Three Essays in Corporate Finance

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Declaration

This thesis includes working papers where I am the sole or joint author. The thesis draws on the following working papers:

1. "Managerial Heterogeneity in Risk-Taking Incentives: How Does It Affect Firm Risk and Performance?"
   - Author: Thao Thi Phuong Hoang
   - Status: submitted and under review by reviewers
   - Candidate contribution to research: Research design, data acquisition, research execution, data analysis, and manuscript preparation.
2. "Common Lender, Ex-Banker Director, and Corporate Investment"
   - Authors: Thao Thi Phuong Hoang, Kentaro Asai, and Takeshi Yamada
   - Status: in preparation for submission
   - Candidate contribution to research: Research design, research execution, data analysis, and manuscript preparation.
3. "Polarized Corporate Boards"
   - Authors: Thao Thi Phuong Hoang, Phong Ngo, and Le Zhang
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Abstract

This thesis consists of three essays focusing on three distinct aspects of corporate finance that have not been fully examined in the literature. In each aspect, the thesis attempts to explore the role of key decision makers in shaping corporate outcomes. The first essay concentrates on top management team while the other two focus on directors.

The first chapter "Managerial Heterogeneity in Risk-Taking Incentives: How Does It Affect Firm Risk and Performance?" examines an unexplored dimension of managerial risk-taking: heterogeneity in risk-taking incentives among top executives. When top managers collectively make important decisions, the heterogeneity may lead to conflicts between self-interested managers, consequently affecting corporate decisions and performance. Consistent with this premise, the chapter finds that firms operated by top managers with more divergent risk-taking incentives tend to take fewer risks and suffer inferior performance. The chapter also explores the mechanisms of those effects: more divergent risk-taking incentives are associated with attenuated investment efficiency, lower R&D, and less likelihood of M&A transactions. The findings underscore the notion that the efficiency of corporate decisions depends not only on the average level or strength but also on the divergence of managerial risk-taking incentives.

The second chapter "Common Lender, Ex-Banker Director, and Corporate Investment" examines how a common lender affects its borrowers' outcomes. Due to the government-driven mergers of large banks, many competing firms in Japan resulted in borrowing from a common lender. Investments of competing firms that have a common lender decrease by 15% of the mean. When a common lender can exercise its voice through its former employees serving as firms' executive directors, investments further fall significantly. Competing firms that share a common lender increase markups and profitability ratios, suggesting the lender induces strategic

coordination among its borrowers to reduce their competitive pressures. These effects are stronger for distressed firms, and firms use saved resources from reduced competition for cash cushions.

The third chapter "Polarized Corporate Boards" investigates how political polarization in corporate boards influences the decision to fire a CEO. The analysis shows that political polarization among directors negatively impacts corporate board effectiveness by reducing the CEO forced turnover-performance sensitivity. The results are more pronounced in presidential election years and for firms with more monitoring and advising needs. Polarization also increases the departure likelihood for directors who are ideologically distant from the rest of the board, making boards more politically homogeneous over time. Finally, the chapter shows that polarization in the boardroom lowers firms' investment–Q sensitivity and environmental performance. These findings highlight the real economic cost of political polarization.

Contents

Chapter 1: Managerial Heterogeneity in Risk-Taking Incentives: How Does It Affect Firm Risk and Performance?

1.1. Introduction

Corporations' willingness to take risks in the pursuit of profitable opportunities is essential for economic growth (Baumol et al., 2007; John et al., 2008). Risk-averse managers exposed to firm-specific risks, however, may forego risky but value-enhancing projects. To solve the problem, firms use incentive contracts to encourage managerial risk-taking, thus aligning managerial interest with that of well-diversified shareholders (Haugen & Senbet, 1981; Smith & Stulz, 1985).

This study examines one dimension of risk-taking incentives that has remained unexplored: heterogeneity in risk-taking incentives within the management team. The heterogeneity occurs because of differences among top managers in various aspects, such as managerial characteristics (e.g., risk attitude, age, gender, ability, and experience), compensation structure, and responsibility (Aggarwal & Samwick, 2003). Because top managers work as a team (Aggarwal & Samwick, 2003; Garlappi et al., 2017), heterogeneity in risk-taking incentives impacts team effectiveness, and then firm outcomes. Economic intuition suggests that the impact can be complex. Although a firm's CEO plays a dominating position in the management team, other key executives such as the president, chief operating officer (COO), and chief financial officer (CFO) influence the functional areas of their charge. When all top managers contribute, the firm's decisions inevitably reflect interactions, discussions, compromise, and conflict resolution within the management team of divergent risk-taking incentives.

In this study, I examine a sample of S&P 1500 companies in 1992–2016 to document the effects of managerial heterogeneity in risk-taking on firm risk and performance. There are two competing hypotheses. First, the conflict of interest hypothesis is derived from the similarity–attraction argument that people prefer to work with colleagues of similar traits. Heterogeneous teams, therefore, are vulnerable to conflicts of interest (O'Reilly et al., 1993). The conflicts may arise from heterogeneous beliefs and motivations of self-interested managers. They not only cause disagreements but also deteriorate synergies and consensus within the management team, which in turn hinders efficiency in decision-making (Garlappi et al., 2017). The conflict of interest hypothesis, therefore, predicts a negative relation between the heterogeneity and firm risk as well as performance.

The second hypothesis focuses on the beneficial role of information sharing and active debate. Specifically, the active debate hypothesis argues that because team heterogeneity creates broader perspectives and a greater amount of shared information as well as facilitates active debates, it not only promotes creativity and innovation but also enhances the team's problem-solving ability (Hoffman & Maier, 1961; Wiersema & Bantel, 1992). This implies that when it comes to risk-taking incentives, heterogeneity can lead to rigorous scrutiny and consequently result in improved decisions and more efficient outcomes. The active debate hypothesis, therefore, posits a positive relation between the heterogeneity and firm risk as well as performance.

I measure the heterogeneity as the standard deviation of risk-taking incentives of a firm's top-paid managers. The incentive measure is defined as the sensitivity of an executive's wealth in option holdings to a change in firm risk. My results show that firms run by top executives with more diverse risk-taking incentives are associated with lower risks than their counterparts. On average, for a one-standard-deviation increase in the heterogeneity, the firm's stock volatility—a proxy for total risk—decreases by 4.5% relative to the sample mean. Further, the reduction happens in both systematic and idiosyncratic risks.

Consistent with reduced risk-taking, the further analysis shows a significantly negative effect of the incentive heterogeneity on firm performance. For a one-standard-deviation increase in the heterogeneity, Tobin's Q decreases by 3.7%, industry-adjusted stock return by 2.2%, return on total assets (ROA) by 23.3%, and sales growth by 18.3%, relative to their respective sample means. In support of the conflict of interest hypothesis, the findings suggests that managerial heterogeneity in risk-taking incentives reduces firm risk and consequently the value of the firm.

My results are obtained after controlling for various firm characteristics and managerial attributes. Furthermore, I include firm and year fixed effects to mitigate uncontrolled time-invariant firm characteristics and market-wide time trends. One concern is that CEO selection may play as a confounding factor. A firm with some specific characteristics (including risk and performance) may prefer a specific type of CEO and offer the CEO a specific compensation package that will in turn affect the heterogeneity given the power put in the hands of the CEO. Also, as the CEO can shape the management team and its compensation structure (through recruitment and compensation design), the link between team incentive heterogeneity and firm decisions could be driven by the underlying CEO preference. To address this concern, I replace firm fixed effects with firm-CEO fixed effects to capture the potential impacts of the firm-CEO match and CEO preference. Moreover, to the extent that CEO preference effect is less relevant in a short period after a new CEO's appointment, I repeat the tests for a post-CEO turnover period of two, three, and four years, respectively. The findings remain unchanged in all these robustness tests. If a firm, on purpose, maintains a conservative risk profile at the cost of performance through selecting its management team and creating heterogeneity in risk-taking incentives, the heterogeneity is supposed to have trivial effect on firm outcomes after firm-CEO fixed effects being controlled. By contrast, the negative relation between the heterogeneity and firm risk as well as performance survives not only the firm-CEO fixed effect but also other robustness tests.

In further robustness tests to address endogeneity concerns, I employ two approaches. First, I utilize the change in the accounting treatment of stock options following the adoption of the FAS 123R imposed by the Financial Accounting Standards Board (FASB) in 2005. Although the regulatory change applied to all firms, some firms were affected more than others. Specifically, firms with trivial implied option expenses were less likely to be subject to the FAS 123R. These firms are good candidates for control group. In the contrary, firms with high implied option expenses faced a surge in accounting costs of options. They were more likely to modify their options granted to executives, which might cause changes in risk-taking incentive heterogeneity. Those firms, therefore, potentially constitute treatment group. I use implied option expenses and changes in risk-taking incentive heterogeneity surrounding the FAS 123R to define treated and control firms. Estimating heterogeneous treatment effects in a difference-in-difference framework, I find consistent results of a negative relation between risk-taking incentive heterogeneity and firm risk, as well as performance.

Second, I employ a two-stage least-squares framework. The instrument is the average of risk-taking heterogeneity of firms located in adjacent states of the focal firm and not in the same industry as the focal firm. The rationale is managerial compensation of those firms is correlated with that of the focal firm for two reasons. First, executives of nearby firms are good candidates for executive appointments of the focal firm. Second, the focal firm is more likely to take compensation of nearby firms as a benchmark as it may have to pay a similar package to attract the candidates. Yet those firms are not in the same industry as the focal firm, their compensation structures are less likely to affect firm outcome, except through compensation channel, thus satisfying the exclusion restriction of the instrument variable. The estimations from the two-stage least-squares framework support the baseline results.

The paper also examines mechanisms through which the heterogeneity reduces risk and harms performance. I find that more divergent risk-taking incentives are associated with attenuated investment efficiency, lower R&D, and less likelihood of M&A transactions.

Overall, the findings indicate that firms run by top managers with more divergent risk-taking incentives tend to play it safe, which in turn hinders corporate risk-taking and adversely affects corporate performance. This observation contributes to the existing literature by highlighting the role of an unexplored management characteristic—risk-taking incentive heterogeneity—in corporate decision-making. Aggarwal and Samwick (2003) and Garlappi et al. (2017) suggest that firm policies are collective decisions made by a group. Despite numerous studies of CEO risk-taking behaviour, none have examined the roles of this team characteristic, which is important for apparent reasons. Team heterogeneity may cause disagreements and conflicts in the decision-making process, impairing team synergies and effort coordination. Top managers thus would collaboratively become less willing to take risks and more likely to make inefficient decisions, which would reduce firm value. A related study by Bushman et al. (2015) examines how managerial divergence in effort incentives affects firm performance. They find that firm performance is positively correlated with the dispersion in top executives' pay–performance sensitivities when the dispersion is too low (and negatively correlated when the dispersion is too high). Like Bushman et al. (2015) with respect to managerial effort incentives, my study underscores the notion that the efficiency of corporate decisions depends on not only the average level or strength but also the divergence of managerial risk-taking incentives.

1.2.Prior literature and hypothesis development

Conflicts of interest between stakeholders of a firm have attracted considerable attention from both academics and practitioners. Inspired by agency theory, previous research has concentrated on conflicts between managers and shareholders. Besides private benefits and costly efforts, another explanation for managers acting against the best interest of shareholders is differences in risk preference (Gormley & Matsa, 2016; Haubrich, 1994; Smith & Stulz, 1985). Shareholders are presumably able to diversify risks through their ownership portfolio and thus risk neutral. Contrastingly, managers cannot diversify their employment risk and thus are more risk averse. Risk-averse and self-interested managers may forego risky (albeit profitable) projects in an attempt to maximize their benefits rather than shareholders' value, which causes underinvestment problems and destroys firm value. Therefore, providing proper incentives will enable shareholders to motivate managers to take risks (Haugen & Senbet, 1981; Smith & Stulz, 1985).

