before the merger announcement. I use the same list of mergers from Lewellen & Lowry (2021). Thus, there are 51 mergers from 1990 to 2010 satisfying the condition. The treatment group consists of 1,588 firms collectively from 51 mergers (firms in which both partners hold a block are deleted), forming 1,277 firm pairs with common ownership (combinations). After requiring that ownership data is available in the years prior to the effective date of the merger, these numbers drop to 1,142 pairs in the period of one year before and after the mergers, 846 in the period of two years before and after the merger, and 841 in the period of three years before and after the merger.

I construct the control group by forming a control pair for each treatment pair. I first construct pair of firms in the same merger but belong to two different industries (2000 firm pairs). Then I match these firm pairs to a treatment pair based on their average market capitalization. Moreover, one of the firms in the control pair is in the same industry as the treatment pair (thus, the control pair is from a different merger with the treatment pair). Each treatment pair can have up to three control pairs with replacement based on its nearest average market capitalization. This matching process ensures that both treatment pairs and control pairs experience the same effect from a merger or a new combined institution. However, the treatment group consists of firms in the same industry, whereas the control group consists of firms from two different industries. The control group consists of 2,000 firm pairs in which the target holds 1,000 firms and the acquirer holds 1,000 firms. Figure 3.2 illustrates the construction of both groups.

Figure 3.2: Sample Construction of Common Ownership in Institution Mergers

Figure 3.2 shows the sample construction of common ownership through the institution mergers. Take example of two institution mergers. Merger 1 is between institution A and B, whereas merger 2 is between institution C and D. Firms are noted X1, X2, …, Q2 which are block-held by these four institutions. X1 and X2 are two firms in the same industry X. Thus, there are 3 treatment pairs from two merger 1 and 2. The sample of control pairs is constructed by matching two firms in the same merger but not in the treatment pairs. Each control pair is held by one institutional investor and not in the same industry as the other firm. There are twelve possible control pairs from the two mergers. Each treatment pair is matched with at most three control pairs based on its average market capitalization and where one firm in the control pair belongs to the same industry as the treatment pair (thus the control pair is from different merger with the treatment pair).



The number of control pairs reduces after computing their comovement measures. Dependent variables are the measures of comovement in stock returns of each pair and are the average of one year, two years, or three years of data before and after the mergers. All control variables are computed in the same way as the dependent variable. The short window allows to observe the effect more accurate without too much noise that is irrelevant to the events. On the other hand, the long window allows to capture meaningful changes in returns comovement in response to the exogenous changes in common ownership.

Table 3.6 shows the results without control variables in panel A and with control variables in panel B. The regressions include firm and year fixed effects for one-year data in columns 1 and 2, and only firm fixed effects in columns 3 to 6 as the data are averaged for two years and three years around the institution mergers. The inclusion of firm fixed effects in the DiD estimation framework largely mitigates the concern about time-invariant industry-specific effects (to the extent that firms do not switch industries) and omitted variables that are correlated with both returns comovement and common ownership. I cluster standard errors at the firm level. I perform 500 permutations for each regression in the difference-and-different analysis.

Moreover, the settings also allow me to observe the excessive comovement between same-industry firms and different-industry firms those shares the same common owners. The mergers create a significant shift in the level of common ownership between a firm pair in the same industry, where each firm is block-held by one party before the merger. Thus, the treatment sample consists of firms whose ownership linkages with same-industry firms are likely to increase just because of the merger. On the other hand, the control sample consists of other block-held firms in the same institution's portfolio that are unlikely to experience such changes. I find evidence that treatment firms, relative to control firms, experience an approximately 5.127% (Column 1) to 11.405% (Column 4) larger increase in return comovement surrounding the institution mergers, which rules out the mechanical effect of common ownership.

Table 3. 6: DiD Analysis of Institution Mergers

This table shows the DiD analysis results. In panel A and B, *Treat* equals one for Treatment Pairs and equal zero for Control Pairs. *After* is an indicator for year 1 in Columns 1 and 2; an indicator for year 1 and 2 in Columns 3 and 4; and an indicator for year 1 to 3 in Columns 5 and 6. The regressions include deal fixed effects and year fixed effects. In Columns 1 and 2 the dependent variables are the pairwise comovement measures computed in year -1 and year 1 around the mergers. In Columns 3 and 4, the dependent variables are the average 2-year pairwise comovement measures before and after the mergers. In Columns 5 and 6, the dependent variables are the average 3-year pairwise comovement measures before and after the mergers. All the control variables in Panel B are computed in the same way with the dependent variable. The model controls for firm and year fixed effects. The standard errors are clustered by firm.

Panel A:	f_log11	c_log11	f_log22	c_log22	f_log33	c_log33
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	0.050*	0.105***	0.094***	0.108***	0.051*	0.056
	(1.817)	(2.720)	(2.854)	(2.654)	(1.813)	(1.504)
Treat	-0.041	-0.106*	-0.003	0.055	0.033	0.054
	(-0.778)	(-1.702)	(-0.079)	(0.625)	(0.917)	(0.888)
Post	-0.029	-0.084	0.100***	0.139***	0.129***	0.168***
	(-0.579)	(-1.497)	(6.830)	(7.484)	(8.204)	(8.568)
Constant	0.439***	0.631***	0.361***	0.445***	0.331***	0.412***
	(9.784)	(10.378)	(11.233)	(8.778)	(11.237)	(9.620)
Observations	2,488	2,488	1,862	1,862	1,828	1,828
Adjusted R-squared	0.670	0.747	0.729	0.764	0.717	0.732
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N

Panel B:	f_log11	c_log11	f_log22	c_log22	f_log33	c_log33
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	0.074**	0.157***	0.110***	0.132***	0.070**	0.093***
	(2.235)	(4.195)	(3.646)	(3.690)	(2.406)	(2.622)
Treat	-0.097*	-0.196***	-0.057	-0.034	-0.027	-0.046
	(-1.660)	(-2.912)	(-1.311)	(-0.397)	(-0.692)	(-0.743)
Post	-0.037	-0.103	0.085***	0.108***	0.119***	0.148***
	(-0.626)	(-1.447)	(4.697)	(4.319)	(6.041)	(5.592)
Pair_product_similarity	0.549***	0.590**	0.648***	0.987***	0.653***	1.012***
	(2.664)	(2.050)	(3.228)	(3.515)	(3.200)	(3.429)
Pair_ind_concentration	-1.031***	-1.326***	-0.602***	-0.901***	-0.622***	-0.953***
	(-4.149)	(-4.207)	(-2.942)	(-3.664)	(-3.207)	(-3.896)
Pair_MV	0.449***	0.685***	0.515**	0.589**	0.467**	0.503**
	(2.693)	(3.315)	(2.244)	(2.170)	(2.191)	(2.091)
Pair_analyst_coverage	0.000	0.000***	0.000	0.000**	0.000	0.000**
	(0.928)	(2.662)	(0.878)	(2.037)	(1.116)	(2.142)
Ind_volatility	0.307	-0.303	-0.265	-0.169	0.131	0.467
	(0.500)	(-0.475)	(-0.590)	(-0.280)	(0.271)	(0.674)
Ind_size	0.143**	0.092	-0.055	-0.100	-0.056	-0.099
	(2.123)	(1.030)	(-0.944)	(-1.133)	(-1.202)	(-1.629)
Constant	-0.147	0.324	0.660**	0.961**	0.615***	0.899***
	(-0.462)	(0.783)	(2.373)	(2.267)	(2.778)	(3.087)
Observations	1,883	1,883	1,435	1,435	1,413	1,413
Adjusted R-squared	0.678	0.755	0.739	0.777	0.727	0.751
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N

3.5. Robustness tests and further analysis

3.5.1. Tobit regression

Since my dependent variables ($f_{i,j}$, $C_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}^{d}$) are truncated, I apply the Tobit regression following Khanna & Thomas (2009) to conduct the robustness test for the relationship between common ownership and pair-wise comovement. The advantage of this method over the logistic transformation (Morck et al., 2000) and the Fisher transformation Li (2002), is that it allows to include observations on either boundary. I re-estimate different specifications of the Equation (3.6):

$$Pairwisecomovement = \alpha_0 + \alpha_1 CommonOwnership_{i,j} + \alpha_2 Controls_{i,j} + \varepsilon_{i,j} \quad (3.7)$$

where $PairwiseComovement$ measures are the log transformation of $f_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}$ or $C_{i,j}^{d}$. $CommonOwnership_{i,j}$ is a pairwise common ownership between two firms i and j as computed in Section 3.1. Control variables are defined the same as in Equation (3.6). The regression includes $IndustryConcentration_{i,j}$ measured by the Herfindahl-Hirschman Index to proxy for the level of industry concentration. Firms within the same industry are more likely to correlate in fundamentals. However, adding an industry fixed effect in the Tobit model may cause biased estimates. Thus, I include this variable to proxy for the effect of different industry on price comovement. A more concentrated industry has less competition and higher correlation in stock returns. αs are vectors of estimated coefficients, and $\varepsilon_{i,j}$ is a pairwise error term.

Table 3.7 shows that the results are robust and consistent with the main finding that common ownership is associated with positive comovement in stock returns between a pair of commonly owned firms.

Table 3. 7: Tobit Regression of Comovement on Common Ownership

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, whereas C, and C_log is the logistic transformation of correlation C in their stock returns. Pair GGL is common ownership measure, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. Standard errors are clustered by year and industry.

Panel A:	f		c	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.002***	0.001***	0.005***	0.002***
	(194.260)	(92.59)	(190.691)	(85.48)
Pair_product_similarity		0.556***		0.132***
		(108.80)		(111.04)
Pair_ind_concentration		-0.136***		-0.320***
		(-511.51)		(-480.85)
Pair_MV		0.000***		0.000***
		(21.49)		(45.33)
Pair_analyst_coverage		0.143***		0.345***
		(436.36)		(393.93)
Ind_volatility		-0.031***		0.072***
		(-34.42)		(35.71)
Ind_size		-0.007***		-0.023***
		(-203.59)		(-257.37)
Constant	0.558***	0.609***	0.131***	0.281***
	(17,293.294)	(2942.16)	(1,688.262)	(503.49)
Observations	3,064,481	2,602,451	3,064,481	2,602,451
Pseudo R2	-0.0107	-0.1277	-0.0295	-0.3714
P-value	0	0	0	0

Panel B:	fd		cd	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.000***	0.000***	0.002***	0.001***
	(14.247)	(3.86)	(40.489)	(18.49)
Pair_product_similarity		0.230***		0.450***
		(97.67)		(109.43)
Pair_ind_concentration		0.019***		-0.063***
		(14.70)		(-27.52)
Pair_MV		0.000***		0.000***
		(-34.53)		(-28.33)
Pair_analyst_coverage		0.051***		0.191***
		(46.25)		(86.32)
Ind_volatility		0.605***		1.490***
		(147.22)		(179.63)
Ind_size		-0.018***		-0.046***
		(-127.52)		(-150.17)
Constant	0.574***	0.618***	0.205***	0.346***
	(3,425.093)	(719.46)	(684.993)	(190.44)
Observations	3,064,481	2,602,451	3,064,481	2,602,451
Pseudo R2	0.000550	0.2110	0.000394	0.0206
P-value	0	0	0	0

3.5.2. Product Similarity

The increase in comovement due to common ownership is consistent with several possible mechanisms. One channel through which common ownership could increase comovement in returns is through correlation in earnings news (Massa & Žaldokas, 2017; Park et al., 2019). The second channel is through the exit effects of common owners on the stock returns of both firms in pairs (Edmans et al., 2014). Common ownership can also increase the return comovement by motivating the coordination between firms in a pair. Chemmanur et al. (2016) show that common ownership encourages more explicit collaborations between firms through strategic alliances with a greater number of co-patenting patents and citations among these firms.

This section investigates the third channel, whether common ownership is more likely to increase comovement through coordination between a pair of firms in relation to the level of product similarity. Pairwise common ownership may affect comovement between firms that are in the same industry but not close in product space. When firms are closer in the technology space, technology spillovers among commonly owned firms within the same industry may have more pronounced benefits as the larger the number of firms can benefit from the technological innovations. When innovation lowers marginal costs in the industry so much as to increase industry output, common ownership may even increase welfare.

However, when commonly owned firms are closer in product space, common ownership may instead harm innovation. The reason is that firms whose shareholders own stakes in other same-industry firms selling similar products are less willing to invest in innovation because doing so would steal business away from those other firms. Furthermore, when technological spillovers are relatively small, there is no free-riding problem that common ownership can mitigate. In that case, innovation is a costly tool that improves firm productivity and steals business from competitors, which is more favourable for undiversified shareholders (and consumers) than common owners. In such a situation, more common ownership leads to lower innovation, lower output, and lower welfare. Thus, common ownership may create more binding value between firms with less similarity in their products, positively affecting comovement in their returns. In contrast, firms with high product similarity create less value from innovation collaboration. Therefore, they may have less comovement in stock prices.

Tables 3.8 and 3.9 show the effects of common ownership on pairwise comovement in relation to their product similarity. While Table 3.8 uses the interaction term between the common ownership measure PairGGL and Pair_product_similarity, Table 3.9 divides the sample into two subsamples containing firms with high and low product similarity. Table 3.8 shows that the effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their products. The effect of PairGGL on return comovement in relation with product similarity is given by the formula: 0.008 – 0.027*Pair_product_similarity (in Column 4) with the coefficient estimates statistically different from zero by the Chi-squared statistical tests. One standard deviation increase in the Pair_product_similarity (0.07) leads to a reduction of 0.148% in the effect of common ownership on the return comovement.

Table 3. 8: OLS Regression of Comovement on Common Ownership and Production Similarity 1

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Tables 3.2 and 3.3. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by industry.

	f_log	c_log	fd_log	cd_log
	(1)	(2)	(3)	(4)
PairGGL	0.004***	0.005***	0.005***	0.008***
	(8.299)	(7.187)	(3.768)	(4.954)
Pair_product_similarity	0.310***	0.325***	1.148***	1.006***
	(4.635)	(3.016)	(3.709)	(4.602)
PairGGL X Pair_product_similarity	-0.010**	-0.010	-0.022*	-0.027**
	(-2.477)	(-1.367)	(-1.800)	(-1.988)
Pair_ind_concentration	-0.555***	-0.666***	0.145	-0.199
	(-7.733)	(-7.037)	(1.191)	(-1.458)
Pair_MV	0.000	0.000**	-0.000***	-0.000**
	(0.726)	(2.196)	(-5.700)	(-2.236)
Pair_analyst_coverage	0.556***	0.705***	0.327***	0.624***
	(13.684)	(9.273)	(5.742)	(7.221)
Ind_volatility	0.142	0.198	1.702*	1.498*
	(1.283)	(1.260)	(1.949)	(1.659)
Ind_size	-0.008	-0.013	0.065	0.070
	(-0.321)	(-0.298)	(0.878)	(0.975)
Constant	0.307**	0.376*	-0.204	-0.029
	(2.287)	(1.657)	(-0.554)	(-0.088)
Observations	2,602,250	2,602,250	2,602,250	2,602,250
Adjusted R-squared	0.413	0.448	0.088	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 3. 9: OLS Regression of Comovement on Common Ownership and Production Similarity 2

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Tables 3.2 and 3.3. Panel A shows the effects for the subsample with low product similarity, while Panel B shows the effects for the subsample with high product similarity, divided by the medium product similarity of the sample. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC code. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. Standard errors are clustered by industry.