Existing literature has intensively examined how a CEO's risk-taking incentives affect firm policies and outcomes (e.g., Armstrong & Vashishtha, 2012; Bakke et al., 2016; Coles et al., 2006; Hayes et al., 2012; Knopf et al., 2002; Low, 2009; Mao & Zhang, 2018). Because CEOs sit at the top of the corporate hierarchy and have the power to replace a low-ranking executive who deviates from their preferences (Fee & Hadlock, 2004; Mian, 2001), low-ranking executives may not respond directly to their risk-taking incentives but only to those of the CEO. Risk-taking incentives for other executives, therefore, appear to be ignored.

A few exceptions have investigated effects of CEO and CFO incentives separately on corporate policies. Specifically, Chava and Purnanandam (2010) find that CEO incentives determine leverage and cash balances, whereas CFO incentives determine debt maturity and accounting accruals. Jiang et al. (2010) document that a magnitude of accruals and the likelihood of beating analyst forecasts are more sensitive to equity incentives for the CFO than the CEO. Kim et al. (2011) examine the link between crash risks and CEOs as well as CFO equity incentives. Yet these studies do not examine how divergence in risk-taking incentives between senior managers affects firm policies or outcomes. Nevertheless, Chava and Purnanandam (2010) argue that focusing on both the CEO and the CFO enriches understanding of how managerial incentives shape corporate policies. Their hypothesis also implies that each manager would adopt appropriate policies matching his or her risk preferences.

Empirically, incentive dispersion in top management teams exists. Aggarwal and Samwick (2003) measure incentives as the sensitivity of compensation to firm value and show that CEOs account for 42%–58% of aggregate team incentives. The pay–performance sensitivity is higher for CEOs than for managers with oversight authority (e.g., chairpeople or CFOs). Aggarwal and Samwick (2003) suggest an important role of performance-related incentives in compensating a firm's top managers other than the CEO. Jiang et al. (2010) document differences in risk-taking incentives between CEOs and CFOs. A CFO's equity incentive ratio is approximately 11% of the total compensation, while a CEO's is nearly 24%. Similarly, Chava and Purnanandam (2010) find that CEOs have a much higher sensitivity of compensation to firm value and firm risk than CFOs.

Very few studies have examined the effects of management incentive dispersion on firm outcomes. Bushman et al. (2015) focus on the dispersion of pay–performance sensitivities (or effort incentives) among top executives and find that firm performance is positively correlated with the dispersion in top executives' pay–performance sensitivities when the dispersion is too low (and negatively correlated when the dispersion is too high). The findings indicate that effort coordination between managers, which is influenced by pay–performance sensitivity dispersion, is indeed important in determining firm performance. Dittmann et al. (2017) argue that shareholders consider both effort and risk-taking incentives when designing compensation contracts. Therefore, dispersion in risk-taking incentives certainly plays a non-trivial role in corporate outcomes. Despite its potential importance, risk-taking incentive heterogeneity has remained unexplored.

Heterogeneity may have complex effects on team decision-making. Two competing perspectives exist—the similarity–attraction and the active debate perspectives. The similarity–attraction claims that people prefer to work with colleagues who possess similar traits to reduce uncertainty. Heterogeneous teams, therefore, undermine coordination and synergies. O'Reilly et al. (1993) argue that heterogeneity causes inefficient decision-making, while Li and Hambrick (2005) posit that heterogeneity creates potential conflicts within a team.

In the context of risk-taking, previous studies have found that team heterogeneity in tenure, education, and functional background reduces innovation (Bantel & Jackson, 1989), halts acquisition processes (Nadolska & Barkema, 2014), or curbs firms' competitiveness (Ferrier et al., 2002). These findings facilitate a prediction that divergence in risk-taking incentives is more likely to cause a reduction in the risk level that a firm would choose. Furthermore, implementing risky policies often requires consensus and collaboration between top managers. Edmans et al. (2011) indicate that the level of effort managers are willing to exert depends on synergies between them and other managers. Yet managers with divergent risk-taking incentives favour divergent firm risk profiles that match their preferences, which generates more disagreements and fewer synergies. Thus, risk-taking incentive heterogeneity attenuates the top management team's willingness to take risks.

When top managers exhibit a higher level of disagreement in decision-making, their decisions (or firm policies) are more likely to be inefficient. Garlappi et al. (2017) model disagreements as a source of inefficiency. Additionally, firms less willing to take risks are more likely to suffer inferior performance; that is, risk reduction is value destroying. Together, the conflicts of interest caused by a divergence in risk-taking incentives lead to lower risk and inferior performance. I therefore present the first hypothesis—the conflict of interest hypothesis—as follows:

H1. As conflicts of interest caused by divergent risk-taking incentives deteriorate consensus and coordination, managerial heterogeneity in risk-taking incentives is negatively associated with firm risk and performance.

Conversely, the active debate perspective believes that diversity among team members not only promotes creativity and innovation but also improves problem-solving capacity as diverse members bring to their team broader perspectives and a greater amount of shared information. Hoffman and Maier (1961) argue that high levels of heterogeneity enhance a team's breadth of perspective, cognitive resources, and overall problem-solving capacity. Additionally, heterogeneity facilitates active debate and information sharing (Wiersema & Bantel, 1992).

Heterogeneity enhances the quality of decision-making as discussions among team members create high-quality managerial decisions (Jehn, 1995; Pelled et al., 1999). Therefore, risk-taking incentive heterogeneity may encourage managers to perform their due diligence when involved in discussions of firm policies with others. Consequently, corporations are more likely to accept risky but profitable projects to increase firm value, given that the top management team scrutinizes these projects. There is evidence that heterogeneity in tenure, education, and functional background is associated with superior performance (Carpenter, 2002; Hambrick et al., 1996; Richard, 2000). These findings lead to a prediction that heterogeneity in risk-taking incentives is positively associated with corporate risk and performance. The alternative hypothesis—the active debate hypothesis—is thus presented as follows:

H2. As group heterogeneity enhances the quality of decision-making, managerial heterogeneity in risk-taking incentives is positively associated with firm risk and performance.

1.3. Empirical strategy

1.3.1. Measuring risk-taking incentive heterogeneity

In this study, I define risk-taking incentive heterogeneity as the dispersion of risk-taking incentives among top managers. Managers' risk-taking incentives are a function of their compensation packages and risk aversion. Extant literature has widely accepted that equity-based compensation provides incentives for managers to take risks (e.g., Armstrong & Vashishtha, 2012; Coles et al., 2006; Core & Guay, 2002; Kim et al., 2011; Low, 2009). Additionally, managers' risk attitudes affect how compensation packages are designed to incentivize them (e.g., Becker, 2006; Cain & McKeon, 2016; Chava & Purnanandam, 2010; Haubrich, 1994; Holmstrom & Milgrom, 1991). In an equilibrium, risk-taking incentives provided by a compensation contract reflect a manager's willingness to take risks. In this regard, the sensitivity of a manager's wealth to a change in firm risk—vega—has become a prevalent proxy for managerial risk-taking incentives (e.g., Armstrong & Vashishtha, 2012; Bakke et al., 2016; Coles et al., 2006; Hayes et al., 2012).

Consistent with prior empirical work, I employ vega as a proxy for managerial risk-taking incentives. Risk-taking incentive heterogeneity is measured as the standard deviation of vega of the top-five highest-paid managers. Vega is measured by the partial derivative of managers' wealth with respect to their firm's stock return volatility and derived from the Black–Scholes option valuation model (Core & Guay, 2002). Coles et al. (2006) provide a complementary description of vega calculations considering changes in how firms report option packages since 2006. I follow the two papers to calculate vega as described in Appendix A1.

Prior literature has usually examined both vega and delta (the change in the dollar value of the executive's wealth for 1% change in stock price) as risk-taking and effort incentives are equally important (Armstrong et al., 2013; Dittmann et al., 2017). Further, they are highly correlated. I calculate delta for each executive and the standard deviation of delta of the top management team. However, unlike vega dispersion—a direct proxy for risk-taking incentive heterogeneity, delta dispersion is somewhat ambiguous due to delta's ambiguous effects on risk-taking. Delta also provides managers with incentives to alter their firm's risk, but the direction of the effect is inconclusive.

Specifically, as a change in managers' wealth for a change in stock price, delta incentivizes managers to play safe by magnifying their exposure to their firm's risk. Yet delta also encourages managers to take risks that produce a sufficient increase in equity value. Therefore, dispersion in delta renders it increasingly difficult to interpret its meaning. One may argue that delta divergence between executives may create divergent risk preferences because taking risks is the norm to increase firm value. In this case, delta dispersion, like vega dispersion, would capture risk-taking incentive heterogeneity. Alternatively, delta dispersion may reflect tournament incentives among executives, which can generate greater exertions by low-ranking executives. In this regard, it is challenging to predict how delta dispersion affects firm outcomes. Nevertheless, delta dispersion may capture risk-taking incentive heterogeneity to an extent. I control delta dispersion to avoid overestimating the effects of vega dispersion on firm outcomes.

1.3.2. Empirical model

I estimate a regression of firm outcomes on managerial heterogeneity in risk-taking incentives to test the two hypotheses. Firm outcomes in year t are regressed on the heterogeneity and control variables measured in year $t-1$. Consistent with Coles et al. (2006), Chava and

Purnanandam (2010), and Bushman et al. (2015), I employ a pooled regression model with fixed effects in the general form as follows:

$$Y_{it} = \beta_0 + \beta_1 Vega\_Std_{it-1} + \beta_2 Z_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1.1)$$

In Equation (1.1), Y represents firm outcomes (firm risk or performance). $Vega\_Std$ captures the risk-taking incentive heterogeneity among top managers and Z represents a set of controls. In the baseline model, I include firm (α_i) and year (γ_t) fixed effects to control for unobservable factors such as firm culture or macroeconomic conditions. All standard errors are clustered at the two-digit SIC code level to account for possible correlations among observations of firms in the same industry.[1]

Vega is endogenous by nature (Armstrong & Vashishtha, 2012; Coles et al., 2006; Low, 2009). While managerial risk-taking incentives influence corporate outcomes, causality is likely to move in the other direction. For example, managers may possess private information about firm prospects and alter their option holdings to maximize their payoff, which raises a concern of reverse causality. Another concern is simultaneity. Specifically, when designing a compensation contract, boards are likely to anticipate the effects of equity incentives on a manager's decisions and incorporate their expectation into the contract. In this case, compensation and firm outcomes are jointly determined.

Yet risk-taking incentive heterogeneity is measured as the dispersion of vega in top management team; it is less likely that an individual's opportunistic actions solely drive the heterogeneity. Further, although boards, to some extent, can predict possible effects of executives' incentives on their actions and account for them when designing compensation contracts, it is

[1] The results are robust to clustering standard errors at the firm-level.

challenging for the boards to anticipate and contract all complex incentive-related interactions between top executives. In other words, risk-taking incentive heterogeneity is less susceptible to reverse causality and simultaneity. Nevertheless, several steps have been undertaken to mitigate endogeneity concerns. First, to address concerns regarding omitted variables that affect both vega dispersion and corporate outcomes, I include fixed effects to capture unobservable factors. Second, to alleviate concerns of simultaneity, I use the one-year lagged value of incentive variables. Further analyses to address endogeneity concerns are presented in robustness tests.

One may argue that the match between a firm and a CEO and/or CEO preference can drive both the heterogeneity and firm outcomes. A firm with some specific characteristics may be looking for a specific type of CEO and offering a specific risk-taking incentive. Further, as the CEO dominates the management team, he or she can interfere in the hiring process and compensation of low-ranking executives. For example, the CEO may hire a specific CFO and exert influence on designing compensation for the CFO to achieve a desired risk-taking incentive dispersion that serves the CEO's preference. If so, both firm outcomes and risk-taking incentive heterogeneity are driven by the firm-CEO match and/or CEO preference.

In modern corporations, decisions on how to compensate a manager is delegated to the board of directors. Compensation schemes are determined in practice as an agreement between managers and the firm (through the board compensation committee) and approved by the board. Chhaochharia and Grinstein (2009) confirm that the board plays a significant role in CEO compensation. Nevertheless, several studies have argued that a CEO has the authority to replace a low-ranking executive who does not meet the CEO's preferences (Fee & Hadlock, 2004; Mian, 2001). Therefore, it is possible that a CEO appoints low-ranking executives and influences the executives' equity-based compensation to achieve the CEO's desired structure of risk-taking incentives in the top management team. Thus, the observed relationship between risk-taking incentive dispersion and firm outcomes is a reflection of the CEO's preference. The firm-CEO match and/or CEO preference can be captured by CEO incentives and firm-CEO fixed effects. Therefore, I first control for CEO incentives. Second, besides the baseline model, I also report results when replacing firm fixed effects with firm-CEO fixed effects.

Furthermore, if a CEO can choose a top management team that serves the CEO's preference, the inclusion of CEO fixed effects should help capture most of sources of heterogeneities such as heterogeneities in risk attitude, gender, ability, and responsibility. Nevertheless, CEO fixed effects may not capture experience heterogeneity which tends to be time-varying. In a robustness check, I control for the standard deviation of tenure across top managers as a proxy for experience heterogeneity. The results are quantitatively similar and not reported for brevity.

The dependent variables are firm risk and performance. Total risk is measured as the natural logarithm of the annualized variance of daily stock returns (Coles et al., 2006). To further examine how risk-taking heterogeneity affects a firm's systematic and idiosyncratic risks, I perform risk decomposition using the Fama–French three-factor model. First, I regress excess stock return (stock return net of risk-free rate) on excess market return, size factor, and market-to-book factor using daily returns in each year. Next, I use estimated betas to calculate predicted and residual returns. Systematic and idiosyncratic risks are computed as the natural logarithm of the annualized variance of predicted and residual returns.

Firm performance is measured by Tobin's Q, industry-adjusted stock return, ROA, and sales growth. Tobin's Q is defined as the sum of market value of equity and book value of debt and preferred shares divided by total assets. Industry-adjusted stock return is annualized stock return net of the industry mean return. ROA is income before tax, interest, and depreciation to total assets. Sales growth refers to the increase in current year sales compared to the previous year.

To address a concern of pay dispersion being correlated with vega dispersion and firm outcome, I control for pay dispersion (measured as the natural logarithm of one plus the standard deviation of total compensation among top managers). As managers' attributes partly determine risk-taking incentives, there may be a concern that heterogeneity in risk-taking incentives actually reflects heterogeneity in demographic characteristics like age or gender. To alleviate this concern, I control for age dispersion and gender diversity. Age dispersion is measured as the standard deviation of age, and gender diversity is the ratio of male managers within the top management team.

Other variables include firm size, leverage, investment, and R&D. Firm size is measured as the natural logarithm of total assets; leverage is computed as the ratio of debt to equity; investment is measured as capital expenditures divided by lagged total assets; and R&D is research and development expenditures to total assets. To address a concern that CEO power may affect both vega dispersion and corporate outcomes, I control for duality—whether the CEO is also the chairperson.

1.3.3. Data

I obtain data on executive compensation and other managerial characteristics from the ExecuComp database from 1992 to 2016 (1992 marks the year that ExecuComp began providing data on compensation for the top-five highest-paid executives of firms in the S&P 1500). I define the top management team as the top-five highest-paid executives. Using this dataset, I compute incentive variables. Consistent with previous studies, I take the natural logarithm of one plus the variable level.

Other variables computed from the ExecuComp database include the standard deviation of total compensation among top executives, the standard deviation of age, and the ratio of male executives in the top management team. In addition, information from ExecuComp is used to identify whether duality occurs in a firm each year.

I gather stock return from the Center for Research in Security Prices (CRSP). Data on risk-free rate, market return, size factor, and market-to-book factor are collected from Kenneth French's webpage[2] and used to perform risk decomposition. Finally, I obtain financial statement information from Compustat to calculate firm characteristic variables. Consistent with previous literature, I exclude financial and utility firms. I merge the ExecuComp database with the Compustat and CRSP databases. The final sample comprises 29,322 firm-year observations from 1992 to 2016. All variables, except for dummy variables, are winsorised at the 1st and 99th percentiles.

1.4. Empirical results

1.4.1. Summary statistics

Table 1.1 presents descriptive statistics of the variables used in this study. Panel A presents managerial incentive variables, Panel B firm characteristics, Panel C firm risk profile, and Panel D correlation matrix. On average, the risk-taking incentive dispersion is $41,930. The means of CEO delta and vega are $519,420 and $109,960. Consistent with prior research (e.g., Coles et al., 2006;

[2] The web address is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french.

Core & Guay, 2002), vega and delta are highly skewed; therefore, the measures of risk-taking incentive heterogeneity are also skewed.

Regarding performance in Panel B, on average, sample firms have a Tobin's Q of 2.08, a stock return of 16%, an ROA of 3%, and a sales growth of 12%. Panel C shows that the mean of total risk (annualized variance of daily stock returns) is 0.24. The average systematic risk and idiosyncratic risks derived from the Fama–French three-factor model are 0.07 and 0.17.

Panel D demonstrates that incentive variables are highly correlated; for example, the correlation between Vega_Std and CEO vega is 0.91. It is not surprising because CEO vega is a direct input into the calculation of Vega_Std. This high correlation raises a concern of multicollinearity. Nevertheless, the greater the multicollinearity, the greater the standard errors, which indicates that it will be harder to reject the null when multicollinearity is present. If the independent variable of interest—Vega_Std—maintains incremental explanatory power after controlling for other highly correlated variables, the multicollinearity issue should not affect the interpretation.

Table 1.2 provides a more detailed picture of risk-taking incentive heterogeneity. Panel A depicts a distribution of Vega_Std across major industries, while Panel B across firm size quintiles. Overall, the mining industry has the smallest Vega_Std, whereas the manufacturing and service industries have the largest Vega_Std. Panel B shows that the heterogeneity is increasing in firm size. It also depicts a positive relationship between firm size and CEO vega. Large firms appear to reward executives with more divergent risk-taking incentives because they tend to offer their CEOs generous incentive packages.

Table 1.1: Summary statistics

This table presents summary statistics of the variables used in this study. Panel A provides descriptive statistics for incentive variables, Panel B depicts firm characteristics, and Panel C displays firm risk profile. Vega_Std is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. Size is total assets (in $ million). Leverage is the ratio of total debt to total assets. TobinQ is defined as the sum of market value of equity and book value of debt and preferred shares divided by total assets. Capex is capital expenditures divided by lagged total assets. R&D is research and development expenditures to total assets. ROA is the ratio of income before tax, interest, and depreciation to total assets. Growth is the change in current year sales compared to the previous year. Unadjusted return is annualized stock return. Duality is a dummy variable that takes one if the CEO is also the chairperson. Comp_Std is the standard deviation of total compensation across top managers (in $ thousand). Age_Std is the standard deviation of age across top managers. Gender diversity is the ratio of male managers in the top management team. Total_Risk is the annualized variance of daily stock returns. Systematic and idiosyncratic risks are measured by the annualized variance of predicted returns and residuals, respectively, from the Fama–French three-factor model. All variables, except dummy variables, are winsorised at the 1% and 99%.

	N	Mean	Std_Dev	Min	Median	Max
	Panel A: Incentive variables					
Vega_Std ($ thousand)	29,322	41.93	59.62	0.00	16.84	265.12
Delta_Std ($ thousand)	28,591	239.76	376.02	1.39	86.05	1735.90
CEO vega ($ thousand)	28,287	109.96	158.92	0.00	44.14	655.79
CEO delta ($ thousand)	27,592	519.42	800.01	0.09	202.76	3582.24
	Panel B: Firm characteristics					
Size ($ million)	29,319	6544.64	24820.35	3.43	1318.73	797769.00
Leverage	29,212	0.44	1.06	0.00	0.18	12.00
TobinQ	29,313	2.08	1.44	0.56	1.64	11.97
Capex	29,043	0.07	0.07	0.00	0.04	0.48
R&D	29,319	0.03	0.07	0.00	0.00	0.68
ROA	29,264	0.03	0.24	-1.22	0.08	0.42
Growth	29,017	0.12	0.33	-0.81	0.07	3.98
Unadjusted return	29,124	0.16	0.10	-0.87	-0.09	3.12
Duality	29,322	0.40	0.49	0.00	0.00	1.00
Comp_Std ($ thousand)	29,277	1606.73	1747.09	39.32	963.60	8254.79
Age_Std	28,370	6.61	3.25	0.71	6.15	18.97
Gender diversity	29,322	0.94	0.11	0.00	1.00	1.00
		Panel C: Firm risk profile				
Total_Risk	29,116	0.24	0.32	0.01	0.15	4.63
Sys_Risk_FF	29,116	0.07	0.10	0.00	0.04	0.70
Unsys_Risk_FF	29,116	0.17	0.25	0.01	0.10	4.07
		Panel D: Correlation matrix				
		Vega_Std	Delta_Std	CEO vega		
	Delta_Std	0.53				
	CEO vega	0.91	0.43			
	CEO delta	0.55	0.92	0.50		

1.4.2. Risk-taking incentive heterogeneity and corporate risk-taking

Two competing hypotheses exist regarding how managerial heterogeneity in risk-taking incentives affects firm risk. The conflict of interest hypothesis argues that divergence in risk-taking incentives causes conflicts and disagreements between managers, which impedes coordination and synergies in managerial decisions, especially in risk-taking policies. Consequently, risk-taking incentive heterogeneity negatively relates to firm risk. Contrastingly, the active debate hypothesis suggests that risk-taking incentive heterogeneity facilitates efficient decisions as managers with divergent preferences engage in active discussions. Therefore, firms are more willing to accept risky but profitable projects provided that top managers scrutinize these projects.

A high level of risk-taking incentive dispersion is predominantly driven by a high level of risk-taking incentive for CEOs, which is characterized by their strong correlation. After controlling for the CEO incentives, the negative effect of risk-taking incentive heterogeneity on firm risk reflects conflicts between a strongly incentivized CEO and other weakly incentivized managers. Although CEOs sit at the top of the corporate hierarchy, other executives oversee their area of authority. As the top management team implements corporate policies, risk-taking incentives for executives other than the CEO play an essential role in the outcomes of the firm, or, particularly, the risk level taken by the firm.

Table 1.3 presents the baseline results in which the dependent variables are total, systematic, and idiosyncratic risks. The independent variable of interest is Vega_Std—a reasonably unambiguous proxy of risk-taking incentive heterogeneity. The first two columns display the results for total risk, the next two for systematic risk, and the last two for the idiosyncratic risk. All columns depict a strong and consistent association between Vega_Std and firm risk, indicating that firms with higher risk-taking incentive heterogeneity experience a reduction in both systematic and idiosyncratic risks.

Table 1.2: Distribution of risk-taking incentive heterogeneity

This table provides a detailed distribution of risk-taking incentive heterogeneity across main industries (Panel A) and firm size quintiles (Panel B). Vega_Std is the standard deviation of vega across top five highest-paid managers—a proxy for risk-taking incentive heterogeneity. CEO vega is vega of the firm's CEO. Vega calculation is summarized in Appendix A1. Firm size is the natural logarithm of total assets. Vega_Std and CEO vega are calculated as the average of all firm-year observations in a particular industry or firm size quintile and in $ thousand unit.