Panel A:	f_log	c_log	fd_log	cd_log
Low product similarity	(1)	(2)	(3)	(4)
PairGGL	0.004***	0.006***	0.004***	0.007***
	(12.857)	(12.377)	(5.701)	(7.474)
Pair_product_similarity	0.396***	0.490***	1.756***	1.486***
	(3.252)	(3.595)	(3.339)	(4.070)
Pair_ind_concentration	-0.494***	-0.588***	0.098	-0.200
	(-7.336)	(-6.737)	(0.600)	(-1.325)
Pair_MV	0.000	0.000*	-0.000***	-0.000
	(0.359)	(1.663)	(-3.063)	(-1.543)
Pair_analyst_coverage	0.543***	0.643***	0.253***	0.523***
	(11.877)	(7.326)	(4.285)	(6.076)
Ind_volatility	0.100	0.102	1.539**	1.102
	(1.066)	(0.698)	(2.147)	(1.585)
Ind_size	-0.005	-0.007	0.060	0.094
	(-0.341)	(-0.323)	(1.019)	(1.490)
Constant	0.273***	0.324***	-0.223	-0.208
	(3.722)	(2.716)	(-0.783)	(-0.680)
Observations	1,503,106	1,503,106	1,503,106	1,503,106
Adjusted R-squared	0.339	0.373	0.074	0.101
Industry FE & Year FE	Y	Y	Y	Y

Panel B:	f_log	c_log	fd_log	cd_log
High product similarity	(1)	(2)	(3)	(4)
PairGGL	0.002***	0.003***	0.002**	0.004***
	(5.890)	(4.696)	(2.074)	(3.426)
Pair_product_similarity	0.227***	0.268**	0.905***	0.815***
	(3.831)	(2.311)	(3.125)	(4.222)
Pair_ind_concentration	-0.657***	-0.791***	0.319***	-0.136
	(-12.968)	(-11.456)	(2.740)	(-1.104)
Pair_MV	0.000	0.000**	-0.000***	-0.000***
	(0.795)	(2.141)	(-5.820)	(-3.348)
Pair_analyst_coverage	0.545***	0.720***	0.408***	0.700***
	(13.005)	(10.675)	(5.973)	(7.280)
Ind_volatility	0.148	0.254	1.903	1.850
	(1.236)	(1.456)	(1.476)	(1.413)
Ind_size	-0.013	-0.019	0.123	0.088
	(-0.388)	(-0.335)	(1.285)	(1.263)
Constant	0.366**	0.443	-0.479	-0.077
	(2.001)	(1.426)	(-0.868)	(-0.203)
Observations	1,099,124	1,099,124	1,099,124	1,099,124
Adjusted R-squared	0.463	0.495	0.099	0.127
Industry FE & Year FE	Y	Y	Y	Y

3.5.3. Aggregate effects of institutional investors

Tables 3.10 replicate the main results in Table 3.5 to investigate whether the positive effect of common ownership on pairwise comovement exists without the requirement of significant 5% ownership from the common owners on each firm. Tables A.3.2 – A.3.5 in the Appendix replicate the main results in Tables 3.4, 3.6, 3.8, and 3.9, respectively. Interestingly, the results show that these effects persist and are even stronger than the results in Table 3.5 at some points. By removing the restriction of 5% ownership, the number of common owners between two firms increases substantially. The aggregate effects of a larger number of common owners are more likely associated with high comovement in returns between firm pairs.

Table 3. 10: OLS Regression of Comovement on Aggregate Common Ownership – Detrended Data

This table shows the effects of AggregatePairGGL on two detrended measures of pairwise comovement, comovement fd_log and correlation Cd_log. Fd_log is the logistic transformation of comovement fd in stock returns of firm pair, whereas Cd_log is the logistic transformation of correlation C in their stock returns. AggregatePairGGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with any ownership percentage in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC code. Ind_size is industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. Standard errors are clustered by industry.

	fd_log		cd_log	
	(1)	(2)	(3)	(4)
AggregatePairGGL	0.007**	0.004**	0.024***	0.010***
	(2.106)	(2.439)	(5.529)	(5.668)
Pair_product_similarity		1.106***		0.278**
		(3.464)		(2.430)
Pair_ind_concentration		0.146		-0.653***
		(1.128)		(-7.285)
Pair_MV		-0.000***		0.000
		(-5.598)		(1.505)
Pair_analyst_coverage		0.322***		0.676***
		(5.647)		(9.560)
Ind_volatility		1.702**		0.203
		(1.971)		(1.360)
Ind_size		0.063		-0.014
		(0.936)		(-0.344)
Constant	0.414***	-0.192	0.265***	0.381*
	(3.884)	(-0.547)	(9.166)	(1.760)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.082	0.088	0.284	0.451
Industry FE & Year FE	Y	Y	Y	Y
Cluster by Industry	Y	Y	Y	Y

3.6. Conclusion

Comovement in returns is an important determinant of market risk and stability. My main finding is that increased common ownership leads to greater comovement in returns. In terms of economic magnitude, a one-unit increase in PairGGL (or incentives level) will increase 0.300% comovement and a 0.401% correlation in stock returns of firms in a pair. This is consistent with the idea that the market views common ownership as a mechanism to exercise joint control. The results are robust after controlling for time trends and various empirical specifications. The effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their product. This negative relationship implies that the lower product similarity, the more effect of common ownership on pairwise comovement. My study is consistent with previous studies, which suggest that comovement at the market level is due to correlated fundamentals and blurred firm boundaries (Bertrand et al., 2002; Khanna & Thomas, 2009). Common ownership serves as a mechanism for joint control across firms. The market considers firms with common ownership relevant, possibly because it allows for coordination in firm activities, efficient resource allocation, and cross-monitoring (He & Huang, 2017; Morck et al., 2000).

My findings are important for both market participants and policymakers. My result that common ownership leads to increased comovement in returns may deepen the U.S. government's current concerns on the market impacts of common ownership. The increasing likelihood of shocks spreading across stocks due to common ownership may impact systemic risk and the propensity for flash crashes. Moreover, comovement in returns is a source of systematic risk that affects expected return premiums. Therefore, high comovement between firms with common ownership can raise their cost of capital and influence the actual economy through their investment levels. If all firms eventually become collectively controlled by a single institution, the impact of common ownership on market stability should become readily obvious.

3.7. Appendices

3.7.1. Measures of comovement: R2 and decomposition of variance analysis

A vast of literature measures comovement in returns using R-squared from regressions of individual stock returns on market returns (Roll, 1988). An aggregate R-squared measure represents the proportion of the variation in firm returns explained by total market variation, whereas (1 – R2) is inferred to represent the share of firm-specific variation (Jin & Myers, 2006). To investigate whether pairwise comovement contributes a proportion to market-level return variation, I first compute the total market and industry variation which is estimated widely using R-squared measure obtained from the following market model for each fiscal year:

$$Ret_{it} = \alpha + \beta_1 MktRet_t + \beta_2 MktRet_{t-1} + \beta_3 IndRet_t + \beta_4 IndRet_{t-1} + \varepsilon_{it} \quad (3.14)$$

I regress daily returns Ret_{it} in a fiscal year t for commonly owned firm i on value-weighted market returns $MktRet$ and industry returns $IndRet$ for firms in the same 3-digit SIC industry (with firm i's daily returns excluded) in both year t and t-1. Lagged industry and market returns are added to control for potential non-synchronous trading biases associated with the daily return data (Scholes & Williams, 1977). Eventually, I average the annual R-squared for all commonly owned firms to observe the market-level effects, which equals 0.1537. On average, 15.37% of the variation in returns of commonly owned firms can be explained by market and industry variation, and nearly 85% are left undescribed by these effects. Thus, this chapter attempt to answer whether ownership overlapped by institutional investors can explain for this undefined 85% by being associated with pairwise comovement among commonly owned firms. The results show that common ownership network measures do contribute to market-level variation, accounting for a portion of the overall variation. The firm-specific residuals are reduced when the measure of common ownership is included, improving the overall fit of the regression equation. The benchmark R^2 of the regression (when only the market index is included as a dependent variable) is 0.117 and adding the industry index for each firm increases the R^2 to 0.150. Almost 15% of total variation in stock price returns is attributable to market and industry effects. Next, common ownership network index is added to the regression in turn. Along with the market and industry indexes, produces an R^2 of 0.170. That is, adding the common ownership network index increase the extent of return variation explained by the regression. Since the R^2 value is larger than for the market model regressions, the results suggest that common ownership network is important factor in explaining variation in returns.

3.7.2. Tables

Table A.3. 1. Variable Definitions

This table shows the definition for all variables in Chapter 3.

Variable	Definition	Data source
PairGGL	The measure of common ownership effect on firm managerial incentives, computed by aggregating the effects of all common institutional owners between two firms who hold at least 5% ownership in each firm (blockholders).	Refinitiv's 13F
f	The measure of return comovement which is equal to one (zero) if the two firms always move in the same (opposite) directions.	CRSP
C	The measure of correlation in return between pairs of firms.	CRSP
fd	The detrended measure of return comovement using simple linear regression following Khanna and Thomas (2009) to remove the value of its average trend over the year.	CRSP
Cd	The detrended measure of return correlation using simple linear regression following Khanna and Thomas (2009) to remove the value of its average trend over the year.	CRSP
f_log	The logistic transformation of f	CRSP
C_log	The logistic transformation of fd	CRSP
fd_log	The logistic transformation of C	CRSP
Cd_log	The logistic transformation of Cd	CRSP
Pair_product_similarity	the similarity in products between two firms provided by Hoberg & Philips (2016)	Hoberg & Phillips (2016)
Pair_ind_concentration (Pair_ind_HHI)	the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms.	WRDS
Pair_MV	The average market capitalization between two firms	CRSP
Pair_analyst_coverage	The number of common analysts between two firms	IBES Academic
Ind_volatility	The industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry.	CRSP
Ind_size	The industry size where the two firms operate in, computed by the log number of firms in that industry	CRSP

Table A.3. 2. OLS Regression of Comovement on Aggregate Common Ownership

This table shows the effects of AggregatePairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, whereas C, and C_log is the logistic transformation of correlation C in their stock returns. AggregatePairGGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with any ownership percentage in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg & Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by industry.

	f_log		c_log	
	(1)	(2)	(3)	(4)
AggregatePairGGL	0.018***	0.007***	0.024***	0.010***
	(6.580)	(6.702)	(5.529)	(5.668)
Pair_product_similarity		0.273***		0.278**
		(4.088)		(2.430)
Pair_ind_concentration		-0.546***		-0.653***
		(-8.046)		(-7.285)
Pair_MV		-0.000		0.000
		(-0.416)		(1.505)
Pair_analyst_coverage		0.536***		0.676***
		(14.047)		(9.560)
Ind_volatility		0.145		0.203
		(1.358)		(1.360)
Ind_size		-0.009		-0.014
		(-0.382)		(-0.344)
Constant	0.230***	0.312**	0.265***	0.381*
	(11.954)	(2.439)	(9.166)	(1.760)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.240	0.415	0.284	0.451
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table A.3. 3. Tobit Regression for DiD Analysis of Institution Mergers

This table shows the DiD analysis results. In panel A and B, *Treat* equals one for Treatment Pairs and equal zero for Control Pairs. Post is an indicator for year 1 in Columns 1 and 2; an indicator for years 1 and 2 in Columns 3 and 4; and an indicator for years 1 to 3 in Columns 5 and 6. The regressions include deal fixed effects and year fixed effects. In Columns 1 and 2 the dependent variables are the pairwise comovement measures computed in year -1 and year 1 around the mergers. In Columns 3 and 4, the dependent variables are the average 2-year pairwise comovement measures before and after the mergers. In Columns 5 and 6, the dependent variables are the average 3-year pairwise comovement measures before and after the mergers. All the control variables in Panel B are computed in the same way with the dependent variable. The model controls for firm and year fixed effects. The standard errors are clustered by firm.

Panel A:	f_11	c_11	f_22	c_22	f_33	c_33
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	-0.004	-0.039***	0.023***	0.047***	0.012**	0.023
	(-0.700)	(-2.804)	(3.870)	(3.066)	(2.103)	(1.549)
Treat	0.071***	0.217***	0.061***	0.175***	0.063***	0.162***
	(18.752)	(20.541)	(15.366)	(17.217)	(16.500)	(17.090)
Post	0.015***	0.032***	0.024***	0.063***	0.031***	0.078***
	(4.422)	(3.717)	(6.969)	(7.405)	(9.149)	(9.464)
Constant	0.561***	0.151***	0.558***	0.137***	0.554***	0.128***
	(231.897)	(24.817)	(256.243)	(27.655)	(270.688)	(27.558)
Observations	2,234	2,234	1,654	1,654	1,625	1,625
Pseudo R2	-0.111	-0.706	-0.162	-0.784	-0.160	-0.563
P-value	0	0	0	0	0	0
Chi-square test	736.2	739.7	873	996.7	876.5	841.7

Panel B:	f_11	c_11	f_22	c_22	f_33	c_33
	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	-0.003	-0.021	0.026***	0.057***	0.018***	0.042***
	(-0.44)	(-1.345)	(4.63)	(3.859)	(3.52)	(3.218)
Treat	0.054***	0.149***	0.037***	0.100***	0.036***	0.084***
	(11.17)	(11.841)	(8.16)	(8.487)	(8.81)	(8.243)
Post	0.012***	0.027***	0.018***	0.047***	0.023***	0.056***
	(3.49)	(3.291)	(-5.53)	(5.480)	(6.27)	(6.724)
Pair_product_similarity	0.198***	0.713***	0.260***	0.831***	0.260***	0.769***
	(5.50)	(7.739)	(6.41)	(7.788)	(7.25)	(8.089)
Pair_ind_concentration	-0.341***	-0.941***	-0.273***	-0.724***	-0.257	-0.666***
	(11.55)	(-12.020)	(-10.74)	(-10.866)	(-12.15)	(-11.705)
Pair_MV	0.073***	0.207	0.120**	0.311**	0.113***	0.287***
	(1.55)	(1.598)	(2.46)	(2.425)	(2.57)	(2.732)
Pair_analyst_coverage	0.000**	-0.000	0.000	0.000	0.000	0.000
	(-2.21)	(-1.044)	(-1.45)	(0.303)	(-0.84)	(0.879)
Ind_volatility	-0.065	0.096	-0.171**	-0.363*	-0.260**	-0.570**
	(-1.47)	(0.798)	(-2.06)	(-1.779)	(-2.41)	(-2.387)
Ind_size	-0.007***	-0.022***	-0.005***	-0.014***	0.004***	-0.011***
	(5.73)	(-7.554)	(-4.20)	(-4.732)	(-3.10)	(-3.632)
Constant	0.625***	0.329***	0.615***	0.284***	0.611***	0.270***
	-114.59	(22.410)	(114.33)	(20.141)	(117.07)	(21.218)
Observations	1,894	1,894	1,436	1,436	1,415	1,415
Pseudo R2	-0.1915	-1.308	-0.2509	-1.207	-0.2527	-0.915
P-value	0	0	0	0	0	0
Chi-square test	1284	1285	1256	1250	1278	1297
Bootstrapping (times)	500	500	500	500	500	500

Table A.3. 4. OLS Regression of Comovement on Aggregate Common Ownership and Product Similarity 1

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Tables 2.2 and 2.3. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. AggregatePairGGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with any ownership percentage in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg & Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by industry.

	f_log	c_log	fd_log	cd_log
	(1)	(2)	(3)	(4)
AggregatePairGGL	0.011***	0.014***	0.010***	0.018***
	(9.438)	(8.026)	(4.326)	(7.116)
AggregatePairGGL X Pair_product_similarity	-0.028***	-0.030*	-0.045**	-0.064***
	(-3.212)	(-1.894)	(-1.968)	(-2.782)
Pair_product_similarity	0.314***	0.322***	1.172***	1.036***
	(4.346)	(2.842)	(3.651)	(4.501)
Pair_ind_concentration	-0.543***	-0.649***	0.152	-0.184
	(-7.822)	(-7.122)	(1.249)	(-1.369)
Pair_MV	0.000	0.000	-0.000***	-0.000***
	(-0.949)	(1.034)	(-6.873)	(-2.963)
Pair_analyst_coverage	0.534***	0.674***	0.318***	0.602***
	(13.816)	(9.389)	(5.55)	(7.117)
Ind_volatility	0.147	0.205	1.705*	1.505*
	(1.320)	(1.300)	(1.952)	(1.665)
Ind_size	-0.009	-0.013	0.064	0.069
	(-0.331)	(-0.306)	(0.862)	(0.947)
Constant	0.305**	0.373	-0.204	-0.03
	(2.254)	(1.640)	(-0.549)	(-0.088)
Observations	2,602,250	2,602,250	2,602,250	2,602,250
Adjusted R-squared	0.416	0.452	0.088	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table A.3. 5. OLS Regression of Comovement on Aggregate Common Ownership and Product Similarity 2

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Tables 2.2 and 2.3. Panel A shows the effects for the subsample with low product similarity, while Panel B shows the effects for the subsample with high product similarity, divided by the medium product similarity of the sample. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. AggregatePairGGL is the measure of common ownership, computed by aggregating the effects of all common institutional owners between two firms with any ownership percentage in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg & Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. Standard errors are clustered by industry.