Panel A: Risk-taking incentive heterogeneity across main industries

Industry	N	Vega_Std	CEO vega
Mining	1,213	28.14	74.32
Construction	410	37.81	88.98
Manufacturing	14,209	43.73	114.33
Whole trade and retail trade	4,203	41.83	105.23
Services	5,095	42.55	108.66
Total	25,130		

Panel B: Risk-taking incentive heterogeneity and firm size

Firm size quintile	N	Vega_Std	CEO vega
1	5,864	10.53	26.28
2	5,864	18.82	46.49
3	5,864	31.55	77.64
4	5,864	53.04	133.68
5	5,863	98.42	262.70
Total	29,319		

Specifically, the coefficient of Vega_Std in Column (1) is −0.027 and significant at the one percent level. The coefficient becomes even larger in magnitude (−0.035) after I control for firm-CEO fixed effects instead of firm fixed effects, indicating that the firm-CEO match and/or CEO preferences do not drive the negative correlation between Vega_Std and total risk. The coefficients indicate that an increase of one standard deviation in Vega_Std, on average, is associated with a decrease of 4.5% in stock return volatility compared to the mean. The result is consistent with the conflict of interest hypothesis—risk-taking incentive heterogeneity provokes disagreements among members of the top management team—which renders the whole team reluctant to take risks. The rationale is conflicts between managers undercut effort coordination and consensus that are necessary for firm risk-taking; that is, heterogeneity in risk-taking incentives is an internal driver of diminishing corporate risk-taking.

Table 1.3: Risk-taking incentive heterogeneity and firm risk

This table presents the estimates from a regression of firm risk on risk-taking incentive heterogeneity. The dependent variables are total risk, systematic risk, and idiosyncratic risk. Total risk is the natural logarithm of the annualized variance of daily stock returns. Systematic and idiosyncratic risks are derived from the Fama–French three-factor model. Systematic risk is the natural logarithm of the annualized variance of predicted returns from the model and idiosyncratic risk is the natural logarithm of annualized variance of residuals. The independent variable of interest is Vega_Std, which is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Size is the natural logarithm of total assets. TobinQ is defined as the sum of market value of equity and book value of debt and preferred shares divided by total assets. Leverage is the ratio of debt to equity. Capex is capital expenditures divided by lagged total assets. ROA is the ratio of income before tax, interest, and depreciation to total assets. Return is annualized stock return net of the industry mean return. Duality is a dummy variable that takes one if the CEO is also the chairperson. Comp_Std is the natural logarithm of one plus the standard deviation of total compensation across top managers. Age_Std is the standard deviation of age across top managers. Gender is the ratio of male managers in the top management team. All independent variables are lagged by a year. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and adjusted R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Total risk	(2) Total risk	(3) Sys. risk	(4) Sys. risk	(5) Idio. risk	(6) Idio. risk
Vega_Std	-0.027***	-0.035***	-0.024***	-0.034***	-0.029***	-0.034***
	(0.009)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)
Delta_Std	0.003	0.004	-0.004	0.006	0.002	0.000
	(0.008)	(0.007)	(0.010)	(0.009)	(0.009)	(0.008)
CEO vega	-0.011	-0.002	-0.015	0.000	-0.008	-0.001
	(0.007)	(0.005)	(0.009)	(0.007)	(0.007)	(0.005)
CEO delta	-0.015**	-0.026***	0.012	-0.019*	-0.025***	-0.029***
	(0.007)	(0.006)	(0.014)	(0.011)	(0.008)	(0.007)
Size	-0.144***	-0.076***	-0.028	-0.004	-0.184***	-0.101***
	(0.025)	(0.019)	(0.035)	(0.033)	(0.023)	(0.018)

Table 1.3 continued

	(1) Total risk	(2) Total risk	(3) Sys. risk	(4) Sys. risk	(5) Idio. risk	(6) Idio. risk
TobinQ	0.042^{***}	0.039^{***}	0.069^{***}	0.058^{***}	0.025^{**}	0.024^{**}
	(0.015)	(0.013)	(0.022)	(0.019)	(0.012)	(0.011)
Leverage	0.194^{***}	0.163^{***}	0.109^{***}	0.081^{***}	0.219^{***}	0.188^{***}
	(0.013)	(0.014)	(0.014)	(0.016)	(0.013)	(0.015)
Capex	0.751^{***}	0.531^{***}	0.982^{***}	0.652^{**}	0.653^{***}	0.493^{***}
	(0.220)	(0.191)	(0.296)	(0.251)	(0.191)	(0.164)
ROA	-1.010^{***}	-0.776^{***}	-0.761^{***}	-0.553^{***}	-0.998^{***}	-0.746^{***}
	(0.159)	(0.148)	(0.174)	(0.166)	(0.150)	(0.140)
Return	0.041^{***}	0.038^{***}	0.100^{***}	0.101^{***}	0.018^{*}	0.022^{**}
	(0.011)	(0.009)	(0.016)	(0.015)	(0.010)	(0.009)
Duality	0.026^{*}	0.027	0.025	0.030	0.029^{*}	0.025
	(0.015)	(0.017)	(0.021)	(0.025)	(0.016)	(0.016)
Comp_Std	0.018^{**}	0.016^{**}	0.021^{**}	0.019^{*}	0.013^{*}	0.011^{*}
	(0.007)	(0.007)	(0.009)	(0.011)	(0.007)	(0.006)
Age_Std	-0.006^{**}	-0.004^{**}	-0.007^{**}	-0.003	-0.006^{**}	-0.005^{**}
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Gender diversity	0.016	0.000	0.023	0.020	0.009	-0.008
	(0.060)	(0.069)	(0.070)	(0.089)	(0.067)	(0.067)
Firm FE	Y	N	Y	N	Y	N
Year FE	Y	Y	Y	Y	Y	Y
Firm-CEO FE	N	Y	N	Y	N	Y
N	22,641	21,192	22,641	21,192	22,641	21,192
R-squared	0.786	0.847	0.716	0.789	0.783	0.839

To further examine the effects of risk-taking incentive heterogeneity on firm risk, I decompose the total risk into systematic and idiosyncratic risks using the Fama–French three-factor model. A firm's systematic risk exposure should depend on such factors as business risk and financial leverage. As other studies in the literature of managerial risk-taking, we control for such factors and examine whether or how top managers are motivated in risk-taking and consequently how the firm's systematic risk is impacted. The results are consistent with those in the first two columns, as the estimates continue to depict a strong relationship between the heterogeneity and systematic as well as idiosyncratic risks. Additionally, it is interesting to note that Vega_Std exhibits a more consistent pattern compared to other incentive variables. Overall, firms that provide executives with more divergent risk-taking incentives tend to witness a reduction in both systematic and idiosyncratic risks.

In summary, the results suggest that risk-related conflicts between top executives impair coordination and synergies necessary to conducting risk-taking policies. As a result, top executives with divergent risk-taking incentives tend to curtail their firms' exposure to systematic and idiosyncratic risks. The evidence confirms a non-trivial role of risk-taking incentives for non-CEO executives in determining firm risk level through their risk-related interactions. Heterogeneity in risk-taking incentives among top executives provides consistent and incremental explanatory power above CEO incentives. Therefore, the findings reinforce Aggarwal and Samwick's (2003) argument that corporate decisions are made by a team. They also imply that a focus on CEO incentives while neglecting interactions between executives may undermine a firm's efforts of encouraging management to take risks.

1.4.3. Risk-taking incentive heterogeneity and firm performance

The conflict of interest hypothesis predicts that an increase in risk-taking incentive heterogeneity among top executives is associated with a decrease in firm performance. The reason is firms are less willing to take risks in the presence of disagreements between high-ranking executives. An unwillingness to take risks erodes firm performance. Further, disputes between executives may lead to suboptimal decisions (Garlappi et al., 2017). Conversely, the active debate hypothesis implies that risk-taking incentive heterogeneity improves the quality of decision-making, which creates better performance. I test the two hypotheses by examining different aspects of performance, including Tobin's Q, industry-adjusted stock return, ROA, and sales growth. The results are presented in Table 1.4.

Columns (1) and (2) show the result for Tobin's Q. Despite the high correlations between incentive variables raising the multicollinearity concern, heterogeneity in risk-taking incentives retains incremental explanatory power beyond CEO incentive and preference. Specifically, the coefficients of Vega_Std vary from −0.055 to −0.048. The coefficients imply that an increase of one standard deviation in Vega_Std, on average, results in a decrease of 0.05 standard deviation in Tobin's Q (a decrease of 3.7% vs. mean Tobin's q of 2.08). This magnitude is significant when compared to Bushman et al.'s (2015) documented effect of less than 2% of the pay–performance sensitivity dispersion on Tobin's Q.

Columns (3) and (4) in Table 1.4 display results where the dependent variable is industry-adjusted stock return. The coefficients of Vega_Std are negative though significant only in Column (3). Specifically, the coefficients of Vega_Std range from −0.012 to −0.004. Regarding economic significance, an increase of one standard deviation in Vega_Std, on average, results in a decrease of 2.2% in stock return compared to the industry mean.

The results of ROA and sales growth are presented in the last four columns of Table 1.4. I continue to find a negative association between the heterogeneity and ROA, as well as sales growth. For ROA, the coefficients of Vega_Std are negative and statistically significant in Columns (5) and (6). Specifically, the coefficients vary from −0.005 to −0.004, which indicates that a one-standard-deviation increase in Vega_Std, on average, results in a decrease of 0.007 in ROA (a decrease of 23.3% vs. mean ROA of 0.03). The magnitude of this effect is much larger than that of pay–performance sensitivity dispersion on ROA in Bushman et al. (2015), which varied between 3.7%–6.7%. For sales growth, the coefficients of Vega_Std are negative and statistically significant in Columns (7) and (8). The coefficients vary from −0.018 to −0.012, indicating that a one-standard-deviation increase in Vega_Std, on average, results in a decrease of 0.022 in sales growth. This corresponds to a 18.3% change relative to the sample mean of 0.12.

Overall, firms that provide more divergent risk-taking incentives for executives suffer inferior performance in both stock market and accounting measures. The evidence of a detrimental effect on corporate performance advocates the hypothesis that risk-taking incentive heterogeneity—a source of conflicts among executives—causes inefficiency.

Table 1.4: Risk-taking incentive heterogeneity and firm performance

This table presents the estimates from a regression of firm performance on risk-taking incentive heterogeneity. The dependent variables are TobinQ—the sum of market value of equity and book value of debt and preferred shares divided by total assets); industry-adjusted return—annualized stock return net of the industry mean return; ROA—the ratio of income before tax, interest, and depreciation to total assets; and sales growth— the change in current year sales compared to the previous year. The independent variable of interest is Vega_Std, which is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Size is the natural logarithm of total assets. Leverage is the ratio of debt to equity. Capex is capital expenditures divided by lagged total assets. Duality is a dummy variable that takes one if the CEO is also the chairperson. Comp_Std is the natural logarithm of one plus the standard deviation of total compensation across top managers. Age_Std is the standard deviation of age across top managers. Gender is the ratio of male managers in the top management team. All independent variables are lagged by a year. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and adjusted R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) TobinQ	(2) TobinQ	(3) Return	(4) Return	(5) ROA	(6) ROA	(7) Growth	(8) Growth
Vega_Std	-0.048*	-0.055***	-0.012*	-0.004	-0.005***	-0.004*	-0.018***	-0.012**
	(0.025)	(0.020)	(0.007)	(0.008)	(0.002)	(0.002)	(0.006)	(0.005)
Delta_Std	0.089***	0.097***	-0.027***	-0.043***	0.006***	0.006***	0.018***	0.017***
	(0.024)	(0.025)	(0.005)	(0.008)	(0.002)	(0.002)	(0.003)	(0.003)
CEO vega	-0.043*	-0.040*	-0.003	0.002	0.000	-0.002	0.001	-0.009
	(0.022)	(0.021)	(0.005)	(0.007)	(0.001)	(0.002)	(0.006)	(0.006)
CEO delta	0.170***	0.125***	-0.020***	-0.065***	0.010***	0.011***	0.031***	0.037***
	(0.023)	(0.021)	(0.005)	(0.010)	(0.002)	(0.002)	(0.006)	(0.006)
Size	-0.653***	-0.604***	-0.188***	-0.241***	-0.019***	-0.021***	-0.106***	-0.132***
	(0.081)	(0.065)	(0.014)	(0.023)	(0.005)	(0.007)	(0.006)	(0.008)
Leverage	0.035***	0.038***	0.094***	0.129***	0.000	0.000	-0.009**	-0.012**
	(0.012)	(0.010)	(0.014)	(0.017)	(0.002)	(0.001)	(0.004)	(0.006)
Capex	0.262	-0.171	-0.630***	-0.641***	0.085**	0.048	0.371***	0.289***
	(0.295)	(0.170)	(0.094)	(0.115)	(0.039)	(0.030)	(0.066)	(0.072)
ROA	1.336***	0.970***	-0.090	-0.200			-0.642***	-0.835***
	(0.419)	(0.281)	(0.077)	(0.127)			(0.200)	(0.240)
Duality	-0.055**	-0.011	0.018**	0.041***	0.001	0.001	0.001	-0.002
	(0.027)	(0.026)	(0.008)	(0.009)	(0.004)	(0.004)	(0.008)	(0.007)
Comp_Std	0.084***	0.065***	0.004	0.005	0.005***	0.004***	0.004	0.003
	(0.010)	(0.015)	(0.006)	(0.007)	(0.002)	(0.001)	(0.005)	(0.005)