Panel A:	f_log	c_log	fd_log	cd_log
Low product similarity	(1)	(2)	(3)	(4)
AggregatePairGGL	0.011***	0.015***	0.008***	0.017***
	(12.042)	(9.862)	(9.031)	(13.010)
Pair_product_similarity	0.382***	0.471***	1.748***	1.468***
	(3.147)	(3.485)	(3.306)	(3.993)
Pair_ind_concentration	-0.482***	-0.573***	0.105	-0.185
	(-7.447)	(-6.842)	(0.642)	(-1.235)
Pair_MV	-0.000**	0.000	-0.000***	-0.000**
	(-2.064)	(0.100)	(-3.839)	(-2.359)
Pair_analyst_coverage	0.516***	0.606***	0.238***	0.488***
	(12.762)	(7.640)	(4.214)	(5.961)
Ind_volatility	0.105	0.108	1.542**	1.109
	(1.114)	(0.742)	(2.148)	(1.590)
Ind_size	-0.005	-0.008	0.059	0.092
	(-0.391)	(-0.362)	(0.989)	(1.436)
Constant	0.274***	0.325***	-0.218	-0.202
	(3.759)	(2.748)	(-0.757)	(-0.649)
Observations	1,503,106	1,503,106	1,503,106	1,503,106
Adjusted R-squared	0.344	0.379	0.074	0.101
Industry FE & Year FE	Y	Y	Y	Y
Panel B:	f_log	c_log	fd_log	cd_log
High product similarity	(1)	(2)	(3)	(4)
AggregatePairGGL	0.006***	0.008***	0.006***	0.006***
	(4.727)	(3.972)	(2.581)	(2.581)
Pair_product_similarity	0.205***	0.236**	0.798***	0.798***
	(3.427)	(2.014)	(4.122)	(4.122)
Pair_ind_concentration	-0.645***	-0.774***	-0.125	-0.125
	(-12.913)	(-11.462)	(-1.023)	(-1.023)
Pair_MV	0.000	0.000	-0.000***	-0.000***
	(0.028)	(1.423)	(-3.933)	(-3.933)
Pair_analyst_coverage	0.528***	0.696***	0.686***	0.686***
	(12.989)	(10.729)	(7.502)	(7.502)
Ind_volatility	0.150	0.257	1.851	1.851
	(1.229)	(1.456)	(1.412)	(1.412)
Ind_size	-0.013	-0.018	0.088	0.088
	(-0.377)	(-0.325)	(1.251)	(1.251)
Constant	0.364*	0.440	-0.078	-0.078
	(1.957)	(1.397)	(-0.203)	(-0.203)
Observations	1,099,124	1,099,124	1,099,124	1,099,124
Adjusted R-squared	0.466	0.498	0.127	0.127
Industry FE & Year FE	Y	Y	Y	Y

Chapter 4

Corporate Culture and the Cost of Debt[19]

4.1. Introduction

Debt serves as the essential source of long-term capital for US firms. New bond issuance with maturities longer than one year grew in value from $669.4 billion in 2002 to $1,377.6 billion in 2018 and remained resilient through the coronavirus pandemic with $1,961.1 billion in 2021[20]. In contrast, the entire new stock issue in 2002, 2018, and 2021 was $27.2 billion, $48.8 billion, and $153.6 billion, respectively. Thus, a slight change in lending rates might drastically change capital allocation and have substantial economic implications (Bai et al., 2019). Two primary determinants of the interest rate that lenders charge borrowers are default risk and protection to lenders in the event of default, such as bond covenants and third-party guarantees. Prior studies have discovered various financial risk-related firm and debt-issuance characteristics as factors affecting the probability that a firm will meet its debt obligations. However, the default risk also depends on other factors, such as information environment and agency conflicts between the firm and its debtholders.

Corporate culture is a system of shared values and norms that define appropriate attitudes and behaviors of all members within a firm (CrÉMer, 1993; Van den Steen, 2010b). Li, Mai, et al. (2021) define a corporate culture that encompasses five cultural values: integrity, respect, teamwork, innovation, and quality. A firm with a high score in integrity, for example, emphasizes the higher important degree of integrity in its discussions on financial performance. Giannetti & Yafeh (2011) indicate that lenders with more cultural distance from borrowers offer smaller international syndicated bank loans with higher interest rates and require third-party guarantees. Firms in collective societies also have higher cost of debt (Chui et al. (2016) and lower corporate debt ratios than firms in mastery or individualistic countries (Chui et al. (2002). However, these

[19] This chapter is co-authored with my main supervisor Prof. Yulia Merkoulova and co-supervisor Dr. Emdad Islam
[20] The data is available at http://www.sifma.org

studies focus on the effects of national culture on the cost of debt. Little has been known about the effect of a firm's corporate culture on the interest rate lenders offer. Thus, this study investigates whether corporate culture affects the yield spread of its newly issued bonds.

Corporate culture can affect the cost of debt through three possible channels. First, firms with strong culture are more likely to meet debt obligations because their executives and employees are empowered to focus on long-term perspectives. These firms are also more resilient in difficult times than firms with weak culture by maintaining existing workforces and adopting new technologies to develop different products (Li, Liu, et al., 2021). Second, firms that value innovation and quality can alleviate information risk by signaling their commitment to the quality of their inventions (Bhattacharya & Ritter, 1983). Third, Bushman et al. (2004) find that strong culture firms have lower litigation risks and more disclosure transparency. In firms that value high integrity and respect, executives are less likely to profit from private information (Jiang et al., 2021), and employees are more willing to report fraud (Sengupta, 1998). Such an enhanced information environment with high integrity of accounting reports reduces default risks and allows creditors to monitor potential violations in their debt agreements better (Francis et al., 2005).

Using a sample of the U.S. public firms with corporate culture data from 2002 to 2017, I document that firms with strong culture have lower yield spreads than firms with weak culture. The result is robust to different specifications and controls, such as firm and bond characteristics. However, an omitted variable bias may exist in establishing the influence of corporate culture on firms' bond yield spread. For example, firms might build their corporate culture based on unpredictable business features, and these traits could impact a firm's yield spread at the same time. Thus, to account for time-invariant firm-specific omitted variables, I lag the culture measures in all regressions to evaluate its influence on yield spread in the subsequent year. The results hold in all the tests.

I also perform a path analysis to investigate the underlying mechanism through which corporate culture influences yield spread. The main assumption is that corporate culture is the direct path that affects yield spread via two indirect paths of creditworthiness and information asymmetry. First, I study the direct impact of corporate culture on yield spread and find that firms with strong culture, on average, have approximately 10% lower yield spreads than similar firms with weak culture. Second, I test two possible explanations: improvement in the creditworthiness of corporate bonds and reporting transparency (lower information asymmetry). I show that strong cultural firms are associated with better credit ratings and information environment. I also examine whether corporate culture has a more significant impact on riskier firms since the impact of corporate culture on the cost of debt is often more evident for these companies. Thus, I assess the effect of corporate culture on the yield spreads separately for firms with a) relatively high and low leverage ratios and b) relatively high and low levels of historical variability in stock returns. The result shows that the effect of corporate culture is more pronounced for riskier firms with higher leverage ratios and return volatility.

This study makes two contributions to the literature. First, it adds to the growing literature that seeks to comprehend how corporate culture affects corporate policies and performance - by demonstrating how it correlates with firm default risk and information environment. Second, this study adds to the cost of debt literature by indicating a new factor affecting pricing in debt markets, namely culture incentive.

The remainder of this chapter proceeds as follows. Section 4.2 reviews relevant literature and discuss hypotheses development. Section 4.3 describes the data and relevant summary statistics. Section 4.4 discusses my main findings, while Section 4.5 discusses the channels through which corporate culture may affect yield spread. Section 4.6 provides robustness checks, and section 4.7 concludes.

4.2. Relevant literature and hypothesis development

4.2.1. Corporate culture

Corporate culture plays an importance role on the performance of a firm. The five most often-mentioned values by the S&P 500 firms on their corporate websites are *innovation*, *integrity, respect*, *quality,* and *teamwork* (Guiso, Sapienza, & Zingales, 2015). The most dominant value is innovation (80%), followed by honesty and respect (70%). Interestingly, 60% of S&P 500 companies place a premium on quality, while only half places a premium on teamwork. Only twelve businesses advocate for all five cultural values.

Unlike traditional control systems with rules and procedures, a firm forms its culture through employee interaction and the social construction of reality (Berger & Luckmann, 1967). While cultural values are important for employees to fulfill, cultural norms keep their day-to-day practices towards these values. For example, a firm with integrity culture will have a norm of motivating employees to report unethical outcomes. A strong culture reflects a high goal alignment and motivation among employees to reinforce cultural values. Its effectiveness depends on the alignment of and the interaction between values and norms, and with legal requirements.

A firm can build homogeneous views (i.e., corporate culture) by hiring people who share its values (Van den Steen, 2005, 2010a). Strong culture firms also increase its chances of attracting and retaining employees with similar beliefs, reducing costs of internal cultural inspiration. Kreps (1990) classifies corporate culture as an intangible asset that is structured to guide human behavior in unanticipated situations. When certain actions are not verifiable or impossible to explain in advance by contracts or recurrent interaction, building a standard way of doing things (i.e., corporate culture) addresses these issues. Employees can follow corporate norms when faced with difficult choices that are not explicitly stated in the company policy (O'Reilly & Chatman, 1996). For example, during the difficult time of the coronavirus pandemic, a strong culture empowers managers and employees to make consistent decisions and efforts toward long-term perspectives (Li, Liu, et al., 2021).

Edmans (2011) and Oswald, Proto, and Sgroi (2015) find that happy employees are more driven and effective. Customers also favor businesses that value their employees (Luo and Bhattacharya, 2006; Edmans, 2011; Albuquerque, Koskinen, & Zhang, 2019). Strong culture firms have higher firm value as measured by Tobin's Q than weak cultural firms (Li, Mai, et al., 2021). Strong culture firms are also more likely to have higher operational efficiency with more asset and inventory turnovers (consistent with Graham, Harvey, Popadak, and Rajgopal (2017)) and better corporate governance in term of CEO wealth-performance and pay duration. Compared to firms with weak culture in innovation value during the pandemic, strong culture firms in innovation value are more adaptable to digital transformation and new product creation, which maintains and attracts consumers. Technology-oriented cultural firms are also associated with better stock market performance and higher profit margins in 2020 (Li, Liu, et al., 2021).

4.2.2. The cost of debt

The cost of debt depends on the probability of bankruptcy which lenders evaluate a firm's financial performance. A firm that better protects creditors' interest with a stable cash flow and certain future profitability often pay lower borrowing costs (Pogue & Soldofsky, 1969; Bai et al., 2019). Governance mechanisms can reduce default risk by monitoring managerial performance and mitigating agency costs and information asymmetry between the firm and its lenders. Anderson, Mansi, & Reeb (2003) show that large undiversified shareholders mitigate diversified equity claimants' incentives to expropriate bondholder wealth. Elyasiani, Jia, & Mao (2010) show that institutional ownership stability has a more detrimental impact on borrowing rates of firms that show severe information asymmetry and agency costs of debt. On the other hand, Michael & William (1976) show that firms with diversified shareholders are more likely to seize bondholder wealth by doing asset substitution with risky investment. A small board of directors with efficient communication and timely decision-making can borrow at a lower interest rate (Lorca, Sánchez-Ballesta, & García-Meca, 2011).

Financial reports are a primary source of information for lenders to evaluate firm performance and financial soundness. Standard & Poor's considers accounting quality as a main factor to establish the rating of an industrial bond issue. Firms can obtain lower interest rate from lenders by reducing lenders' and underwriters' perception of default risk with timely and detailed disclosures of their accounting reports (Sengupta, 1998). A fully independent audit committees with large size and high meeting frequency who insure the quality of financial reports are also negatively related to the cost of debt (Anderson, Mansi, & Reeb, 2004). In contrast, firms with weak internal control over accounting reports have higher credit spread (Dhaliwal, Hogan, Trezevant, & Wilkins, 2011).

Corporate culture is an implicit factor affecting borrowing costs. Firms that value employees with high welfare scores prefer long-term debt over short-term debt (Boubaker, Chourou, Haddar, & Hamza, 2019), especially in human-capital-intensive industries and firms with lower labor union-membership rate. Using long-term debt allows firms to avoid cutting expenditures connected to employee perks to enhance its immediate cash flow demands for short-term debt payment. Employee well-being policies promote sustainability by fostering loyal relationships with workers over time, allowing firms to gain a competitive advantage and a better market position in the long run (Neubaum & Zahra, 2006). Bauer, Derwall, & Hann (2009) find that firms with stronger employee relations enjoy lower borrowing rates, higher credit ratings, and lower firm-specific risk. These findings support stakeholder theory that a firm enforces strong commitment to employee well-being genuinely to strengthen its reputation in the market, enhancing the shareholders' engagement, avoiding costly strikes, and boosting the employees' productivity.

However, Ben-Nasr & Ghouma's (2018) research supports the agency theory, which holds that managers try to use generous employee welfare plans to reduce employees' likelihood of reporting management wrongdoings. Plans for employee wellness assist managers in managing profitability and hiding negative news from investors. They find that high levels of employee welfare standards increase the risk of stock price crashes. Unionization can affect a firm's overall culture by impacting the working conditions and prevailing atmosphere (Farber, 1986). Unionized workplaces often have higher wages, better employee benefits, and more protection from discrimination and mistreatment by management. According to Campello, Gao, Qiu, & Zhang (2015), unionization grants workers in Chapter 11 bankruptcy unique privileges. Unionization is linked to lengthier bankruptcy court processes, more bankruptcy emergencies and recalls, greater bankruptcy costs, and higher bankruptcy expenses, all of which exacerbate bondholder losses. On the other hand, Hoffmann, Kleimeier, Mimiroglu, & Pennings (2019) demonstrate that inventive firms might utilize patents to communicate their ideas' quality to address these information asymmetry issues and make loans more accessible (consistent with Bhattacharya & Ritter (1983)). Jiang, John, Li, & Qian (2018) find that firms in countries with greater religiosity have higher credit ratings and lower costs of debt. The effect of religiosity is more pronounced for firms with greater information asymmetry, during recessions, and when the lender is a small bank.

4.2.3. Hypothesis development

This study focuses on the association between corporate culture and firm bond yield spread. I hypothesize that corporate culture will help to reduce the yield spread of newly issued bonds. Strong culture empowers executives and employees to focus on long-term perspectives and obtain good financial ratios. These firms are also more resilient in difficult time by remaining existing workforces and focusing on adopting technologies to develop new products (Li, Liu, et al., 2021). Thus, firms with good corporate culture can have a higher probability to pay back debt. My first hypothesis therefore is:

H1: Corporate culture is negatively associated with bond yield spread.

Good financial records associated with a strong corporate culture can lead to better bond credit rating, which in turn reduces the cost of debt. My second hypothesis is:

H2: Corporate culture is positively associated with bond credit rating.