Table 1.4 continued

	(1) TobinQ	(2) TobinQ	(3) Return	(4) Return	(5) ROA	(6) ROA	(7) Growth	(8) Growth
Age_Std	-0.009**	-0.005	-0.001	0.003*	0.000	0.000	-0.003***	-0.001
	(0.004)	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Gender diversity	0.106	0.072	0.070**	0.058*	-0.010	-0.005	-0.013	0.008
	(0.086)	(0.070)	(0.035)	(0.035)	(0.011)	(0.008)	(0.017)	(0.020)
Risk	0.022	-0.003	0.010	0.017	-0.018***	-0.009***	-0.027***	-0.029***
Firm FE	Y	N	Y	N	Y	N	Y	N
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm-CEO FE	N	Y	N	Y	N	Y	N	Y
N	22,601	21,185	22,639	21,191	22,607	21,186	22,618	21,175
R-squared	0.665	0.762	0.318	0.397	0.619	0.723	0.304	0.400

There are several reasons that cause a firm's risk-taking heterogeneity to be off equilibrium and prevent the firm from quickly adjusting to the right level of heterogeneity. Bushman et al (2016) argue that managers' pay-performance sensitivity can deviate from optimal levels as the managers exercise options and rebalance portfolios for idiosyncratic reasons. In particular, if idiosyncratic shocks differentially affect pay-performance sensitivity across individual executives while boards are unable to immediately re-establish optimality across team members, pay-performance sensitivity dispersion may drift away from optimal levels for a period of time. Furthermore, as market conditions frequently change and peer companies' compensation packages also vary from year to year, firms are unlikely to know at all times what the true optimal compensation structure is.

Murphy (2012) highlights that due to significant public visibility, boards are subjected to intense scrutiny from investors, media, regulators, and politicians regarding executive compensation decisions and processes. To protect themselves, compensation committees justify individual managers' pay packages by calibrating them against those of peer managers in the market. This practice may limit degrees of freedom in choosing stock and option grants for each individual manager that bring back the optimal pay-performance sensitivity configuration within management team.

Theories suggest that heterogeneity in risk-taking incentives among managers matters. This chapter empirically verifies this premise. In summary, the findings highlight implications for compensation policy when it comes to creating appropriate incentive schemes for top executives. It is widely acknowledged that shareholders provide stock and option grants for their managers to restrain the extent of agency problems. If firms, however, disproportionately focus on CEO incentive alignment and overlook that of other top executives, the firms may inadvertently generate conflicts between them, which in turn could destroy firm value. The implication of the result is that firms should try to minimize such heterogeneity. Firms can adjust compensation packages of individual managers to reduce the heterogeneity. On one hand, firms have many elements to adjust in a compensation package (salary, bonus, options). On the other hand, firms face adjustments costs and difficulty in achieving the optimal incentive structure. Furthermore, there are complexities in compensation design and multi-factors firms have to take into account (ability, suitability and availability) in their executive appointment decisions. Bushman et al. (2016) find document that firms only narrow around 60 percent of the current gap between target pay-performance sensitivity dispersion and actual dispersion over the subsequent year.

1.4.4. Risk-taking incentive heterogeneity and corporate policies

As risk-taking incentive heterogeneity is negatively associated with firm risk and performance, an interesting follow-up question is about mechanisms through which the heterogeneity affects firm outcomes. This section examines corporate policies firms would adopt when divergent risk-taking incentives occur. Specifically, I focus on several critical corporate policies to comprehend how the heterogeneity affects managerial decisions. The policies of interest include investment, R&D, leverage, and M&A decisions.

Table 1.5 presents the relationship between the corporate policies and risk-taking incentive heterogeneity. Column (1) shows the result where the dependent variable is capital expenditures. To simultaneously examine the effect of the heterogeneity on investment and investment efficiency, besides Vega_Std, I include an interaction between it and Tobin's Q. The coefficient of the interaction allows us to test whether the heterogeneity moderates how investment responds to Tobin's Q, i.e., investment opportunities. I do not find a significant effect of Vega_Std on investment itself but on investment–Q sensitivity. The coefficient on the interaction is negative and significant at one percent level. Specifically, the coefficient of −0.001 implies that a one-standard-deviation increase in the vega dispersion would reduce investment–Q sensitivity by 15.5%. Garlappi et al. (2017) argue that disagreements within a decision-making group cause conflicts of interest and spell inefficiency. In this regard, the dampened investment–Q sensitivity supports the notion that risk-taking incentive heterogeneity underlies disagreements among executives, thus reducing investment efficiency. The result fortifies previous evidence of the negative association between the heterogeneity and firm performance.

Table 1.5: Risk-taking incentive heterogeneity and firm policies

This table presents the estimates from a regression of firm policies on risk-taking incentive heterogeneity. The corporate policies of interest are Capex, R&D, leverage, and M&A. Capex is capital expenditures divided by lagged total assets. R&D is research and development expenditures to total assets. Leverage is the ratio of debt to equity. M&A is a dummy variable that takes one if a firm completes an M&A transaction in a given year. The independent variable of interest is Vega_Std, which is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Control variables are similar to those in baseline regressions. All independent variables are lagged by a year. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations, adjusted R-squared, and Pseudo R-squared are given in the last three rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Capex	(2) R&D	(3) Leverage	(4) M&A
Vega_Std	0.001	-0.001*	0.009	-0.039**
	(0.001)	(0.000)	(0.010)	(0.020)
Vega_Std * TobinQ	-0.001***			
	(0.000)			
Delta_Std	0.002**	0.000	-0.031**	0.000
	(0.001)	(0.000)	(0.014)	(0.020)
CEO vega	-0.000	0.001**	0.017**	0.024*
	(0.001)	(0.000)	(0.008)	(0.014)
CEO delta	0.003***	-0.000	-0.111***	0.027
	(0.001)	(0.001)	(0.021)	(0.020)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	N
Industry FE	N	N	N	Y
Year FE	Y	Y	Y	Y
N	22,656	22,812	22,604	22,829
R-squared	0.715	0.849	0.498	-
Pseudo R-squared	-	-	-	0.06

Column (2) in Table 1.5 presents the results for R&D expenditures—a catalyst for corporate innovation. Given the uncertain nature of innovations, the conflict of interest hypothesis predicts a negative correlation between the heterogeneity and R&D expenditures as divergent risk-taking incentives discourage the top management team from taking risks. The result supports the conjecture as the coefficient of Vega_Std is negative and statistically significant. Specifically, the coefficient of −0.001 indicates that a one-standard-deviation increase in Vega_Std would reduce

0.002 in R&D. This corresponds to a 4.3% change relative to the sample mean of R&D. The result implies that divergence in risk-taking incentives among top executives induces firms to adopt less risky strategies. In this case, it translates into a reduction in innovation.

Column (3) in Table 1.5 shows the result of leverage. I do not find that the heterogeneity affects firm leverage as the coefficient of Vega_Std is positive and insignificant. Column (4) presents the result for M&A decisions. I employ a logistic model in which the dependent variable is a dummy that takes one if a firm completes at least one M&A transaction in a year. Data on M&A transactions are obtained from the Thomson Reuters SDC Platinum database. I focus only on successful M&A transactions. The coefficient of Vega_Std is negative and significant, indicating that the heterogeneity negatively affects the likelihood of a firm conducting an M&A transaction. Specifically, a one-standard-deviation increase in Vega_Std from the mean would reduce the likelihood of accomplishing an M&A by 2%. While M&A transactions are complex decisions that involve a great deal of discussion and coordination between top executives, high levels of risk-taking incentive heterogeneity complicate collaboration between executives. Consequently, firms with differing risk-taking incentives among top executives are less likely to initiate and complete an M&A transaction.

Furthermore, when I split the M&A deals into diversified and related deals, I find larger effect of heterogeneity on the likelihood of related deals. This is consistent with the notion that because related deals imply higher risk than diversified deals and heterogeneity induces firms to take a lower level of risk, the negative effect of heterogeneity on related deals is larger.

Overall, the results of avenues by which risk-taking incentive heterogeneity operates complement the previous findings of negative correlations between the heterogeneity, firm risk, and performance. Additionally, they are consistent with that the heterogeneity introduces disagreements and conflicts, then undermines coordination and consensus between executives. As a result, firms are less willing to take risks and more likely to endure inefficiencies.

1.5. Robustness tests

1.5.1. Adjusted measure of vega

While the unadjusted vega used in the main analysis captures the absolute extent of a manager's risk-taking incentives, it may fail to reflect the relative extent of risk-taking incentives among executives with different payoffs. For instance, a CEO has a vega of $100,000 and a CFO of $80,000; however, the CEO's wealth is also higher (e.g., $1 million vs. the CFO's $0.5 million). Equity-based incentives thus may be more meaningful to the CFO than to the CEO. An adjusted vega, therefore, should take into account the difference in wealth between these two executives. Because the two measures (unadjusted and adjusted) capture different extents of a manager's risk-taking incentives, they are both worth investigating. As data on executive wealth are not available, I use salary as a proxy for wealth.[3] Salary usually accounts for the most part of compensation, is relatively stable over time, and reflects the difference in rank between executives. Specifically, the adjusted vega is the ratio between unadjusted vega and salary, measuring vega per unit of salary. I calculate adjusted risk-taking incentive heterogeneity by computing the standard deviation of the adjusted vega.

I repeat the main analyses with the adjusted measures of incentive variables in Table 1.6. Panel A shows the results for corporate outcomes while Panel B for corporate policies. I continue to find a negative association between Vega_Std and firm outcomes, confirming that firms

[3] Scaling vega by total compensation may introduce noise because total compensation consists of options granted in the current year. Nevertheless, the results remain quantitatively similar when total compensation is used to calculate adjusted vega.

providing managers with more divergent incentives are more likely to take fewer risks and suffer worse performance. Also, those firms tend to have lower investment efficiency, spend less in R&D, and complete fewer M&A deals. The results are consistent with those using the unadjusted measure of vega, implying that the findings are robust across the two alternative measures of vega.