The risk of innovation failure and the uncertainty of R&D investment payoffs are potential sources of asymmetric information. Firms that value innovation and quality can alleviate information risk by signaling their commitment on the quality of their inventions, and thus lowering yield spreads (Bhattacharya & Ritter, 1983). Moreover, executives who value high integrity and respect are less likely to exploit private information for personal gain (Jiang et al., 2021). Besides, employees with these values are more willing to report frauds, which helps enhance corporate disclosure transparency (Sengupta, 1998). Strong corporate culture also reduces reporting and litigation risks, making creditors better able to monitor potential violations in their debt agreements (Bushman et al., 2004). Given that an enhanced information environment with low asymmetry risk and high integrity of accounting report can reduce default risks (Brogaard, Li, & Xia, 2017; Francis et al., 2005), creditors may offer debt with lower costs to firms with strong culture. Thus, the third hypothesis is:

H3: Corporate culture is negatively associated with information risk.

4.3. Data and variable construction

4.3.1. Data and sample

I obtain firm-level measure of corporate culture from Li, Mai, et al. (2021). The data on yield to maturity, bond credit rating, and other characteristics are from the Mergent Fixed Income Securities Database (FISD) Database. The information on constant maturity Treasury security series is published by the Federal Reserve Bank of New York. The control variables include both issue- and firm-level control variables. I collect information on stock prices and returns from the Center for Research in Security Prices (CRSP). I collect information on firm specific accounting data from Compustat. I obtain institutional ownership data from the Thomson Reuters Institutional Holdings (13F) Database. To mitigate the effects of outliners, I winsorize all continuous variables at the first and 99th percentiles. Consistent with prior studies (e.g., (Cheng & Subramanyam, 2008), I exclude from the sample financial firms with SIC codes from 6000 to 6999 and utility firms with SIC codes from 4900 to 4999 as these firms may be subject to different capital requirements and regulation, biasing the analysis. The final sample consists of 4,685 firm-year observations from 2002 to 2017. The detailed description of the variables is provided in Table A.4.1. in the Appendices.

4.3.2. Corporate culture measure

My firm-level measure of corporate culture from, Li, Mai, et al. (2021), encompasses five cultural values: innovation, integrity, quality, respect, and teamwork. These metrics are scored according to how significant the value is in the firm's earnings calls – the weighted count of the words associated with each value divided by the total number of words in the earning calls at the end of the fiscal year. A firm with high score in integrity, for example, is one that emphasizes the higher important degree of integrity in their discussions on financial performance. Each cultural value is validated to be positively and significantly associated with shared values and practices by employees that has been partially calculated in other studies (Guiso et al., 2015), providing a comprehensive measure to examine the implications of having a strong corporate culture on firm activities.

Because the measure is available from 2002 to 2017, my empirical test setting covers this time frame. The main explanatory variable in this study is the measure of corporate culture - Sum_culture which is total continuous scores of five cultural values. A higher cultural score is associated with stronger corporate culture overall. The indicator variable Strong_culture has a value of 1 if the total of a firm's five cultural value scores in a year is in the top quintile across all firms, and 0 otherwise. I divide the five cultural values into two categories: strong culture in people, which measures integrity, respect, and teamwork; and strong culture in technology, which measures innovation and quality. Similarly, these measures have a value of 1 if its total cultural value score in a year is in the top quintile across all firms and 0 otherwise.

4.3.3. Bond data

I obtain information on corporate bonds from the Mergent FISD Database. I focus on new issues data with direct transaction prices as it is more accurate than the secondary data with matrix prices following Elton, Gruber, Agrawal, & Mann (2001) and Qi, Roth, & Wald (2010). I require that bonds are issued in U.S. dollars to examine various benchmark interest rates and prevent any potential currency conversion issues. I only include corporate fixed- and floating-rate bonds and notes in my sample, excluding any convertible bonds, asset-backed securities, and non-corporate rates.

The main independent variable in the analysis, the cost of debt, is the natural logarithm of bond yield spread at the time of the bond issue. The yield spread for fixed-rate bonds is defined as the difference between the yield-to-maturity on a corporate bond and its duration-equivalent risk-free bond. The yield-to-maturity on a corporate bond is defined as the discount rate that equates the present value of the future cash flows to the security price. Risk-free bonds are the constant maturity Treasury security series published by the Federal Reserve Bank of New York in its H15 release. If no duration-equivalent Treasury security is available to match the corporate bond's duration, the yield-to-maturity on the Treasury security is calculated as the linear interpolation between the two closest maturity matches. The interest rate of floating-rate bonds equals to the rate of a reference bond or index (typically LIBOR) plus the credit spread. Therefore, I measure the yield spread for floating-rate bonds equal to the credit spread plus the difference between the interest rate of reference index with the yield on its equivalent Treasury security over the first interest period. I include a dummy variable for floating-rate bond in the regression to account for a potential mismeasurement between fixed-rate bond yield spreads and floating-rate bond yield spreads.

Bond credit ratings measures the bond's perceived risk and are constructed following Qi et al. (2010). For each bond issuance reported in FISD, I convert the letter rating from the three largest rating agencies, Standard & Poor's (S&P), Moody's, and Fitch, into a number between 21 (for AAA-rated bonds) and 1 (for D rated bonds). I then average the rating scores to get the final rate. For example, a firm with ratings of A1 from Moody's and A+ from S&P would have an average score of 18.

4.3.4. Control variables

The models contain both firm- and bond issue-level control variables. The data on firm financial information is obtained from Compustat, including firm size, leverage, market-to-book ratio, profitability, firm risk, and block holdings. I use the natural logarithm of total assets to proxy for firm size, which captures information and any residual risk effect. Large firms are expected to have lower risk and pay lower borrowing costs based on the economies of scale (Blackwell, Noland, & Winters, 1998; Petersen & Rajan, 1994). Leverage is measures as the book value of total debt divided by the market value of total assets. Leverage ratios are positively associated with default risk and, therefore, a higher cost of debt. Sale growth is a proxy for growth. Myers (1977) argues that growth opportunities are intangible assets that cannot be used as collateral in the event of default, thus negatively affecting the cost of debt. Profitability is defined as earnings before interests, taxes, depreciation, and amortization, normalized by total assets. High-profitable firms are expected to have lower debt costs as they have a higher ability to pay back the debt. In addition to leverage that accounts for variations in firm's capital structure and default risk (as do credit ratings, firm size, and duration), I also include a measure of stock return volatility computed by the standard deviation of stock returns for the prior 12 months to reinforce the results. Firms that are riskier with more volatile stocks have a higher cost of debt. Institutional ownership represents the holdings of all institutional shareholders of the firm's outstanding equity.

Security-specific variables include bond liquidity, duration, covenants, and dummy variables for callable bonds, puttable bonds, and floating rate bonds. Bond liquidity is measured by the natural logarithm of bond issuance size divided by firm total assets. A large issuance size provides better bond liquidity and, thus, a lower yield spread (Warga, 1992; Yu, 2005). Duration is the length of time (in years) since a bond is issued until it is due. Bonds with longer maturity are expected to be riskier according to liquidity premium theory, thus bearing higher interest rates (Helwege & Turner, 1999). I include year and two-digit SIC code industry fixed effects to control for any time or industry invariant factors. Standard errors are clustered at the firm level since bonds of the same firm could be correlated with each other.

4.3.5. Summary statistics

Table 4.1 Panel A provides the summary statistics. The median yield spreads are approximately 1.75 percent higher than the corresponding Treasury securities; however, the spread is skewed with a mean of 2.26 percent. The average bond has a credit rating of 12.272. Most bonds are issued with fixed rates, covenants (72.7%), and call options (95.3%). 3.4% of bonds are issued with put options. An average firm has a total cultural value of 5.310, where each cultural value has the lowest value of 0 and the highest value of 10. Firms with total cultural values in the top quartile are classified as strong culture firms, while firms in the other quartiles are classified as weal culture firms. Panel B shows correlation coefficients for the variables of interest. As predicted, corporate culture is positively correlated with credit rating (0.199) and negatively correlated with yield spread (-0.193). High cultural value is also correlated with large firms, lower leverage, higher profitability, and lower risks. Strong culture firms are likely to issue smaller issuance sizes with covenants and longer duration.

Table 4. 1: Summary Statistics and Coefficient Correlations

Panel A shows the summary statistics of all variables, and Panel B shows the coefficient correlations. Sum_culture is the total five cultural value scores of a firm, including integrity, respect, teamwork, innovation, and quality. The yield spread is defined as the difference between the yield-to-maturity on a corporate bond and its duration-equivalent risk-free bond for fixed-rate bonds and as the credit spread plus the difference between the interest rate of reference index and the yield on its equivalent Treasury security over the first interest period for floating-rate bonds. Other variables are described in Table A.4.1.

Panel A:	N	Mean	Std Dev	Median	25^{th} Pctl	75^{th} Pctl
Firm-level:						
Sum_culture	4,685	5.310	2.416	4.860	3.579	6.434
Strong_culture	4,685	0.250	0.433	0.000	0.000	0.000
Strong_culture_people	4,685	0.250	0.433	0.000	0.000	0.000
Strong_culture_tech	4,685	0.251	0.434	0.000	0.000	1.000
Firm size	4,685	2.547	1.902	2.433	1.214	3.631
Sale_growth	4,685	0.371	0.180	0.353	0.245	0.477
Leverage	4,596	0.121	0.305	0.060	-0.004	0.167
Profitability	4,549	0.111	0.092	0.111	0.071	0.155
Firm risk_5y	4,674	0.104	0.066	0.084	0.060	0.126
Firm risk_1y	4,674	0.089	0.060	0.072	0.051	0.107
Inst Ownership	2,424	0.775	0.172	0.807	0.683	0.902
Issue-level:						
Yield_spread	4,685	2.261	2.365	1.752	0.931	3.336
Log(Yield_spread)	4,261	0.672	0.810	0.673	0.128	1.262
Credit rating	4,173	12.272	3.631	13.000	9.500	14.667
Log(Issue_size)	3,573	3.875	1.209	3.936	3.049	4.747
Log(Duration)	4,685	2.187	0.646	2.169	1.705	2.319
Bond covenants	4,675	0.727	0.446	1.000	0.000	1.000
Callable bonds	4,136	0.953	0.211	1.000	1.000	1.000
Putable bonds	4,656	0.034	0.180	0.000	0.000	0.000
Floating rate	4,683	1.010	0.120	1.000	1.000	1.000

Table 4.1: continued

Panel B:	Yield spread	Credit rating	Sum_ culture	Sum_ culture_ people	Sum_ culture _tech	Issue size	Duration	Covenant	Firm size	Leverage	Sale growth	Profita-bility	Firm risk
Credit rating	-0.567*												
Sum_culture	-0.193*	0.199*											
Sum_culture_people	-0.086*	0.085*	**0.768***										
Sum_culture_tech	-0.216*	0.223*	**0.911***	0.436*									
Issue_size	0.285*	**-0.663***	-0.226*	-0.065*	-0.277*								
Duration	-0.212*	0.094*	0.041*	-0.014	0.067*	-0.189*							
Covenants	-0.243*	0.357*	0.113*	0.027	0.141*	-0.324*	0.137*						
Firm size	-0.187*	0.680*	0.147*	0.071*	0.160*	**-0.893***	0.023	0.219*					
Leverage	0.192*	-0.374*	-0.087*	-0.065*	-0.081*	0.340*	-0.108*	-0.157*	-0.282*				
Sale_growth	0.014	-0.188*	-0.01	0.062*	-0.054*	0.195*	-0.038	-0.077*	-0.166*	0.063*			
Profitability	-0.126*	0.194*	0.029	-0.130*	0.125*	-0.220*	0.140*	0.077*	0.019	0.023	-0.008		
Firm risk	0.351*	-0.477*	-0.148*	-0.072*	-0.161*	0.410*	-0.128*	-0.206*	-0.386*	0.161*	0.023	-0.257*	
Institutional ownership	-0.122*	-0.134*	0.005	0.023	-0.009	0.111*	0.012	0.037	-0.132*	-0.096*	0.044	-0.083*	-0.097*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.4. Corporate culture and bond yield spread

4.4.1. The baseline model

I examine the effect of corporate culture of the firm cost of debt using the baseline model of pooled ordinary least squares (OLS) as defined below:

$$YieldSpread_{i,t} = \alpha + \beta Culture_{i,t} + \gamma Controls_{i,t} + Industry_i + Year_t + \varepsilon_{i,t} \quad (4.1)$$

where i and t denote firm and year, respectively. $Industry$ and $Year$ capture industry and year fixed effects, respectively. ε is the error term. Dependent variable is the natural logarithm of yield spread. The main explanatory variable of interest is Sum_culture. Firm-level control variables consist of firm size (the natural logarithm of total assets), leverage, market-to-book ratio, profitability, firm risk (the standard deviations of stock price in previous twelve months), and institutional holdings. Issue-level control variables include bond liquidity (the natural logarithm of issue size), the natural logarithm of duration, the indicators for issues with covenants, put options, call options, and bond types (bonds with fixed interest rates or floating rates).

The effects of corporate culture on yield spread are presented in Table 4.2. Column 1 presents the results without control variables, while Columns 2 present the results with firm-level controls and Column 3 present the results with both firm- and issue-level control variables. All regressions include industry and year fixed effects since industry affiliation is one of several factors shaping corporate culture (Graham et al., 2017). The standard errors in all regressions are clustered at the firm level to address the potential correlation in error terms among bond issues of the same firm.

The results in all columns indicate that bond yield spread is negatively associated with corporate culture, consistent with Hypothesis 1. The corporate culture coefficients are statistically significant at the 1% level. The magnitude of the coefficients in Table 4.2 indicates that one standard deviation increase in corporate cultural values leads to a reduction of 8.438%[21] in firm yield spread (Column 3). The coefficients of control variables are generally consistent with prior literature (Bates, Kahle, & Stulz, 2009; Dittmar, Mahrt-Smith, & Servaes, 2003). Specifically, yield spreads are negatively related to firm size, profitability, bond covenants, and put options, whereas positively related to leverage, firm risk, institutional ownership, and call options.

[21] That equals to (exp(0.076)-1)* 2.416/2.261

Table 4. 2: Effects of Corporate Culture on Yield Spread

This table shows the effects of corporate culture on bond yield spread. Sum_culture is the total five cultural value scores of a firm, including integrity, respect, teamwork, innovation, and quality. The yield spread is defined as the difference between the yield-to-maturity on a corporate bond and its duration-equivalent risk-free bond for fixed-rate bonds and as the credit spread plus the difference between the interest rate of reference index and the yield on its equivalent Treasury security over the first interest period for floating-rate bonds. Other variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Log(Yield spread)			
	(1)	(2)	(3)	(4)
Sum_culture	-0.146***	-0.116***	-0.076***	-0.087***
	(-6.837)	(-5.745)	(-3.700)	(-3.436)
Firm size		-0.108**	-0.222***	-0.315***
		(-2.343)	(-3.707)	(-4.296)
Leverage		2.077***	1.790***	1.426***
		(6.306)	(4.894)	(3.145)
Sale_growth		0.240	0.259	0.403
		(1.505)	(1.426)	(1.612)
Profitability		-1.037*	-2.107***	-2.325***
		(-1.774)	(-3.297)	(-2.802)
Firm risk		8.603***	9.714***	8.933***
		(6.465)	(7.843)	(6.106)
Inst_ownership				-1.095***
				(-3.033)
Bond liquidity			0.129*	0.094
			(1.776)	(1.098)
Bond duration			0.022	-0.112
			(0.364)	(-1.517)
Bond covenants			-0.701***	-0.736***
			(-6.950)	(-6.201)
Callable bonds			1.616***	1.470***
			(5.802)	(4.210)
Putable bonds			-4.405***	-4.410***
			(-16.262)	(-15.010)
Floating rate			0.094	-0.058
			(0.381)	(-0.220)
Constant	3.035***	1.690***	0.400	2.513***
	(22.265)	(7.671)	(0.704)	(3.289)
Observations	4,682	4,454	3,172	2,130
Adjusted R-squared	0.239	0.333	0.587	0.604
Max. VIF	1.00	1.14	1.92	1.82
Industry FE & Year FE	Y	Y	Y	Y

4.4.2. Effects of each cultural value

To investigate which cultural value plays a more important role in driving lower cost of debt for a firm, I test the Equation 4.1 separately for each cultural value. The culture focuses on human values such as integrity and respect could improve the reliability of accounting system by encouraging employees to report frauds and dispiriting managers from extracting private information (Jiang et al., 2021). The culture focuses on technology, on the other hand, pay more attention to the innovation and product quality which are among the key determinants of a firm's cash flow. Table 4.3 (next page) shows the results. The key independent variable of interest in each column is the score of each culture value: integrity, respect, teamwork, innovation, and quality. Surprisingly, the culture scores on human values, such as integrity and teamwork, have little influence on lowering lending rate from creditors. On the other hand, both coefficients of innovation and quality are statistically significant at 1% level. The results suggest that creditors pay more attention to the technology aspects in a firm's corporate culture when pricing a bond issuance.