Table 1.6: Risk-taking incentive heterogeneity and firm outcomes and policies - Alternative measure

This table presents the estimates from a regression of firm outcomes and policies on risk-taking incentive heterogeneity captured by the adjusted measure. Panel A shows the results of firm outcomes while Panel B shows those of firm policies. In Panel A, the dependent variables are total risk—the natural logarithm of the annualized variance of daily stock returns; TobinQ—the sum of market value of equity and book value of debt and preferred shares divided by total assets); industry-adjusted return—annualized stock return net of the industry mean return; ROA—the ratio of income before tax, interest, and depreciation to total assets; and sales growth—the change in current year sales compared to the previous year. In Panel B, the dependent variables are Capex—capital expenditures divided by lagged total assets; R&D—research and development expenditures to total assets; Leverage—the ratio of debt to equity; and M&A—a dummy variable that takes one if a firm completes an M&A transaction in a given year. The independent variable of interest is Vega_Std, which is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta are scaled by executive salary and their calculations are summarized in Appendix A1. Control variables are similar to those in baseline regressions. All independent variables are lagged by a year. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and adjusted R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel A

	(1) Risk	(2) TobinQ	(3) Stock return	(4) ROA	(5) Growth
Vega_Std	-0.256***	-0.616***	0.138	-0.023	-0.179*
	(0.089)	(0.211)	(0.088)	(0.018)	(0.094)
Delta_Std	-0.003	0.029	-0.004	0.006*	0.019***
	(0.016)	(0.040)	(0.014)	(0.003)	(0.006)
CEO vega	-0.231***	-0.428**	-0.191***	-0.011	-0.047
	(0.058)	(0.163)	(0.050)	(0.011)	(0.045)
CEO delta	0.033***	0.213***	-0.067***	0.011***	0.042***
	(0.009)	(0.031)	(0.015)	(0.002)	(0.005)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm-CEO FE	Y	Y	Y	Y	Y
N	21,148	21,141	21,147	21,142	21,131
R-squared	0.847	0.762	0.389	0.719	0.396

Table 1.6 continued

Panel B

	(1) Capex	(2) R&D	(3) Leverage	(4) M&A
Vega_Std	0.025*	-0.016***	0.011	-0.259
	(0.015)	(0.005)	(0.114)	(0.395)
Vega_std*TobinQ	-0.019***			
	(0.006)			
Delta_Std	0.003*	0.001	-0.015	-0.059
	(0.002)	(0.001)	(0.022)	(0.041)
CEO vega	0.003	0.005	-0.113	0.164
	(0.004)	(0.004)	(0.070)	(0.225)
CEO delta	0.003**	-0.001*	-0.036**	0.045**
	(0.001)	(0.001)	(0.015)	(0.021)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	N
Industry FE	N	N	N	Y
Year FE	Y	Y	Y	Y
N	22,607	22,762	22,554	22,780
R-squared	0.714	0.849	0.489	-
Pseudo R-squared	-	-	-	0.06

1.5.2. Short windows after CEO turnover

In the main analysis, I control for firm-CEO fixed effects to rule out the possibility that a match between a firm and CEO can drive both the heterogeneity and firm outcomes and/or that CEOs can interfere the recruitment process and compensation of low-ranking executives to serve their personal preferences. Another approach to alleviating the effects of CEO preference is to focus on short windows immediately after the new CEO's appointment. Even if CEOs could build their teams with their personal preferences in mind, it still takes time—CEOs' preferences are less relevant in the early stages of their tenures. Therefore, the analyses are repeated in timeframes of two, three, and four years after the appointment of a new CEO. The results are reported in Table 1.7 and quantitatively similar to previous results. Importantly, the effect is larger within two years after a CEO succession and becomes smaller when CEO tenure increases. The findings are consistent with the premise that the CEO effect is suppressed to some extent when the CEO is newly appointed but becomes stronger overtime. Nevertheless, the within-team interaction sustains its effect on firm outcomes.

Unexpected variation in heterogeneity is likely to occur after CEO turnover, and it should apply to both forced turnovers and other turnovers. However, in the sense that it is possibly more difficult for the board to make desired adjustments in forced turnover events, the variation should be larger with forced turnovers. Consistent with that, the magnitude of change in Vega_Std surrounding forced turnovers is significantly higher than that of routine turnovers. In particular, after a forced turnover, Vega_Std drops more than after a routine turnover. Because of a small sample issue, I only repeat the analysis of 4-year window for forced CEO turnover. The results are reported in the last panel of Table 1.7. Overall, the results are similar to those of routine turnovers though most of the coefficients are insignificant for which the reason may be the small sample size of forced turnovers.

Overall, the robustness tests indicate that the CEO effects are less likely to drive the findings. Instead, the negative associations between the heterogeneity and firm risk and performance reflect interactions between managers with different risk-taking incentives. The results highlight the concept that corporate policies are collaborative decisions and that their efficiency is determined by not only strength but also the dispersion of managerial risk-taking incentives.

Table 1.7: Risk-taking heterogeneity and firm outcomes: Short windows after new CEO appointments

This table presents the estimates from a regression of firm outcomes on risk-taking incentive heterogeneity for short windows of 2, 3, and 4 years after new CEO appointments. The dependent variables are total risk—the natural logarithm of the annualized variance of daily stock returns; TobinQ—the sum of market value of equity and book value of debt and preferred shares divided by total assets); Return—annualized stock return net of the industry mean return; ROA—the ratio of income before tax, interest, and depreciation to total assets; and sales growth—the change in current year sales compared to the previous year. The independent variable of interest is Vega_Std, which is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Control variables are similar to those in baseline regressions. All independent variables are lagged by a year. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and adjusted R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Risk	(2) TobinQ	(3) Return	(4) ROA	(5) Growth
2 years after new CEO appointments					
Vega_Std	-0.038***	-0.052*	-0.022	-0.007***	-0.022**
	(0.013)	(0.031)	(0.016)	(0.002)	(0.009)
N	9,072	9,036	9,071	9,039	9,059
R-squared	0.817	0.699	0.379	0.668	0.409
3 years after new CEO appointments					
Vega_Std	-0.032**	-0.048*	-0.024*	-0.006***	-0.020**
	(0.012)	(0.028)	(0.012)	(0.002)	(0.009)
N	12,065	12,026	12,064	12,031	12,045
R-squared	0.813	0.696	0.366	0.658	0.379
4 years after new CEO appointments					
Routine turnovers					
Vega_Std	-0.032***	-0.045	-0.020*	-0.005***	-0.018**
	(0.012)	(0.030)	(0.011)	(0.002)	(0.008)
N	14,436	14,398	14,435	14,402	14,418
R-squared	0.809	0.689	0.357	0.646	0.352
Forced turnovers					
Vega_Std	-0.072***	-0.007	-0.003	-0.003	-0.019
	(0.025)	(0.049)	(0.030)	(0.005)	(0.016)
N	1,613	1,609	1,613	1,609	1,610
R-squared	0.795	0.678	0.230	0.689	0.205
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

1.5.3. Difference-in-difference with heterogenous treatment effects induced by the FAS 123R

In this section, I employ an alternative approach to examine the relationship between the heterogeneity and corporate outcomes. Specifically, I exploit the change in the accounting treatment of stock options following the adoption of the FAS 123R in 2005. When implementing the FAS 123R, the FASB required firms to use the option fair value (the Black–Scholes value of the option on the grant date) in the income statement.[4] Before this, firms could choose to report expenses of granted options at their intrinsic value, which were generally trivial because almost all granted options were at the money. Hayes et al. (2012) argue that implementing the FAS 123R represents an exogenous change in the accounting costs of stock options.

Ferri and Li (2020) argue that the change in option-based compensation following the FAS 123R correlates with the firm-specific expected accounting impact. They verify that firms with higher implied option expenses before the FAS 123R significantly reduced their option grants. Because the FAS 123R applied to all firms, it is challenging to identify treated and control firms. They therefore classify firms into four categories based on the pre-FAS implied option expense. They argue that firms in the two bottom quartiles are less likely to be affected by FAS 123R while those in the two top quartiles are more likely to subject to FAS 123R. In the spirit of Ferri and Li (2020), I also employ implied option expense to overcome the difficulty in identifying control groups. While Ferri and Li (2020) focus on CEO option pay, I focus on heterogeneity in risk-taking incentives across managers which is affected by reduction in option pay for individual managers, yet the direction of the effect is not obvious. Reducing option pay for each manager unnecessarily

[4] See Bakke et al. (2016) for a more detailed discussion of the FAS 123R.

reduces dispersion between them. I therefore employ a difference-in-difference framework with heterogeneous treatment effects.

Following Ferri and Li (2020) and Hayes et al. (2012), I collapse the panel to a single pre-FAS and a single post-FAS period. Specifically, I compute an average of the heterogeneity for each firm in pre-FAS (2002–2004) and post-FAS (2005–2006) periods. I calculate the within-firm variation of the variable over the two periods, which reflects changes in the heterogeneity surrounding the event.

Next step is to identify treatment and control groups. I use implied option expense in 2001 to rank firms into terciles.[5] Firms in the first tercile were less likely to be affected by the FAS 123R while those in the third were more willing to change options packages granted to their managers. In the first tercile, I define control firms as firms without a change in risk-taking incentive heterogeneity over the two periods. In the third tercile, I define treated firms as firms with a change over the two periods. In other words, control firms are those less affected by the FAS 123R and thus not changing executive option pay. Treated firms, by contrast, are more subject to the FAS 123R and thus reducing option pay, creating changes in the heterogeneity.

Using the sample of treated and control firms, I estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 \Delta Vega\_Std_i * Post_t + \beta_2 \Delta Vega\_Std_i + \beta_3 Post_t + \beta_4 Z_{it-1} + \varepsilon_{it} \quad (2) \quad (1.2)$$

Where $\Delta Vega\_Std$ is the change in Vega_Std surrounding the FAS 123R for each firm. $Post$ is the dummy which takes value one for the post-FAS period. Other variables are similar to

[5] The result is quantitatively similar if firms are divided into quartiles where control firms are in the bottom quartile and the treated in the top.

those in Equation (1.1). We expect that the change in Vega_Std after the FAS 123R is negatively correlated with firm risk and performance.

Table 1.8: Difference-in-difference analysis with heterogenous treatment effects induced by the FAS 123R

This table presents the estimates from a difference-in-difference analysis with heterogenous treatment effects induced by the FAS 123R. The dependent variables are firm risk, TobinQ, return, ROA, and sales growth. Risk is the natural logarithm of the annualized variance of daily stock returns. TobinQ is defined as the sum of market value of equity and book value of debt and preferred shares divided by total assets. Return is annualized stock return net of the industry mean return. ROA is the ratio of income before tax, interest, and depreciation to total assets. Growth is the change in current year sales compared to the previous year. ΔVega_Std is changes in Vega_Std over the 2002-2004 and 2005-2006 periods. Vega_Std is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Post is a dummy variable taking value one for the 2005-2006 period. Treated firms are firms in the top tercile of implied option expenses in 2001 with a non-zero ΔVega_Std. Control firms are firms in the bottom tercile with a zero ΔVega_Std. Control variables are similar to those in baseline regressions. All variables, except dummy variables, are winsorised at 1% and 99%. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and adjusted R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Risk (1)	TobinQ (2)	Return (3)	ROA (4)	Growth (5)
ΔVega_Std * Post	-0.036**	-0.093***	0.005	-0.004*	0.010
	(0.015)	(0.025)	(0.010)	(0.002)	(0.008)
ΔVega_Std	0.030	0.124***	0.008	0.007**	0.011*
	(0.022)	(0.025)	(0.008)	(0.003)	(0.006)
Post	-0.440***	-0.056	0.048***	-0.026***	-0.015
	(0.051)	(0.044)	(0.016)	(0.006)	(0.011)
Delta_Std	-0.005	0.208***	-0.006	0.010***	0.019***
	(0.015)	(0.045)	(0.007)	(0.002)	(0.007)
CEO_vega	-0.081***	-0.020	-0.016***	-0.001	-0.007*
	(0.014)	(0.038)	(0.006)	(0.001)	(0.003)
CEO_delta	0.024*	-0.035	0.004	0.003	0.005
	(0.012)	(0.026)	(0.007)	(0.002)	(0.005)
Controls	Y	Y	Y	Y	Y
N	3,557	3,556	3,557	3,568	3,557
R-squared	0.459	0.148	0.017	0.277	0.096

Table 1.8 presents the estimates of Equation (1.2). The negative coefficients of the interaction $\Delta Vega\_Std_i * Post$ indicate that firms with an increase in risk-taking incentive heterogeneity ensuing the FAS 123R are associated with lower firm risk, Tobin's Q, and ROA. Overall, the results from the FAS 123R strengthen those obtained from the main analysis.

1.5.4. Instrumental variable approach

In a further test, I estimate the Equation (1.1) using a two-stage least-squares framework. The instrument is the average of Vega_Std of firms located in adjacent states of the focal firm and not in the same industry as the focal firm. The rationale is managerial compensation of those firms is correlated with that of the focal firm for two reasons. First, executives of nearby firms are good candidates for executive appointments of the focal firm. Yonker (2017) shows that firms are more likely to hire local CEOs because of lower costs of searching or soft information. Second, the focal firm is more likely to take compensation of nearby firms as a benchmark because it may have to pay a similar package to attract the candidates. Bouwman (2012) documents a strong correlation in CEO compensation between nearby firms. The instrument thus satisfies relevance condition. At the same time, the adjacent firms are not in the same state and same industry as the focal firm; their compensation structures thus are less likely to affect the focal firm's outcomes, except through compensation channel.

Table 1.9 presents the 2SLS estimation. I regress the heterogeneity on the instrument and controls. The Cragg-Donald Wald F-statistic is bigger than the thumb rule of 10 across regressions, indicating a significant correlation between the endogenous and instrumental variables, satisfying the relevance condition. The second-stage results show that Vega_Std is negatively correlated with firm risk, ROA, and sales growth. They yet again confirm previous findings and support the hypothesis that risk-taking incentive heterogeneity causes conflicts between top managers, leading to lower risk and inferior performance.

1.5.5. Risk-taking incentive heterogeneity among high-ranking executives

In the baseline analysis, I define the top management team as a group of the five highest-paid executives. One may argue that only high-ranking executives—CEO, CFO, COO, and president—can influence firm policies. Therefore, including managers other than high-ranking executives may introduce noise to the analysis. Despite expecting that managers' privileges and responsibilities are closely associated—that is, managers with generous compensation should complete important tasks and make crucial decisions—the effect of risk-taking incentive heterogeneity among high-ranking executives on firm outcomes should be examined. Specifically, I focus on the CEO, CFO, COO, and president. I identify those positions using each manager's title from the ExecuComp dataset. Next, I replicate the baseline analysis with the group of high-ranking executives. The results are consistent with previous findings and are not reported for brevity. Overall, risk-taking incentive dispersion among high-ranking executives is negatively associated with firm risk and performance. Importantly, the consistency suggests that risk-taking incentive heterogeneity among top-paid or high-ranking executives affects firm outcomes similarly. It also indicates that risk-taking incentives for managers other than high-ranking executives contribute to firm outcomes because they influence their area of responsibility.

To summarize, the robustness tests reinforce the prediction that managerial heterogeneity in risk-taking incentives, as a source of conflicts of interest among managers, reduces both corporate risk and performance. It is the norm that firms provide managers with risk-taking incentives to harmonize divergent risk preferences between them and shareholders. Yet firms that provide more divergent risk-taking incentives within the management team are more likely to suffer from inefficient decisions. The findings suggest that equal attention should be paid to divergent risk preferences among managers as corporate outcomes result from interactions within the top management team.

1.6.Conclusion

This study examines an unexplored aspect of managerial risk-taking—heterogeneity in risk-taking incentives among top managers. As managers are utility maximizers and influenced by different risk-taking incentives, the heterogeneity can create conflicts and disagreements in the decision-making process. Consequently, top managers, as a team, are less willing to take risks and more likely to implement suboptimal corporate policies. Consistent with the prediction, I find a strong negative relationship between the heterogeneity and the level of firm risk. Further, the findings indicate that the heterogeneity results in value deterioration, which is characterized by a decline in stock and accounting performance measures.

The significant relationship between risk-taking incentive heterogeneity and firm outcomes is particularly noteworthy because it emphasizes the importance of investigating risk-related interactions among top managers other than risk-taking incentives for CEOs. The focus on CEOs or disregard for conflicts in top management teams may do more harm than good as it ignores crucial issues in an organization.

The study provides insight into how the risk-related interaction among managers, other than that between managers and shareholders, affects firm outcomes. Additionally, the study discusses the implications for corporate compensation design. If firms disproportionately focus on CEO compensation and overlook risk-related conflicts among top managers, or if firms separately construct compensation contracts for each manager without considering potential conflicts within the management team, the contracts may trigger managers' actions deviating from the firms' expectations.

Table 1.9: Two stage-least-squares (2SLS) analysis

This table presents the estimates from a 2SLS regression. The dependent variables are firm risk, TobinQ, return, ROA, and sales growth. Risk is the natural logarithm of the annualized variance of daily stock returns. TobinQ is defined as the sum of market value of equity and book value of debt and preferred shares divided by total assets. Return is annualized stock return net of the industry mean return. ROA is the ratio of income before tax, interest, and depreciation to total assets. Growth is the change in current year sales compared to the previous year. Vega_Std is the standard deviation of vega across top-five highest-paid managers—a proxy for risk-taking incentive heterogeneity. Delta_Std is the standard deviation of delta across these managers. CEO vega (delta) is vega (delta) of the firm's CEO. Vega and delta calculations are summarized in Appendix A1. The incentive-related variables are measured as the natural logarithm of one plus the variable level. Instrument is the mean of Vega_Std of firms located in adjacent states of the focal firm and not in the same industry as the focal firm. Control variables are similar to those in baseline regressions. All variables, except dummy variables, are winsorised at 1% and 99%. Columns with the label 1st present first-stage results. Columns with the label 2nd present second-stage results. Robust standard errors clustered at the 2-digit SIC code level are given in brackets. The number of observations and Cragg-Donald Wald *F*-statistic are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	Risk		TobinQ		Return		ROA		Growth	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Instrument	0.081***		0.076***		0.076***		0.080***		0.076***	
	(0.029)		(0.029)		(0.029)		(0.030)		(0.029)	
Vega_Std		-1.565**		-0.168		0.149		-0.256*		-0.340**
		(0.756)		(0.572)		(0.151)		(0.149)		(0.152)
Delta_Std	0.138***	0.210*	0.140***	0.079	0.140***	-0.027	0.140***	0.043**	0.140***	0.051**
	(0.018)	(0.108)	(0.018)	(0.084)	(0.018)	(0.024)	(0.018)	(0.021)	(0.018)	(0.022)
CEO_vega	0.585***	0.886**	0.583***	0.085	0.583***	-0.095	0.556***	0.138*	0.583***	0.193**
	(0.012)	(0.445)	(0.012)	(0.329)	(0.012)	(0.087)	(0.013)	(0.083)	(0.012)	(0.089)
CEO_delta	-0.059***	-0.100*	-0.044**	0.245***	-0.044**	0.012	-0.046**	-0.001	-0.044**	0.021**
	(0.021)	(0.057)	(0.020)	(0.049)	(0.020)	(0.010)	(0.021)	(0.008)	(0.020)	(0.010)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	21,636	21,636	21,629	21,629	21,634	21,634	21,811	21,811	21,619	21,619
Cragg-Donald Wald	12.074		10.735		10.754		11.384		10.795	

Appendix A1. Delta and vega calculations

Formulas

Option value = $Se^{-dT}N(Z) - Xe^{-rT}N(Z - \sigma\sqrt{T})$

$Z = [\ln(S/X) + T(r - d + \sigma^2/2)]/\sigma\sqrt{T}$

Delta = $e^{-dT}N(Z) * (S/100)$

Vega = $e^{-dT}N'(Z)S\sqrt{T} * (0.01)$

N: cumulative distribution function

N': normal density function

S: stock price

X: exercise price

σ: expected volatility

r: risk-free rate

d: expected dividend yield

T: time to maturity

Estimates of some parameters

Expected volatility: annualized standard deviation of stock returns estimated over the 60 months prior to the beginning of the fiscal period

Expected dividend yield: average of dividend yield over the current year and the two prior years

Risk-free rate: from Federal Reserve website for "Treasury constant maturities". The website provides data for 1, 2, 3, 5, 7, and 10-year Treasury securities. I interpolate the rates to obtain the risk-free rates for 4, 6, 8, and 9 years. If the option maturity is more than 10 years, I use the 10-year rate.

New format (since 2006)

I obtain the number of unexercised exercisable and unexercised unexercisable options, exercise price, and expiration date of option from Execucomp.

To compute the overall delta, I sum the delta of options and the delta of shares. I use both restricted and unrestricted shares to calculate delta from shares. I assume the delta of shares is one.

For vega of the equity portfolio, I use only the vega of options and assume that vega of shares is zero.

Old format (prior 2006)

I calculate option value, delta, and vega for three option portfolios:

(i) For the current year's option grants: I obtain the number of options granted during that year, exercise price, and maturity.

(ii) For the portfolio of previously granted unexercisable options: I subtract the number of options granted in the current year from the number of unexercisable options to get the number of previously granted unexercisable options. I subtract the intrinsic value of the current year's grants from the reported intrinsic value of all unexercisable options to obtain the intrinsic value of previously granted unexercisable options, then divide it by the number of previously granted unexercisable options to obtain the average intrinsic value. The average exercise price of each previously granted unexercisable option is the stock price minus the average intrinsic value. The maturity of previously granted unexercisable options equals the actual maturity of current year option grants minus 1. If there are no grants in the current year, I assume the average maturity of previously granted unexercisable options is 9 years.

(iii) For the portfolio of previously granted exercisable options: I divide the realizable value by the number of exercisable options to obtain the average intrinsic value. I calculate the average exercise price by subtracting the average intrinsic value from the stock price. The maturity of exercisable options equals the maturity of unexercisable options minus 3.

Finally, the delta is the sum of the delta of current year options, the delta of the portfolio of previously granted options (both exercisable and unexercisable), and the delta from the shares owned by the executive. The vega is the sum of the vega of the current year options as well as previously granted options (both exercisable and unexercisable).

2. Chapter 2: Common Lender, Ex-Banker Director, and Corporate Investment

2.1. Introduction

In the early 1920s, J.P. Morgan's bankers sat on the boards of its borrowers in the transportation sector, coordinating the strategies of its borrowers at the sacrifice of consumer welfare. This anecdote exemplifies that a shared lender ("common lender") of firms competing in the same product market induces horizontal coordination among the firms to reduce their likelihood of bankruptcy and maximize the value of loan portfolio (Poitevin, 1989).[6] Therefore, an anti-competitive concern regarding a common lender emerges, like that of a common owner.[7] While the hypothesis is intuitive, empirical studies on the anti-competitive effect of a common lender ("common lender effect") are relatively limited. More importantly, channels of the common lender effect have yet to be explored extensively. This paper complements the literature by not only providing evidence on the common lender effect but also exploring the channels that facilitate it.

To examine the common lender effect, we utilize the mergers of large Japanese commercial banks from 1995 to 2004 as exogenous shocks that create common lender linkages among firms.[8] As these large banks have nationwide branch networks that include borrowers in different industries, a merger of such banks creates a common lender for firms in a wide range of industries. We focus on capital investment—a principal input for a firm's production—and markup/profitability ratio—a proxy for a firm's surplus per unit produced—to infer the extent of product market competition.[9] In particular, we examine if the effect of common lenders supports

[6] Common investors may also reduce coordination costs of colluding firms by working as a shared information hub.
[7] It is particularly a concern due to an increasing concentration of the banking sector in developed economies. See the prior literature (e.g., Bikker and Haaf, 2002; Fernholz and Koch 2016; Janicki and Prescott, 2006; Laeven, Ratnovski, and Tong, 2016) for an increasing concentration of the banking sector in developed economies.
[8] Our approach is also motivated by the anecdote: A chemical giant in Japan, Sumitomo Chemical, attempted to merge with another giant, Mitsui Chemical, following the merger between their relationship banks (Sumitomo and Sakura) which formed the SMBC (Sumitomo Mitsui Banking Corporation), although the merger attempt failed.
[9] Gutierrez and Philippon (2017) find a negative relationship between investment and product market concentration.

the anti-competition hypothesis that implies a negative impact on investment and a positive one on markup and profitability ratio.