4.4.3. Strong vs weak corporate culture

This section observes whether there is a significant discrepancy in the relation between corporate culture and yield spread between firms with strong and weak corporate culture. Firms are divided into 5 quintiles based on sum cultural value, sum human cultural value, sum technology cultural value, integrity, respect, teamwork, innovation, and quality. Firms are assigned to have strongest corporate culture if a firm's total score of five cultural values is in the top quintile across all firms, and 0 otherwise. The classification procedure is the same for other cultural measures. Table 4.4 shows the results.

Overall, the results are consistent with Table 4.3 where respect, innovation, and quality are three cultural values that are negatively associated with bond yield spread. In most columns, the magnitude of negative relation between cultural values and yield spread increases from the first quintile to the fifth quintile.

Table 4. 3: Effects of Each Cultural Value on Yield Spread

This table shows the effects of each cultural value on bond yield spread. The independent variables of interest in each model are 5 cultural values, including integrity, respect, teamwork, innovation, and quality. The dependent variable is yield spread. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Log(Yield spread)				
	(1)	(2)	(3)	(4)	(5)
Integrity	-0.005				
	(-0.039)				
Respect		-0.229*			
		(-1.759)			
Teamwork			-0.083		
			(-1.161)		
Innovation				-0.182***	
				(-3.725)	
Quality					-0.187***
					(-2.731)
Firm size	-0.335***	-0.324***	-0.333***	-0.321***	-0.324***
	(-4.589)	(-4.404)	(-4.589)	(-4.460)	(-4.440)
Leverage	1.529***	1.515***	1.514***	1.390***	1.472***
	(3.345)	(3.304)	(3.311)	(3.062)	(3.236)
Sale_growth	0.382	0.404	0.395	0.365	0.382
	(1.534)	(1.620)	(1.572)	(1.469)	(1.525)
Profitability	-2.181**	-2.354***	-2.218***	-2.204***	-2.211***
	(-2.580)	(-2.882)	(-2.596)	(-2.645)	(-2.614)
Firm risk	8.900***	8.932***	8.945***	8.780***	8.950***
	(6.078)	(6.123)	(6.094)	(6.029)	(6.088)
Inst_ownership	-1.040***	-1.070***	-1.044***	-1.068***	-1.081***
	(-2.846)	(-2.935)	(-2.862)	(-2.968)	(-2.981)
Bond liquidity	0.082	0.089	0.085	0.084	0.090
	(0.962)	(1.030)	(1.003)	(0.994)	(1.064)
Bond duration	-0.113	-0.117	-0.111	-0.116	-0.109
	(-1.541)	(-1.583)	(-1.522)	(-1.554)	(-1.487)
Bond covenants	-0.750***	-0.748***	-0.747***	-0.727***	-0.752***
	(-6.265)	(-6.289)	(-6.234)	(-6.105)	(-6.324)
Callable bonds	1.499***	1.489***	1.484***	1.492***	1.491***
	(4.266)	(4.252)	(4.221)	(4.273)	(4.281)
Putable bonds	-4.433***	-4.394***	-4.434***	-4.422***	-4.432***
	(-15.047)	(-14.771)	(-15.073)	(-15.059)	(-15.102)
Floating rate	-0.037	-0.053	-0.035	-0.057	-0.048
	(-0.143)	(-0.200)	(-0.135)	(-0.219)	(-0.181)
Constant	2.026***	2.208***	2.088***	2.442***	2.263***
	(2.669)	(2.910)	(2.737)	(3.207)	(2.986)
Observations	2,130	2,130	2,130	2,130	2,130
Adjusted R-squared	0.600	0.602	0.601	0.605	0.602
Max VIF	1.80	1.81	1.8	1.82	1.81
IndustryFE & Year FE	Y	Y	Y	Y	Y

Table 4. 4: Effects of Different Degree of Cultural Values on Yield Spread

This table shows the effects of corporate culture on bond yield spread for different level of cultural values. The independent variables of interest in each column are culture, culture in people, and culture in technology in Panel A and five cultural values in Panel B, including integrity, respect, teamwork, innovation, and quality. The dependent variable is yield spread. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

Panel A:	Log(Yield_spread)		
CV – Cultural Variable	Culture	Culture_people	Culture_tech
	(1)	(2)	(3)
2nd quintile CV	-0.374***	0.005	-0.439***
	(-2.641)	(0.038)	(-2.828)
3rd quintile CV	-0.436***	-0.218*	-0.700***
	(-3.009)	(-1.707)	(-4.456)
4th quintile CV	-0.613***	-0.211	-0.693***
	(-3.848)	(-1.379)	(-4.230)
5th quintile CV	-0.679***	-0.244	-0.837***
	(-3.858)	(-1.569)	(-4.430)
Firm size	-0.312***	-0.326***	-0.323***
	(-4.282)	(-4.416)	(-4.556)
Leverage	1.458***	1.526***	1.393***
	(3.232)	(3.362)	(3.088)
Sale_growth	0.417*	0.404	0.348
	(1.664)	(1.615)	(1.432)
Profitability	-2.329***	-2.267***	-2.324***
	(-2.850)	(-2.716)	(-2.808)
Firm risk	8.850***	8.912***	8.574***
	(6.059)	(6.046)	(5.942)
Inst ownership	-1.103***	-1.067***	-1.101***
	(-3.064)	(-2.905)	(-3.103)
Bond liquidity	0.093	0.085	0.089
	(1.085)	(0.990)	(1.066)
Bond duration	-0.115	-0.110	-0.117
	(-1.565)	(-1.499)	(-1.594)
Bond covenants	-4.366***	-4.410***	-4.343***
	(-14.810)	(-14.888)	(-14.820)
Callable bonds	1.478***	1.486***	1.447***
	(4.253)	(4.224)	(4.144)
Putable bonds	-0.748***	-0.758***	-0.747***
	(-6.303)	(-6.264)	(-6.343)
Floating rate	-0.078	-0.051	-0.069
	(-0.303)	(-0.197)	(-0.260)
Constant	2.505***	2.164***	2.760***
	(3.311)	(2.852)	(3.594)
Observations	2,130	2,130	2,130
Adjusted R-squared	0.606	0.601	0.609
IndustryFE	Y	Y	Y
Year FE	Y	Y	Y

Table 4. 4. continued

Panel B:	Log(Yield_spread)				
CV – Cultural Variable	Integrity	Respect	Teamwork	Innovation	Quality
	(1)	(2)	(3)	(4)	(5)
2nd quintile CV	-0.215*	-0.239*	-0.177	-0.381***	-0.124
	(-1.899)	(-1.826)	(-1.458)	(-2.678)	(-0.772)
3rd quintile CV	-0.092	-0.383***	-0.122	-0.587***	-0.303**
	(-0.693)	(-2.679)	(-0.924)	(-3.835)	(-1.977)
4th quintile CV	0.053	-0.311**	-0.007	-0.413***	-0.440***
	(0.421)	(-2.268)	(-0.052)	(-2.693)	(-2.770)
5th quintile CV	-0.181	-0.385**	-0.216	-0.834***	-0.427**
	(-1.242)	(-2.296)	(-1.245)	(-4.386)	(-2.435)
Firm size	-0.337***	-0.328***	-0.327***	-0.315***	-0.320***
	(-4.620)	(-4.536)	(-4.421)	(-4.448)	(-4.468)
Leverage	1.538***	1.500***	1.530***	1.397***	1.507***
	(3.398)	(3.304)	(3.337)	(3.077)	(3.296)
Sale_growth	0.366	0.427*	0.400	0.367	0.372
	(1.501)	(1.717)	(1.604)	(1.515)	(1.474)
Profitability	-2.178**	-2.224***	-2.271***	-2.195***	-2.218***
	(-2.567)	(-2.644)	(-2.752)	(-2.680)	(-2.602)
Firm risk	8.927***	8.939***	8.911***	8.611***	8.795***
	(6.064)	(6.073)	(6.113)	(5.953)	(6.067)
Inst ownership	-1.049***	-1.059***	-1.060***	-1.094***	-1.063***
	(-2.880)	(-2.933)	(-2.909)	(-3.056)	(-2.987)
Bond liquidity	0.080	0.092	0.087	0.098	0.094
	(0.935)	(1.084)	(1.009)	(1.186)	(1.120)
Bond duration	-0.112	-0.107	-0.118	-0.113	-0.114
	(-1.513)	(-1.467)	(-1.600)	(-1.540)	(-1.546)
Bond covenants	-4.422***	-4.431***	-4.413***	-4.396***	-4.399***
	(-15.169)	(-15.095)	(-14.875)	(-14.938)	(-14.966)
Callable bonds	1.480***	1.510***	1.502***	1.444***	1.479***
	(4.236)	(4.270)	(4.322)	(4.117)	(4.243)
Putable bonds	-0.747***	-0.732***	-0.748***	-0.718***	-0.754***
	(-6.193)	(-6.152)	(-6.301)	(-6.101)	(-6.356)
Floating rate	-0.057	-0.038	-0.033	-0.050	-0.058
	(-0.225)	(-0.144)	(-0.126)	(-0.193)	(-0.221)
Constant	2.155***	2.216***	2.113***	2.531***	2.296***
	(2.856)	(2.915)	(2.788)	(3.295)	(3.015)
Observations	2,130	2,130	2,130	2,130	2,130
Adjusted R-squared	0.601	0.602	0.601	0.608	0.603
IndustryFE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

4.5. Corporate culture and bond credit ratings

In a similar context, I investigate whether corporate culture boosts creditworthiness. Employees can serve as a firm's internal monitoring of managerial performance, which can contribute to better credit ratings. Managers are less likely to exploit private information for personal gain if fraud or misconduct is reported immediately (Bushman et al., 2004; Jiang et al., 2021; Sengupta, 1998). Given that a more transparent information environment reduces default risks, a strong corporate culture can result in lower default risk and, as a result, a higher credit rating.

Table 4.5 displays the results for the effects of corporate culture on bond rating with a different set of control variables in each column. The results in all columns show that credit rating is positively associated with corporate culture. Table 4.6 examines the relationship between each cultural value and bond credit rating. Firms that prioritize respect, innovation, and quality are more likely to have a higher credit rating, consistent with the findings in Table 4.2. The results in Panel B of Table 4.6 show that strong culture firms (in the quintile with the highest score for sum cultural value) have significantly better credit ratings than weak culture firms, which is consistent with the results in Table A.4.2 in the Appendices when looking at the effect of corporate culture on bond rating for different quintiles.

Table 4. 5: Effects of Corporate Culture on Bond Rating

This table shows the effects of corporate culture on bond credit rating. Sum_culture is the total five cultural value scores of a firm, including integrity, respect, teamwork, innovation, and quality. Bond credit ratings range from 1 to 21 after converting the letter rating from the three largest rating agencies. Other variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Bond Rating			
	(1)	(2)	(3)	(4)
Sum_culture	0.284***	0.060**	0.065*	0.101***
	(5.339)	(2.043)	(1.918)	(2.759)
Firm size		1.253***	1.098***	1.046***
		(20.879)	(10.070)	(10.192)
Leverage		-3.988***	-4.188***	-4.481***
		(-7.895)	(-6.901)	(-7.599)
Sale_growth		-1.162***	-1.463***	-1.463***
		(-5.849)	(-8.533)	(-7.193)
Profitability		12.147***	11.703***	13.117***
		(9.028)	(8.073)	(9.378)
Firm risk		-14.531***	-10.587***	-9.443***
		(-11.511)	(-7.574)	(-6.783)
Inst_ownership				-1.602***
				(-3.310)
Bond liquidity			-0.228**	-0.158
			(-2.277)	(-1.432)
Bond duration			0.142**	0.076
			(2.360)	(1.196)
Bond covenants			0.878***	1.128***
			(5.626)	(7.611)
Callable bonds			1.061**	1.102**
			(2.557)	(2.101)
Putable bonds			-1.129***	-1.033**
			(-3.036)	(-2.505)
Floating rate			0.417	0.583
			(1.190)	(1.507)
Constant	10.780***	9.852***	8.445***	9.046***
	(35.524)	(25.900)	(9.085)	(8.472)
Observations	4,171	3,968	2,958	1,992
Adjusted R-squared	0.299	0.737	0.774	0.783
Max. VIF	1.00	1.15	1.91	1.82
IndustryFE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 4. 6: Effects of Each Cultural Value on Bond Rating

This table shows the effects of each cultural value on bond credit rating. The independent variables of interest in each column are five cultural values, including integrity, respect, teamwork, innovation, and quality. The dependent variable is bond credit rating. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

Panel A:	Bond Rating				
	(1)	(2)	(3)	(4)	(5)
Integrity	0.018				
	(0.092)				
Respect		0.265*			
		(1.691)			
Teamwork			0.245**		
			(2.213)		
Innovation				0.125*	
				(1.670)	
Quality					0.312***
					(2.954)
Firm size	1.076***	1.059***	1.066***	1.064***	1.057***
	(10.463)	(10.322)	(10.420)	(10.499)	(10.362)
Leverage	-4.598***	-4.590***	-4.573***	-4.497***	-4.498***
	(-7.746)	(-7.735)	(-7.697)	(-7.620)	(-7.650)
Sale_growth	-1.436***	-1.469***	-1.471***	-1.426***	-1.444***
	(-6.800)	(-7.140)	(-6.962)	(-6.855)	(-7.111)
Profitability	13.037***	13.122***	13.142***	13.023***	13.072***
	(9.249)	(9.262)	(9.352)	(9.297)	(9.281)
Firm risk	-9.454***	-9.433***	-9.603***	-9.323***	-9.507***
	(-6.678)	(-6.665)	(-6.845)	(-6.672)	(-6.800)
Inst_ownership	-1.670***	-1.653***	-1.637***	-1.644***	-1.617***
	(-3.379)	(-3.376)	(-3.342)	(-3.365)	(-3.287)
Bond liquidity	-0.144	-0.154	-0.153	-0.147	-0.155
	(-1.320)	(-1.400)	(-1.377)	(-1.342)	(-1.429)
Bond duration	0.077	0.081	0.070	0.079	0.070
	(1.205)	(1.260)	(1.097)	(1.239)	(1.103)
Bond covenants	1.142***	1.145***	1.130***	1.124***	1.151***
	(7.662)	(7.732)	(7.576)	(7.602)	(7.793)
Callable bonds	1.117**	1.110**	1.126**	1.096**	1.114**
	(2.165)	(2.159)	(2.174)	(2.087)	(2.183)
Putable bonds	-1.019**	-1.059**	-1.021**	-1.025**	-0.987**
	(-2.504)	(-2.584)	(-2.446)	(-2.507)	(-2.464)
Floating rate	0.563	0.585	0.553	0.577	0.568
	(1.441)	(1.496)	(1.415)	(1.474)	(1.497)
Constant	9.534***	9.389***	9.394***	9.285***	9.167***
	(8.860)	(8.735)	(8.793)	(8.551)	(8.759)
Observations	1,992	1,992	1,992	1,992	1,992
Adjusted R-squared	0.780	0.781	0.781	0.781	0.783
Max VIF	1.79	1.81	1.79	1.83	1.80
IndustryFE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table 4. 6: Continued

Panel B:	Bond Rating				
	(1)	(2)	(3)	(4)	(5)
Sum_culture_people	0.145**				
	(2.071)				
Sum_culture_tech		0.138***			
		(2.647)			
Strong_culture			0.283*		
			(1.893)		
Strong_culture_people				0.300*	
				(1.921)	
Strong_culture_tech					0.312*
					(2.954)
Firm size	1.056***	1.055***	1.068***	1.065***	1.066***
	(10.197)	(10.396)	(10.497)	(10.332)	(10.552)
Leverage	-4.592***	-4.443***	-4.541***	-4.566***	-4.529***
	(-7.718)	(-7.559)	(-7.659)	(-7.692)	(-7.695)
Sale_growth	-1.482***	-1.429***	-1.446***	-1.448***	-1.449***
	(-7.123)	(-6.998)	(-6.909)	(-6.966)	(-6.939)
Profitability	13.152***	13.037***	13.067***	13.070***	13.020***
	(9.332)	(9.316)	(9.292)	(9.293)	(9.296)
Firm risk	-9.561***	-9.335***	-9.359***	-9.634***	-9.269***
	(-6.786)	(-6.713)	(-6.660)	(-6.810)	(-6.578)
Inst_ownership	-1.629***	-1.617***	-1.656***	-1.646***	-1.620***
	(-3.338)	(-3.322)	(-3.378)	(-3.343)	(-3.335)
Bond liquidity	-0.156	-0.152	-0.147	-0.154	-0.149
	(-1.402)	(-1.393)	(-1.338)	(-1.388)	(-1.369)
Bond duration	0.076	0.076	0.076	0.080	0.079
	(1.191)	(1.203)	(1.202)	(1.244)	(1.231)
Bond covenants	1.137***	1.127***	1.139***	1.136***	1.131***
	(7.643)	(7.610)	(7.642)	(7.630)	(7.626)
Callable bonds	1.122**	1.092**	1.153**	1.105**	1.100**
	(2.162)	(2.082)	(2.230)	(2.131)	(2.109)
Putable bonds	-1.046**	-1.012**	-1.047**	-1.043**	-1.048**
	(-2.521)	(-2.491)	(-2.551)	(-2.526)	(-2.566)
Floating rate	0.573	0.580	0.574	0.578	0.582
	(1.469)	(1.503)	(1.456)	(1.469)	(1.458)
Constant	9.304***	9.093***	9.422***	9.530***	9.435***
	(8.705)	(8.492)	(8.778)	(8.851)	(8.788)
Observations	1,992	1,992	1,992	1,992	1,992
Adjusted R-squared	0.781	0.782	0.781	0.781	0.781
Max VIF	1.80	1.82	1.79	1.79	1.80
IndustryFE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

4.6. Path analysis

In this section, I conduct path analyses following prior studies to examine two possible channels through which corporate culture affects the firms' bond yield spread: the improvement in creditworthiness and reduction in information asymmetry (DeFond, Lim, & Zang, 2016; Landsman, Maydew, & Thornock, 2012; Pham, Merkoulova, & Veld, 2022). The improvement in creditworthiness and reduction in information asymmetry can serve as mediator variables affected by corporate culture that, in turn, affect the firms' bond yield spread.

Figure 4. 1: Path Analysis

The figure illustrates the direct and indirect paths through which corporate culture can affect yield spread. I estimate the following models in the path analysis: $Yield\ Spread_t = \beta_0 + \beta_1 * Culture_t + \beta_2 * Creditworthiness_t + \beta_3 * Information\ Risk_t + Controls + \varepsilon_t$ (a); $Creditworthiness_t = \alpha_0 + \alpha_1 * Culture_t + Controls + \varepsilon_t$ (b); $Information\ Risk_t = \mu_0 + \mu_1 * Culture_t + Controls + \varepsilon_t$ (c). The main explanatory variable of interest is the measure of corporate culture. Yield Spread refers to bond yield spread, as discussed in Equation 4.1. Creditworthiness is the credit rating of the issued bond. Information Risk is the logarithm of Corwin and Schultz's (2012) bid-ask spread measure. Controls include firm- and issue-level control variables from the baseline regression in Equation 4.1. Industry and year fixed effects are included in all the models. The path coefficient β_1 is the magnitude of the direct path from corporate culture to yield spread. The path coefficient β_2 (β_3) is the magnitude of the path from creditworthiness (information risk) to yield spread. The path coefficient $\hat{\alpha}_1 \times \hat{\beta}_2$ ($\hat{\mu}_1 \times \hat{\beta}_3$) is the magnitude of the indirect path from corporate culture to yield spread mediated through creditworthiness (information risk).

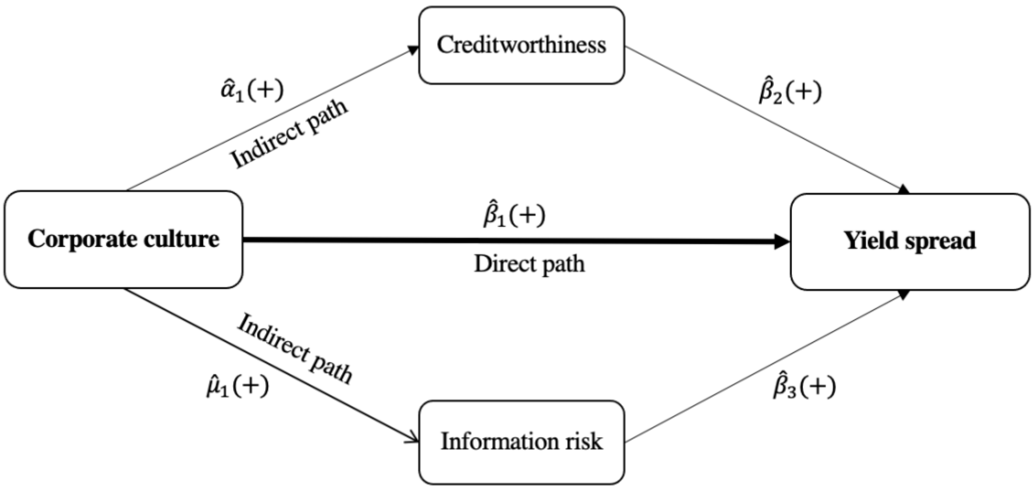


Figure 4.1 and Table 4.7 present a path analysis that examines the effect of corporate culture on bond yield spread through creditworthiness and information risk. I estimate the following models in the path analyses.

$$Yield\ Spread_t = \beta_0 + \beta_1 * Culture_t + \beta_2 * BCreditworthiness_t + \beta_3 * Information\ Risk_t + Controls + \varepsilon_t \quad (4.2a)$$

$$Creditworthiness_t = \alpha_0 + \alpha_1 * Culture_t + Controls + \varepsilon_t \quad (4.2b)$$

$$Information\ Risk_t = \mu_0 + \mu_1 * Culture_t + Controls + \varepsilon_t \quad (4.2c)$$

Yield Spread refers to bond yield spread, as discussed in Equation 4.1. Creditworthiness is the credit rating of the issued bond. Information Risk is the logarithm of Corwin & Schultz's (2012) bid-ask spread measure. The bid-ask spread is estimated using daily high and low prices. A high spread indicates greater information risk. Controls include control variables as specified in the baseline regression in Equation 4.1. The path coefficient β_1 is the effect of the direct path from corporate culture to yield spread. The path coefficient β_2 (β_3) is the effect of the path from bond credit rating (information risk) to yield spread. The path coefficient $\hat{\alpha}_1 \times \hat{\beta}_2$ ($\hat{\mu}_1 \times \hat{\beta}_3$) is the effect of the indirect path from corporate culture to yield spread mediated through creditworthiness (information risk). I use Sobel (1982)'s test statistics to estimate the significance of the indirect effect. Table 4.7 shows the analyses results.

Table 4. 7: Path Analysis: Effects of Corporate Culture on Yield Spread via Paths

The table shows the results for direct and indirect paths through which corporate culture can affect yield spread. I estimate the following models in the path analysis: $Yield\ Spread_t = \beta_0 + \beta_1 * Culture_t + \beta_2 * Creditworthiness_t + \beta_3 * Information\ Risk_t + Controls + \varepsilon_t$ (a); $Creditworthiness_t = \alpha_0 + \alpha_1 * Culture_t + Controls + \varepsilon_t$ (b); $Information\ Risk_t = \mu_0 + \mu_1 * Culture_t + Controls + \varepsilon_t$ (c). The main explanatory variable of interest is the measure of corporate culture. Yield Spread refers to bond yield spread. Creditworthiness is the credit rating of the issued bond. Information Risk is the logarithm of Corwin and Schultz's (2012) bid-ask spread measure. Controls include firm- and issue-level control variables from the baseline regression in Equation 4.1. Industry and year fixed effects are included in all the models. The path coefficient β_1 is the magnitude of the direct path from corporate culture to yield spread. The path coefficient β_2 (β_3) is the magnitude of the path from creditworthiness (information risk) to yield spread. The path coefficient $\hat{\alpha}_1 \times \hat{\beta}_2$ ($\hat{\mu}_1 \times \hat{\beta}_3$) is the magnitude of the indirect path from corporate culture to yield spread mediated through creditworthiness (information risk). The significance of the indirect effect is estimated using (Sobel, 1982) test statistics. The table reports the path coefficients of interest. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Path = Bond rating		Path = Information risk	
	(1)	(2)	(3)	(4)
	Coeff.	p Value	Coeff.	p Value
Direct Path				
P(Corp Culture, Yield Spread)	-0.025	0.204	-0.075***	0.002
Indirect Path				
P(Corp Culture, Path)	0.101***	0.006	-0.000**	0.014
P(Path, Yield Spread)	-0.257***	0.000	38.194***	0.000
P(Corp Culture, Path) x P(Path, Yield Spread)	-0.026***	0.007	-0.011**	0.027
Total effect	-0.051**	0.021	-0.087***	0.001
Mediated % in Total	51.1%		13.0%	
Observations	1,994		2,132	

The results suggest that improving creditworthiness is a significant channel that explains 51.1% of the positive relationship between corporate culture and yield spread. Similarly, information risk is another significant channel that explains 13.0% of the positive relationship between corporate culture and yield spread. Overall, the path analysis shows at least two channels that mediate the effect of corporate culture on yield spread: creditworthiness and information risk.

Tables A.4.3 and A.4.4 in the Appendices show the entire regressions that I run in the path analysis and provide additional results for the relation between corporate culture and yield spread when considering the effect of bond credit rating. In particular, the effects of corporate culture on yield spread are diminished when controlling for bond credit rating and other firm characteristics. However, the effects of corporate culture on yield spread differ for different degrees of bond credit ratings. The relation between corporate culture and yield spread is negative when the bond credit rating is low but reverses when the bond credit rating increases.

4.7. Robustness checks

4.7.1. Multicollinearity

Panel B of Table 4.1 shows a significant correlation between corporate culture and other firm characteristics. Thus, I apply the variance inflation factors (VIF) to check the multicollinearity of each model in Table 4.2. The results show that the VIF scores in each model are less than 5, indicating that the multicollinearity issue is at a moderate level. The VIFs of corporate culture in all models are around 1.1, indicating a moderate correlation between the explanatory variable of interest, corporate culture, and other variables in the model. Thus, the coefficient estimates and statistics in the regressions are reliable.

In unreported table, the VIF scores of all control variable in the models are less than 5, except for the total asset (VIF range of 5.41-5.59) and total issue size (VIF range of 4.99-5.37). The total issue size has a higher correlation with the response variable yield spread than the total issue size. To improve the overall quality of the regression model, I remove the total asset or issuance size and retest the model again. The results in Table 4.8 show that the relation between corporate culture and yield spread is not affected by multicollinearity.

Table 4. 8: Effects of Corporate Culture on Yield Spread with Different Controls

This table shows the effects of corporate culture on bond yield spread after controlling for the multicollinearity between Firm size and Bond liquidity. The independent variables of interest in each column are sum_culture. The dependent variables are yield spread in Columns 1 and 2, bond rating in Column 3 and information risk in Column 4. Equation 4.1 is retested without firm size in Column 1 and without bond liquidity in Columns 2-4. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Log(yield_spread)		Bond rating	Information risk
	(1)	(2)	(3)	(4)
Sum_culture	-0.096***	-0.086***	0.100***	-0.000**
	(-3.894)	(-3.396)	(2.717)	(-2.463)
Firm size		-0.374***	1.149***	-0.002***
		(-8.104)	(16.060)	(-7.866)
Bond liquidity	0.409***			
	(7.395)			
Leverage	1.572***	1.471***	-4.546***	0.006***
	(3.410)	(3.294)	(-7.714)	(3.695)
Sale_growth	0.387	0.418*	-1.486***	0.003***
	(1.499)	(1.708)	(-7.121)	(2.783)
Profitability	-2.472***	-2.313***	13.129***	-0.019***
	(-3.011)	(-2.786)	(9.365)	(-5.257)
Firm risk	9.581***	8.946***	-9.537***	0.159***
	(6.582)	(6.113)	(-6.868)	(20.903)
Inst_ownership	-0.940***	-1.094***	-1.584***	-0.005***
	(-2.626)	(-3.040)	(-3.241)	(-2.850)
Bond duration	-0.129*	-0.113	0.079	-0.001**
	(-1.702)	(-1.541)	(1.249)	(-2.056)
Bond covenants	-4.294***	-4.415***	-1.040***	0.002*
	(-14.556)	(-15.053)	(-2.590)	(1.649)
Callable bonds	1.416***	1.473***	1.144**	-0.001
	(4.098)	(4.224)	(2.219)	(-1.154)
Putable bonds	-0.803***	-0.739***	1.131***	-0.001**
	(-6.739)	(-6.216)	(7.582)	(-2.437)
Floating rate	-0.157	-0.025	0.535	0.001
	(-0.610)	(-0.095)	(1.396)	(1.640)
Constant	0.680	2.943***	8.238***	0.028***
	(1.023)	(4.496)	(9.630)	(11.085)
Observations	2,130	2,130	1,992	2,129
AdjR-squared	0.598	0.604	0.782	0.830
IndustryFE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

4.7.2. Does leverage matter?

Strong cultural firms tend to have lower leverage as shown in Panel B of Table 4.1. Therefore, leverage can be the primary channel that culture affects the yield spread. Thus, this section investigates the effect of corporate culture on yield spread in relation with firm leverage. Each year, I classify firms to four quartiles based on their leverage. Quartile one includes firms with lowest leverage, whereas quartile four includes firms with highest leverage in each year. I estimate the baseline regression in Table 4.2 for each quartile and present the coefficients of corporate culture in Table 4.9 Panel A. I find that the magnitudes of estimates on cultural values are statistically significant in leverage-sorted quartiles 3-4. The relation between corporate culture and yield spread are strongest for firms in quartile four; one standard deviation increase in cultural value scores leads to a reduction of 12.750% of yield spread for firms in quartile three and 16.883% for firms in quartile four. The results indicate that the negative relation between culture and yield spread could be mainly driven by leverage.[22]

One could contend that corporate culture has an impact on firm characteristics like firm risk, which in turn have an impact on the yield spread. To allay this worry, I estimate the base model for groups of firms with various levels of risk in the similar setting to the models I estimate the model for leverage. Depending on the return volatility in the previous year, firms are grouped into four quartiles every year. I then estimate my baseline model in each group and report the results in Panel B of Table 4.9. The estimates for control variables are comparable to those shown in Table 4.2. The results show that corporate culture is negatively associated with yield spread for most firms in the sample (quartiles two to four). The relation is strongest for firms in quartile three with one standard deviation increase in cultural value scores leading to the reduction of 17.586% in yield spread. Whereas the reductions are 7.466% and 9.417% for firms in quartiles two and four. The results suggest that firm risk is an unnecessary factor driving the baseline estimates.

[22] Full-sample analysis with interaction terms will be conducted in future analysis.

Table 4. 9: Effects of Corporate Culture on Yield Spread for Risk Quintiles

This table shows the effects of corporate culture on bond yield spread for different level of firm leverage in Panel A and past return volatility in Panel B. The independent variables of interest in each column are sum_culture. The dependent variable in all columns is yield spread. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

Panel A:	Log(Yield_spread)			
Leverage quintile	Q1 (lowest)	Q2	Q3	Q4 (highest)
	(1)	(2)	(3)	(4)
Sum_culture	-0.052	-0.039	-0.120**	-0.156**
	(-1.606)	(-1.001)	(-2.517)	(-2.171)
Firm size	-0.254***	-0.388***	-0.289***	-0.368***
	(-3.565)	(-4.498)	(-3.153)	(-2.713)
Leverage	0.588	1.989	3.888*	-0.638
	(0.462)	(1.017)	(1.950)	(-0.593)
Sale_growth	0.560*	0.423	0.304	0.337
	(1.686)	(1.490)	(1.172)	(0.804)
Profitability	-3.414**	-2.533**	-5.195***	-0.021
	(-2.374)	(-2.255)	(-3.414)	(-0.017)
Firm risk	1.071	6.569	11.906***	9.029***
	(0.507)	(1.397)	(6.669)	(3.506)
Inst_ownership	0.052	0.083	0.371	-3.035***
	(0.070)	(0.141)	(0.621)	(-4.794)
Bond liquidity	0.136*	-0.036	-0.533**	0.167*
	(1.761)	(-0.374)	(-2.246)	(1.937)
Bond duration	0.063	0.013	0.115	-0.503
	(0.815)	(0.143)	(0.904)	(-1.578)
Bond covenants	-0.853***	-0.665***	-1.088***	-0.693**
	(-4.133)	(-3.491)	(-4.744)	(-2.379)
Callable bonds	1.598***	0.945*	0.818	1.656**
	(2.937)	(1.764)	(1.202)	(2.254)
Putable bonds	-4.230***	-4.642***	-5.143***	-3.196***
	(-12.381)	(-12.516)	(-10.177)	(-3.270)
Floating rate	-0.355	0.032	0.499	2.332*
	(-1.112)	(0.110)	(1.638)	(1.683)
Constant	2.239***	1.899	0.928	4.033**
	(2.747)	(1.620)	(0.745)	(1.992)
Observations	469	618	560	460
AdjR-squared	0.687	0.580	0.642	0.608
IndustryFE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 4. 9: continued

Panel B: Past return volatility	Log(Yield_spread)			
	Q1 (lowest)	Q2	Q3	Q4 (highest)
	(1)	(2)	(3)	(4)
Sum_culture	-0.034	-0.072**	-0.162***	-0.090*
	(-0.828)	(-2.522)	(-2.960)	(-1.749)
Firm size	-0.183*	-0.223**	-0.333**	-0.626***
	(-1.947)	(-2.378)	(-2.492)	(-4.817)
Leverage	1.305**	0.400	2.606***	1.096
	(2.362)	(0.509)	(3.088)	(1.553)
Sale_growth	-0.064	0.356	-0.164	0.661**
	(-0.178)	(1.041)	(-0.469)	(2.339)
Profitability	-8.397***	-6.061***	-2.402	0.935
	(-6.477)	(-4.321)	(-1.535)	(0.995)
Firm risk	-0.706	-1.546	10.349	4.390*
	(-0.112)	(-0.204)	(1.429)	(1.798)
Inst_ownership	0.312	-0.925	-1.110	-1.969***
	(0.752)	(-1.633)	(-1.640)	(-2.714)
Bond liquidity	0.188	0.243**	-0.060	-0.216
	(1.504)	(2.294)	(-0.386)	(-1.320)
Bond duration	0.160*	-0.002	0.085	-1.020***
	(1.864)	(-0.021)	(0.682)	(-2.926)
Bond covenants	-0.345***	-0.526**	-0.888***	-0.554***
	(-2.685)	(-2.545)	(-3.937)	(-2.668)
Callable bonds	-0.012	1.909**	1.197	2.449***
	(-0.020)	(2.149)	(1.450)	(4.900)
Putable bonds	-4.138***	-3.561***	-3.854***	-3.809***
	(-10.613)	(-4.609)	(-8.244)	(-7.622)
Floating rate	-0.358	0.194	-0.813*	0.482
	(-1.229)	(0.318)	(-1.835)	(0.715)
Constant	2.692**	1.892	3.738**	5.948***
	(2.176)	(1.260)	(2.360)	(3.884)
Observations	473	576	552	505
Adjusted R-squared	0.644	0.560	0.542	0.695
IndustryFE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Firm	Y	Y	Y	Y

4.7.3. Financial crisis

The financial crisis of 2008-2009 had a substantial impact on yield spreads and bond credit ratings. As a result, I removed all issuances during this period and re-examined the impact of company culture on bond yield spread and credit rating. Table 4.10 reveals that the significant positive coefficients of corporate culture are still present.

Table 4. 10: Effects of Corporate Culture outside the Financial Crisis period

This table shows the effects of corporate culture on bond yield spread and bond rating outside the financial crisis period in 2008-2009. The independent variables of interest in each column are sum_culture. The dependent variables are bond rating in Column 1, information risk in Column 2 and yield spread in Columns 3 and 4. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Yield Spread	Bond rating
	(1)	(2)
Sum_culture	-0.087***	0.099***
	(-3.303)	(2.694)
Firm size	-0.418***	0.995***
	(-8.219)	(9.008)
Leverage	1.484***	-4.187***
	(3.144)	(-6.903)
Sale_growth	0.545**	-1.473***
	(2.131)	(-7.149)
Profitability	-1.931**	12.897***
	(-2.267)	(8.589)
Firm risk	6.922***	-12.127***
	(4.557)	(-6.191)
Inst_ownership	-1.089***	-1.767***
	(-2.835)	(-3.392)
Bond liquidity	0.514	-0.224*
	(1.333)	(-1.954)
Bond duration	-0.021	0.135*
	(-0.313)	(1.929)
Bond covenants	-0.658***	1.065***
	(-5.106)	(6.874)
Callable bonds	1.513***	0.707
	(3.959)	(1.226)
Putable bonds	-4.577***	-0.630*
	(-16.435)	(-1.851)
Floating rate	-0.032	0.390
	(-0.127)	(1.017)
Constant	2.681***	10.073***
	(3.924)	(8.664)
Observations	1,849	1,722
Adjusted R-squared	0.601	0.780
IndustryFE & Year FE	Y	Y

4.7.4. Endogeneity

The significant effect of corporate culture on yield spread may result from the effect of an unobservable variable that is not included in the baseline model but highly correlated to both cultural values and the yield spread. Thus, I use the past corporate culture measure and an instrumental variable to deal with the endogeneity issue of omitted variables. First, I retest the main results in Tables 4.2 and 4.3 with the historical corporate culture measure in year t-1. The results in Table 4.11 show that the effect of corporate culture remains significantly negative. However, the effect mainly come from the cultural values in technology.

Table 4. 11: Effects of Past Corporate Culture on Yield Spread

This table shows the effects of past corporate culture in year t-1 on yield spread, bond rating and information risk. The independent variables of interest in each column are different cultural values in the year t -1. In Panel A, the dependent variables are yield spreads in Columns 1 and 2, bond rating in Column 4, and information risk in Column 5. In Panel B, the dependent variable in all columns is yield spread. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. Standard errors are clustered by firm.

Panel A:	Log(Yield_spread)			Bond rating	Information risk
	(1)	(2)	(3)	(4)	(5)
Sum_culture_1	-0.061***			0.078**	-0.000**
	(-2.980)			(2.269)	(-2.373)
Sum_culture_people_1		-0.047			
		(-1.168)			
Sum_culture_tech_1			-0.109***		
			(-3.528)		
Firm size	-0.375***	-0.383***	-0.373***	1.135***	-0.002***
	(-7.881)	(-8.024)	(-7.898)	(15.396)	(-7.614)
Leverage	1.559***	1.614***	1.523***	-4.675***	0.007***
	(3.333)	(3.435)	(3.260)	(-7.786)	(3.974)
Sale_growth	0.477**	0.476**	0.467*	-1.460***	0.003***
	(1.977)	(1.970)	(1.930)	(-7.017)	(2.975)
Profitability	-2.354***	-2.319***	-2.320***	13.008***	-0.019***
	(-2.771)	(-2.720)	(-2.720)	(9.308)	(-5.252)
Firm risk	8.853***	8.819***	8.786***	-9.636***	0.160***
	(6.012)	(5.968)	(5.984)	(-6.940)	(21.162)
Inst_ownership	-1.111***	-1.088***	-1.111***	-1.640***	-0.005***
	(-3.053)	(-2.968)	(-3.076)	(-3.332)	(-2.629)
Bond liquidity	-0.108	-0.108	-0.106	0.084	-0.001**
	(-1.460)	(-1.470)	(-1.433)	(1.321)	(-2.130)
Bond duration	-0.753***	-0.765***	-0.748***	1.132***	-0.001**
	(-6.267)	(-6.359)	(-6.213)	(7.479)	(-2.106)
Bond covenants	1.470***	1.473***	1.479***	1.168**	-0.001
	(4.103)	(4.117)	(4.129)	(2.264)	(-1.001)
Callable bonds	-4.454***	-4.469***	-4.456***	-1.055***	0.002
	(-15.227)	(-15.236)	(-15.288)	(-2.629)	(1.544)
Putable bonds	0.025	0.025	0.009	0.478	0.002*
	(0.097)	(0.098)	(0.033)	(1.232)	(1.795)
Floating rate	2.764***	2.520***	2.808***	8.508***	0.028***
	(4.236)	(3.870)	(4.296)	(9.930)	(10.549)
Constant	2,099	2,099	2,099	1,965	2,098
	0.604	0.602	0.605	0.783	0.831
Observations	Y	Y	Y	Y	Y
Adjusted R-squared	Y	Y	Y	Y	Y
IndustryFE	Y	Y	Y	Y	Y

Table 4. 11. continued

Panel B:	Log(Yield_spread)				
	(1)	(2)	(3)	(4)	(5)
Integrity_1	-0.021				
	(-0.173)				
Teamwork_1		-0.163			
		(-1.491)			
Respect_1			-0.026		
			(-0.430)		
Innovation_1				-0.162***	
				(-3.785)	
Quality_1					-0.110*
					(-1.680)
Firm size	-0.384***	-0.381***	-0.385***	-0.373***	-0.381***
	(-8.048)	(-8.004)	(-8.144)	(-7.877)	(-8.073)
Leverage	1.622***	1.626***	1.610***	1.500***	1.602***
	(3.450)	(3.459)	(3.408)	(3.211)	(3.414)
Sale_growth	0.469*	0.483**	0.471*	0.461*	0.473*
	(1.938)	(2.002)	(1.946)	(1.914)	(1.947)
Profitability	-2.280***	-2.398***	-2.281***	-2.304***	-2.304***
	(-2.654)	(-2.848)	(-2.655)	(-2.725)	(-2.669)
Firm risk	8.761***	8.799***	8.782***	8.714***	8.816***
	(5.949)	(5.986)	(5.919)	(5.955)	(5.977)
Inst_ownership	-1.077***	-1.100***	-1.079***	-1.112***	-1.088***
	(-2.936)	(-3.009)	(-2.940)	(-3.093)	(-2.969)
Bond liquidity	-0.107	-0.109	-0.107	-0.109	-0.105
	(-1.459)	(-1.467)	(-1.459)	(-1.464)	(-1.428)
Bond duration	-0.768***	-0.764***	-0.767***	-0.743***	-0.764***
	(-6.373)	(-6.364)	(-6.361)	(-6.193)	(-6.330)
Bond covenants	1.480***	1.481***	1.478***	1.476***	1.482***
	(4.140)	(4.149)	(4.138)	(4.124)	(4.141)
Callable bonds	-4.478***	-4.453***	-4.476***	-4.460***	-4.468***
	(-15.273)	(-15.126)	(-15.270)	(-15.305)	(-15.268)
Putable bonds	0.016	0.014	0.020	0.005	0.015
	(0.060)	(0.055)	(0.076)	(0.020)	(0.058)
Floating rate	2.434***	2.555***	2.446***	2.798***	2.559***
	(3.736)	(3.915)	(3.747)	(4.278)	(3.919)
Constant	2,099	2,099	2,099	2,099	2,099
	0.602	0.603	0.602	0.606	0.603
Observations	Y	Y	Y	Y	Y
Adjusted R-squared	Y	Y	Y	Y	Y
IndustryFE	Y	Y	Y	Y	Y

4.8. Conclusion

In this chapter, I investigate whether corporate culture contributes to the understanding of the variation in the cost of debt for corporations in the United States. I find that strong corporate culture is negatively associated with the cost of debt. The findings hold after controlling for different model specifications and estimation methods. I then utilize path analysis to investigate the channels behind the relationship corporate business culture and yield spread. The key assumption is that corporate culture influences yield spread directly through two indirect paths: creditworthiness and information. The indirect path confirms that strong culture firms have higher credit ratings and more robust informational environments. In the further analysis, I also find that corporate culture has a bigger influence on riskier firms with greater debt ratios and return volatility.

This research contributes to the growing literature on how corporate culture influences corporate policy and performance. The study also suggests a new factor influencing debt pricing, culture incentive, and demonstrates the relationship between corporate culture with the cost of debt through firm creditworthiness and information environment.

4.9. Appendices

Table A.4. 1. Variable Descriptions

This table shows the definition for all variables in Chapter 4.

Variable	Description	Sources
Bond covenants	The indicator variable has a value of 1 if the bond is issued with covenants and 0 otherwise.	FISD
Bond rating	Bond credit ratings that range from 1 to 21 after converting the letter rating from the three largest rating agencies	
Bond duration	The length of time before the bond matures	FISD
Bond liquidity	The natural logarithm of bond offer amount	FISD
Callable bonds	The indicator variable has a value of 1 if the bond is issued with call options and 0 otherwise.	FISD
Firm size	Total natural logarithm of total assets in billions	Compustat
Firm risk	Firm stock return volatility computed by the standard deviation of stock returns for the prior 12 or 60 months.	CRSP
Floating rate	A variable has a value of 1 for bond issuance with fixed interest rate, 2 for floating rate, and 3 for mixed interest rate.	FISD
Inst Ownership	Total institutional ownership of a firm.	13F filings
Leverage	The ratio of debt in current liabilities and total long-term debt divided by total assets	Compustat
Profitability	EBITDA divided by total assets	Compustat
Puttable bonds	The indicator variable has a value of 1 if the bond is issued with put options and 0 otherwise.	FISD
Sale growth	The ratio of change in sales over the previous year	Compustat
Strong_culture	The indicator variable has a value of 1 if the total of a firm's five cultural value scores in a year is in the top quartile across all firms, and 0 otherwise.	K. Li, Mai, et al. (2021)
Strong_culture_people	The indicator variable has a value of 1 if the total of a firm's value scores in integrity, respect, and teamwork in a year is in the top quartile across all firms, and 0 otherwise.	K. Li, Mai, et al. (2021)
Strong_culture_tech	The indicator variable has a value of 1 if the total of a firm's value scores in innovation and quality in a year is in the top quartile across all firms, and 0 otherwise.	K. Li, Mai, et al. (2021)
Sum_culture	The total five cultural value scores of a firm, including integrity, respect, teamwork, innovation, and quality.	K. Li, Mai, et al. (2021)
Yield_spread	The difference between the yield-to-maturity on a corporate bond and its duration-equivalent risk-free bond for fixed-rate bonds or the credit spread plus the difference between the interest rate of reference index and the yield on its equivalent Treasury security over the first interest period for floating-rate bonds.	FISD, CRSP

Table A.4. 2: Effects of Different Degree of Cultural Values on Bond Rating

This table shows the effects of corporate culture on bond credit rating for different level of cultural values. The independent variables of interest in each column are culture, culture in people, and culture in technology in Panel A and five cultural values in Panel B, including integrity, respect, teamwork, innovation, and quality. The dependent variable is bond credit rating. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

Panel A:	Bond Rating		
CV – Cultural Variable	Culture	Culture_people	Culture_tech
	(1)	(2)	(3)
2nd quintile CV	0.129	-0.060	0.301
	(0.669)	(-0.342)	(1.571)
3rd quintile CV	0.352*	0.206	0.378*
	(1.715)	(1.118)	(1.802)
4th quintile CV	0.349	0.054	0.290
	(1.597)	(0.280)	(1.367)
5th quintile CV	0.558**	0.360*	0.596**
	(2.445)	(1.683)	(2.512)
Firm size	1.052***	1.061***	1.058***
	(10.292)	(10.234)	(10.454)
Leverage	-4.507***	-4.564***	-4.534***
	(-7.618)	(-7.720)	(-7.682)
Sale_growth	-1.464***	-1.444***	-1.425***
	(-7.060)	(-6.939)	(-6.838)
Profitability	13.095***	13.049***	13.081***
	(9.388)	(9.285)	(9.419)
Firm risk	-9.311***	-9.643***	-9.179***
	(-6.657)	(-6.780)	(-6.526)
Inst ownership	-1.600***	-1.641***	-1.613***
	(-3.268)	(-3.346)	(-3.321)
Bond liquidity	-0.153	-0.156	-0.151
	(-1.401)	(-1.413)	(-1.393)
Bond duration	0.079	0.078	0.079
	(1.244)	(1.208)	(1.237)
Bond covenants	1.144***	1.131***	1.139***
	(7.699)	(7.617)	(7.745)
Callable bonds	1.115**	1.078**	1.096**
	(2.119)	(2.067)	(2.089)
Putable bonds	-1.080***	-1.062**	-1.072***
	(-2.647)	(-2.563)	(-2.633)
Floating rate	0.585	0.607	0.587
	(1.509)	(1.537)	(1.469)
Constant	9.205***	9.503***	9.163***
	(8.544)	(8.849)	(8.568)
Observations	1,992	1,992	1,992
Adjusted R-squared	0.782	0.781	0.782
Industry FE	Y	Y	Y
Year FE	Y	Y	Y

Table A.4.2. continued

Panel B:	Bond Rating				
CV – Cultural Variable	Integrity	Respect	Teamwork	Innovation	Quality
	(1)	(2)	(3)	(4)	(5)
2nd quintile CV	0.148	0.434**	0.055	0.167	0.010
	(0.989)	(2.402)	(0.335)	(0.918)	(0.052)
3rd quintile CV	0.106	0.382*	-0.065	-0.003	0.450**
	(0.633)	(1.924)	(-0.347)	(-0.017)	(2.083)
4th quintile CV	0.131	0.456**	0.046	-0.022	0.488**
	(0.789)	(2.291)	(0.255)	(-0.112)	(2.168)
5th quintile CV	-0.023	0.594***	0.154	0.180	0.517**
	(-0.116)	(2.732)	(0.770)	(0.806)	(2.099)
Firm size	1.077***	1.069***	1.065***	1.067***	1.053***
	(10.504)	(10.413)	(10.494)	(10.348)	(10.454)
Leverage	-4.620***	-4.574***	-4.543***	-4.568***	-4.592***
	(-7.837)	(-7.673)	(-7.659)	(-7.731)	(-7.888)
Sale_growth	-1.433***	-1.455***	-1.513***	-1.433***	-1.424***
	(-6.807)	(-6.997)	(-7.146)	(-6.791)	(-6.900)
Profitability	13.016***	13.067***	13.149***	12.958***	12.991***
	(9.221)	(9.227)	(9.388)	(9.162)	(9.238)
Firm risk	-9.476***	-9.451***	-9.498***	-9.441***	-9.273***
	(-6.642)	(-6.648)	(-6.812)	(-6.676)	(-6.567)
Inst ownership	-1.683***	-1.646***	-1.642***	-1.670***	-1.660***
	(-3.408)	(-3.333)	(-3.370)	(-3.404)	(-3.377)
Bond liquidity	-0.144	-0.149	-0.157	-0.150	-0.159
	(-1.324)	(-1.362)	(-1.436)	(-1.363)	(-1.460)
Bond duration	0.074	0.078	0.067	0.078	0.077
	(1.146)	(1.196)	(1.052)	(1.213)	(1.207)
Bond covenants	1.138***	1.140***	1.113***	1.142***	1.168***
	(7.692)	(7.697)	(7.470)	(7.735)	(8.029)
Callable bonds	1.123**	1.112**	1.072**	1.106**	1.093**
	(2.162)	(2.147)	(2.049)	(2.145)	(2.118)
Putable bonds	-1.004**	-1.059***	-1.022**	-1.043**	-1.031**
	(-2.475)	(-2.591)	(-2.486)	(-2.571)	(-2.538)
Floating rate	0.555	0.578	0.544	0.606	0.605
	(1.417)	(1.475)	(1.413)	(1.521)	(1.608)
Constant	9.497***	9.499***	9.301***	9.483***	9.277***
	(8.827)	(8.805)	(8.650)	(8.671)	(8.801)
Observations	1,992	1,992	1,992	1,992	1,992
Adjusted R-squared	0.780	0.780	0.782	0.781	0.783
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table A.4. 3: Effects of Corporate Culture on Bond Rating and Information Risk

This table shows the effects of corporate culture on bond yield spread as well as bond rating and information risk. The independent variables of interest in each column are sum_culture. The dependent variables are bond rating in Column 1, information risk in Column 2 and yield spread in Columns 3 and 4. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Bond rating	Information risk	Log(Yield _spread)	Log(Yield _spread)
	(1)	(2)	(3)	(4)
Sum_culture	0.101***	-0.000**	-0.034**	-0.020
	(2.759)	(-2.465)	(-2.003)	(-1.032)
Bond rating			-0.248***	-0.239***
			(-14.607)	(-11.045)
Information risk			35.934***	22.290***
			(7.832)	(2.991)
Firm size	1.046***	-0.002***		-0.037
	(10.192)	(-5.084)		(-0.531)
Leverage	-4.481***	0.006***		0.569*
	(-7.599)	(3.709)		(1.686)
Sale_growth	-1.463***	0.003***		0.294
	(-7.193)	(2.766)		(1.247)
Profitability	13.117***	-0.019***		-2.013***
	(9.378)	(-5.272)		(-3.071)
Firm risk	-9.443***	0.159***		4.243**
	(-6.783)	(20.899)		(2.281)
Inst_ownership	-1.602***	-0.005***		-0.973***
	(-3.310)	(-2.848)		(-3.313)
Bond liquidity	-0.158	0.000		0.156**
	(-1.432)	(0.087)		(2.040)
Bond duration	0.076	-0.001**		-0.032
	(1.196)	(-2.054)		(-0.482)
Bond covenants	1.128***	-0.001**		-0.301***
	(7.611)	(-2.445)		(-3.012)
Callable bonds	1.102**	-0.001		1.339***
	(2.101)	(-1.156)		(2.600)
Putable bonds	-1.033**	0.002*		-5.023***
	(-2.505)	(1.655)		(-12.681)
Floating rate	0.583	0.001		-0.096
	(1.507)	(1.636)		(-0.293)
Constant	9.046***	0.028***	4.435***	3.846***
	(8.472)	(8.685)	(15.075)	(4.533)
Observations	1,992	2,129	4,168	1,991
Adjusted R-squared	0.783	0.830	0.487	0.696
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table A.4. 4: Interaction Effects of Corporate Culture and Bond Rating on Yield Spread

This table shows the interaction effects of corporate culture and bond rating on bond yield spread. The independent variables of interest in each column are sum_culture. The dependent variable in all columns is yield spread. All variables are described in Table A.4.1. The model controls for year and industry fixed effects. The standard errors are clustered by firm.

	Log(Yield_spread)					
					Low bond rating	High bond rating
	(1)	(2)	(3)	(4)	(5)	(6)
Sum_culture	-0.040**	-0.035	-0.025	-0.092***	-0.067**	0.039**
	(-2.256)	(-1.367)	(-1.270)	(-3.103)	(-1.978)	(2.395)
Bond rating	-0.331***	-0.229***	-0.257***			
	(-20.917)	(-7.684)	(-12.263)			
Sum culture x Bond rating				0.105***		
				(3.422)		
Bond rating dummy				-1.205***		
				(-5.835)		
Firm size		-0.129**	-0.052	-0.269***	-0.400***	-0.002
		(-2.208)	(-0.736)	(-3.748)	(-4.330)	(-0.023)
Leverage		0.933**	0.647*	1.551***	1.679***	0.279
		(2.167)	(1.924)	(4.408)	(3.809)	(0.640)
Sale_growth		0.391	0.341	0.673***	0.645**	0.021
		(1.552)	(1.418)	(2.869)	(2.546)	(0.115)
Profitability		-2.118**	-2.239***	-4.397***	-5.252***	-0.793
		(-2.547)	(-3.366)	(-5.820)	(-4.928)	(-1.244)
Firm risk		6.233***	7.707***	9.547***	8.943***	2.055
		(3.917)	(5.259)	(6.616)	(5.621)	(1.139)
Inst_ownership		-2.190***	-1.091***	-0.836***	-0.930**	0.836***
		(-6.244)	(-3.696)	(-2.594)	(-2.552)	(2.637)
Bond liquidity			0.157**	0.170**	0.123	0.158*
			(2.029)	(2.103)	(1.120)	(1.658)
Bond duration			-0.041	-0.041	-0.544***	0.262***
			(-0.616)	(-0.601)	(-3.428)	(6.441)
Bond covenants			-5.017***	-4.758***	-4.352***	-4.885***
			(-12.707)	(-12.251)	(-9.420)	(-18.635)
Callable bonds			1.324**	1.014**	1.675**	0.866*
			(2.550)	(2.082)	(2.309)	(1.765)
Putable bonds			-0.310***	-0.557***	-0.503***	-0.149
			(-3.153)	(-5.155)	(-3.611)	(-1.241)
Floating rate			-0.040	-0.151	-0.183	-0.188
			(-0.127)	(-0.475)	(-0.427)	(-0.745)
Constant	6.561***	6.610***	4.575***	2.693***	3.543***	-1.280
	(32.422)	(12.725)	(5.368)	(3.226)	(3.041)	(-1.511)
Observations	4,171	2,125	1,992	1,992	1,200	788
Adjusted R-squared	0.461	0.496	0.693	0.667	0.631	0.615
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Chapter 5

Conclusions

5.1. Summary of main results and contributions

This thesis consists of three empirical chapters with the first essay focusing on how common ownership affects firm productivity, the second essay examining the impacts of common ownership on pairwise return comovement, and the last essay investigating how corporate culture impact firm cost of debt. Empirical analyses are presented in Chapters 2 to 4. This chapter concludes the thesis by summarizing the empirical analysis conducted in each chapter, reiterating the contributions, and providing directions for future research.

The first essay, presented in Chapter 2, studies the effect of common ownership on firm performance. Extant literature demonstrates that common ownership improves corporate governance and firm performance with higher Tobin-Q and stock returns (He et al., 2019; Kang et al., 2018). However, existing studies do not attempt to identify the specific mechanisms underlying those changes in firm performance which is critical to understand the actual effects of common ownership and how it creates shareholder value. Thus, Chapter 2 fills this gap by investigating the impact of common ownership on firm productivity and the possible channels behind such changes. Consistent with the existing literature, I find that firms with common ownership are significantly more productive than those without this structure. In addition, I find no evidence on the reduction in the total number of a firm's employee and establishments. However, common owners are likely to induce employment reduction at unproductive and peripheral establishments. The findings indicate that common owners shift management attention and resources to where they can deliver the most value to the firm. Common ownership also negatively affects the number of establishments at diversified firms – operate across multiple industry segments, suggesting that common owners tend to concentrate managerial efforts on large segments to optimize the comparative advantage of organizational skill (Maksimovic & Phillips, 2002).

This study adds to the literature on common ownership by tracing value creation back to the manufacturing process. My firm-level analysis explains how common ownership improves firm performance. The finding has linkages to the literature investigating the effects of ownership changes on firm performance on mergers and acquisitions, hedge fund activism, and asset sales (Maksimovic & Phillips, 2001, 2002; Warusawitharana, 2008). This study adds to the body of knowledge about the real effects of informed outside shareholder monitoring, such as large institutional investors (Becker et al., 2011; Clifford & Lindsey, 2016), mutual funds (Appel et al., 2016), and activist hedge funds (Brav et al., 2015; Brav et al., 2008). Common owners who have strong monitoring incentives and industry knowledge are likely to be effective monitoring shareholders.

The second essay, presented in Chapter 3, investigates whether common ownership among firms in the same industry increases stock return comovement. The results show that firm pairs with common ownership have significantly higher comovement in returns than firm pairs without common ownership. After removing the trends in the pairs' data and controlling for unobserved variables that may affect the pair's comovement, the result is robust to alternative empirical specifications. Several mechanisms could be at work in the increased return comovement. I find that common ownership has a stronger effect on pairwise comovement between firms with less product similarity. While common ownership may be advantageous in the product space, it may be detrimental to innovation. Firms with common owners that sell similar products are less willing to invest in innovation for fear of negatively impacting the business of other firms with common owners. Using such a tool may be beneficial to undiversified shareholders (and consumers), but it is costly to common owners. Common ownership may thus create more binding value between firms with different products or firms in the same technology space, increasing their return comovement. Firms with similar products, on the other hand, generate less value from collaboration in innovation, and thus their stock prices may be less correlated.

The findings are significant for both market participants and policymakers. The increase in return comovement among firms following common ownership may exacerbate the US government's current concerns about the market impacts of this structure because the increased likelihood of shocks spreading across stocks may impact systemic risk and the propensity for flash crashes. The impact of common ownership on market stability should be obvious if all firms are eventually controlled by a single institution.

The third essay in Chapter 4 investigates whether corporate culture influences bond yield spread. Corporate culture is defined as a set of shared beliefs and norms that guide appropriate attitudes and behaviors (CrÉMer, 1993; Van den Steen, 2010b). Li, Mai, et al. (2021) define company culture as integrity, respect, teamwork, innovation, and quality. Because executives and staff can focus on the long term, strong cultural organizations are more likely to meet debt obligations. By retaining existing workforces and adopting new technologies to generate different products, these firms are more resilient than weak cultural firms (Li, Liu, et al., 2021). Bushman et al. (2004) show that strong cultural firms have lower lawsuit risks and greater disclosure transparency. Employees are more likely than others to report fraud. Employees are more likely to report fraud (Sengupta, 1998). An improved information environment with high-integrity accounting reports reduces default risks and enables creditors to effectively monitor debt agreement violations (Francis et al., 2005).

I show that strong culture firm have lower yield spreads. These firms have 8.438% lower yield spreads than identical firms with a weak corporate culture. Firms with strong cultural values are more likely to have better credit ratings and information environments. Furthermore, corporate culture benefits riskier firms with higher leverage ratios and higher return volatility. This study adds to the growing body of literature on how corporate culture influences policy and performance by demonstrating how it influences default risk and the information environment. The results also add to previous research demonstrating that corporate culture influences pricing in debt markets with narrower bond yield gaps.

5.2. Recommendations for further research

Chapter 2 demonstrates a positive relationship between common ownership and productivity among firms in the same industry with common ownership. Further research could investigate the impact of common ownership on non-commonly owned firms in the same industry. Improved performance and market share of commonly owned firms may take business away from other industry peers. Thus, non-commonly owned firms may have to push their productivity to catch up with other industry competitors. One limitation of this study is the lack of capital data at the establishment-level. Due to the omission of this data, this study only investigates the increase in production efficiency from a change in the total number of firm employments. As a result, this chapter would benefit from more research into other ways in which common ownership improves productivity at the establishment level, such as by encouraging innovation (that requires additional establishment level data such as process and product patents).

Second, the findings of Chapter 3 have a strong implication for market participants and policymakers. The increased likelihood of shocks spreading across stocks may impact systemic risk and the propensity for flash crashes. The impact of common ownership on market stability should be obvious if a single institution eventually controls all firms. Thus, further studies can investigate the spillover effects among commonly owned firms when a significant liquidity shock happens to a common owner of these firms.

Finally, Chapter 4 studies the effect of corporate culture on the cost of debt. Further research could examine whether and to what extent other firm key stakeholders (such as customers, suppliers, and investors) value corporate culture. Such studies will offer timely empirical evidence to a relatively new but growing literature documenting the economic effects of the corporate culture.

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