Moreover, this paper examines a potential channel of the common lender effect. We use a dataset on directors' previous affiliations and identify ex-bankers that sit on the board of directors. In Japan, firms often appoint ex-bankers formerly affiliated with their relationship banks as directors. Some firms also appoint current bank executives as directors, but this case was rare. Miwa and Ramseyer (2006) document that fewer than one in a hundred had an executive director with a concurrent bank post. Kaplan and Minton (1994) suggest that such ex-banker directors can perform a monitoring role, providing information to their previous employers as a relationship bank, with the ability to withhold funds can present real and costly threats to an ex-banker director at a poorly performing firm. Debtholder-friendly directors do not only exist in Japan, but they also sit on the boards of directors in US companies, where around 6% of large firms have an executive of their main bank lender on the board (Kroszner and Strahanm, 2001). We predict that a common lender can affect its borrowers' management through these directors. Consistent with the prediction, our analysis demonstrates that the effect of a common lender becomes stronger in the presence of an ex-banker director sitting on the firm's board.

Our empirical analysis starts by constructing a firm-level measure for the presence of common lending. Specifically, we count the number of times each firm has been affected by a connection-creating bank merger, which occurs when the firm's relationship bank merges with another relationship bank of any of its peers. Each firm affected by such a bank merger becomes a treated firm, having a new common lender. If the anti-competition hypothesis holds, such a merger causes horizontal coordination among treated firms.

We predict the coordination among treated firms disproportionately shrinks their production through cutting investments. For example, when there is some degree of product differentiation among the competitors, each of treated firms comes to care about the positive externality of its price hike on other treated firms and adopt less aggressive pricing strategy (Deneckere and Davidson, 1985). In contrast, non-treated rivals do not internalize such externality, suggesting that a treated firm raises price more than a non-treated rival. Because higher price is associated with lower production, a treated firm shrinks production, increases markup, and raises profitability ratio more than a non-treated rival.[10]

To test our predictions, we exploit the variations in the timing of a connection-creating bank merger and the difference in the changes in outcomes between treated and non-treated firms within an industry. The benchmark specifications include firm, industry-by-year, and relationship-bank-by-year fixed effects. We include the industry-by-year fixed effects to control for industry-specific trends that may cause a spurious correlation between corporate activities and loan market concentration. For instance, loan markets for low-growth industries may become more concentrated because fewer banks lend to low-growth firms. The relationship-bank-by-year fixed effects absorb any effects specific to the main lenders, including the effects of their stronger bargaining power or restructuring after the bank merger.

We find that a treated firm reduces its investment by around 15% of the mean level. Also, a treated firm's markup and profitability ratio improve after a connection-creating bank merger.[11] The saved resources are used in a debt-friendly manner wherein a treated firm increases its cash

[10] The same prediction holds when there is no product differentiation. See the last paragraph of Section 3.2.1 for detail.
[11] We also compute banks' shares in the market for credit to a given industry to construct a credit-concentration measure at the industry level in the spirit of Saidi and Streitz (2021), which we show to be negatively associated with a firm's investment level and positively correlated with its markup and profitability ratio.

cushions after a connection-creating bank merger but reduces its expenditure for research and development. This result is unique to a common lender, but unlikely for a common owner who would prefer to capture the upsides from innovations as a residual claimant with limited liability. The effects on investment and markup/profitability ratio are stronger in financially distressed firms, suggesting that a common lender has a stronger incentive to coordinate its borrowers when the borrowers are financially distressed, i.e., when the values of loans are sensitive to the fundamentals of the borrowers. Moreover, we document a further reduction of a treated firm's investment by around 20-30% of the mean in the presence of an ex-banker director — an executive director who was formerly affiliated with one of the merging banks. This result implies that a common lender manages to affect the management of its borrowers through its former employees.

We also find a reduction in credit growth by its relationship bank when a firm is affected by a connection-creating bank merger. As the growth of credit positively correlates with corporate investment, the result suggests that a lender reduces its borrowers' investments by adjusting its loan supply. Furthermore, the negative correlation between a connection-creating bank merger and the growth of credit becomes greater in the presence of an ex-banker director. This result suggests that an ex-banker director amplifies the relationship bank's loan supply adjustment, which might explain the incremental effect of an ex-banker director on the investment of a treated firm.

Importantly, however, this incremental effect survives even if we control for the change of credit from the firm's relationship bank. An ex-banker director is likely to have a direct role in advising the treated firm to cut investment, beyond merely facilitating the relationship bank's loan supply adjustment. After accounting for the change of credit, the estimated investment effect of a connection-creating bank merger is no longer significant in the absence of an ex-banker director. This result suggests that a common lender reduces its borrowers' investments mostly by the influence of an ex-banker director sitting on the firm's board, apart from by the adjustment of its loan supply.

Overall, our paper contributes to the literature on the anti-competitive effect of a common investor in three ways. First, the paper explores a channel through which a common lender affects the management of its borrower. Specifically, we provide evidence of a channel in which ex-banker directors play major roles in facilitating the common lender effect.[12] Second, we provide evidence consistent with the common lender effect using firm-level variations in common lender connections, whereas the pioneering literature often uses industry-level variations (e.g., Cetorelli and Strahan, 2006; Saidi and Streitz, 2021). With our firm-level identification strategy, we tease out the effects of industry-specific trends from those of shared lenders.[13] Last, we suggest that a common lender may not necessarily increase corporate innovative activity. Specifically, we find that firms influenced by a common lender use saved resources from reduced competition for cash cushions rather than research and development. This result is complementary to the recent evidence suggesting that common ownership leads to innovation when technological spillovers are sufficiently large (e.g., Antón et al., 2021 for evidence and López and Vives, 2019 for theory) or when common owners are long-term dedicated investors (e.g., Borochin et al., 2020 for evidence). Although common investors are likely to reduce product market competition, they can either increase or decrease corporate innovative activity.

Moreover, our paper contributes to the literature on ex-banker directors by showing that they can facilitate common lender effects. The literature has provided evidence consistent with

[12] Recent evidence by Antón et al. (2022) suggests that modulating managerial incentives is a potential channel of a common ownership effect. They show that managerial incentives are less sensitive to performance in firms with more common ownership, suggesting that performance-insensitive pay might facilitate the anti-competitive effect of common ownership.
[13] Unlike the empirical literature on common lender effects, the empirical literature on the anticompetitive effects of common ownership is growing (e.g., Azar et al., 2018; Gilje et al., 2020; Park and Seo, 2019; Backus et al., 2021).

several hypotheses: (1) Bankers act as financial experts who help firms to acquire funding (e.g., Byrd and Mizruchi, 2005); (2) they monitor the firms because these firms are borrowers or because they hold an equity stake (e.g., Kaplan and Minton, 1994; Morck and Nakamura, 1999; Kroszner and Strahan, 2001); (3) they promote their own business, either as commercial bankers or as investment bankers (e.g., Dittman et al., 2010; Ferreira and Matos, 2012). This paper particularly relates to the second group of the literature because it adds another piece of evidence on the role of ex-banker directors in debt monitoring.

2.2.Financial Crisis and Bank Merger Wave in Japan

The real estate and stock market bubble burst in Japan at the beginning of the 1990s, causing a sudden decline and long-lasting sluggishness of stock and property prices in the country. Particularly, the collapse of the real estate value meant that the banks had to suffer a significant loss in their collateral value since most Japanese banks relied heavily on real estate for collateral (Bank of Japan, 1996; Hoshi, 2001). The Nikkei 225 stock index fell by over 40% in 1990 and property prices of urban land followed this trend in the following year. The downward trend of asset prices continued until the early 2000s. Consequently, Japanese banks faced large amounts of non-performing loans, asset write-offs, and negative profits. Simultaneously, declining stock prices constrained banks from issuing equity to supplement their capital, which resulted in diminishing bank capital.

The Japanese financial system eventually fell into a banking crisis in 1997 and 1998. During the crisis, a few banks became insolvent. Most notably, in November 1997, the Hokkaido Takushoku Bank, one of the large national banks at that time, failed because of eroded capital and diminished liquidity. In March 1998, the capital ratios of major banks in Japan were around 8%, which was the minimum requirement for banks with active international operations, according to the Basel capital adequacy standard at that time. As some banks did not satisfy this standard and others barely did, major banks in Japan needed to be recapitalized via public funds.[14]

Injecting capital with the taxpayers' money required recipient banks to clean up their non-performing loans and regain their capital. Because restructuring and cost-cutting were straightforward ways of recovering profits and returning public funds sooner, this induced a series of mergers in the Japanese banking sector.[15] The Japanese government embraced these mergers. Unlike bank mergers in the US, both the Bank of Japan and the Japanese government engaged in the merger process. Particularly, the Bank of Japan was involved in matching merger partners out of concern for the systemic risk to the banking system (Nakaso, 2001). Thus, bank mergers during that period were largely driven by the government's response to the increased systemic risk of Japan's financial sector rather than by individual bank health (Hosono, Sakai, and Tsuru, 2009).

In this study, we focus on six mergers among large national banks that occurred during the decade between 1995 and 2004. Figure 2.1 lists these mergers and describes the timeline of how the large national banks consolidated during that period. Restructuring of the Japanese banking sector during that decade started in 1995 with the announcement by the Bank of Tokyo and the Mitsubishi Bank to create the Bank of Tokyo-Mitsubishi. In 1999, Sumitomo Bank announced its merger with Sakura Bank to form Sumitomo Mitsui Banking Corporation (SMBC). In the same year, the Dai-Ichi Kangyo Bank (DKB), Fuji Bank, and the Industrial Bank of Japan (IBJ) announced an agreement to consolidate the three banks' operations, which resulted in the formation of Mizuho Group. In 2000, the Sanwa Bank announced to merge with the Tokai Bank to form the

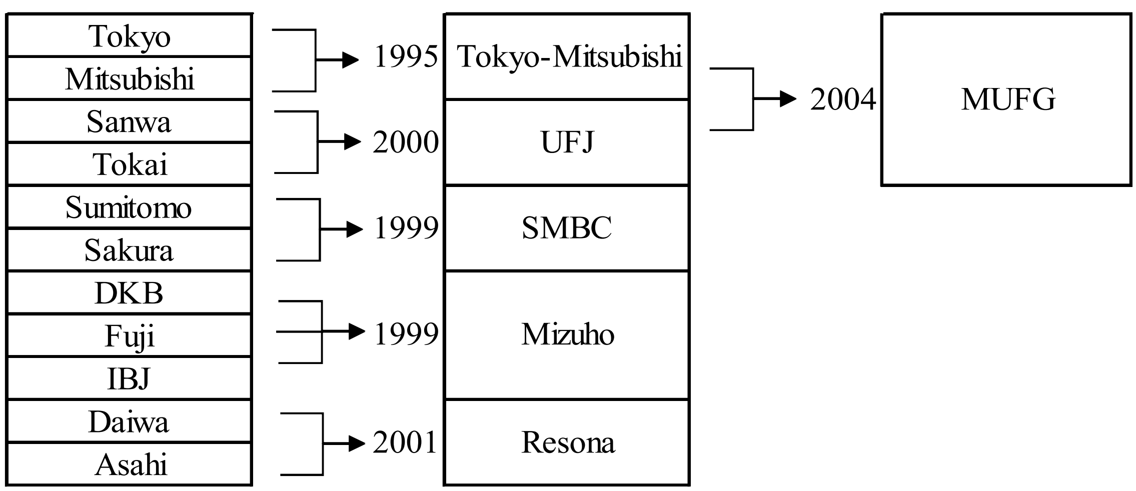
[14] For details of the Japanese financial crisis in the 1990 and the response of the financial authorities, see Nakaso (2001).
[15] Prior study (e.g., Hosono et al., 2009) provides empirical evidence that Japanese major banks that had been recapitalized by the government were more likely to be consolidated.

UFJ Bank. In 2001, Daiwa Bank announced that it would acquire Asahi Bank to form the Resona Group. Finally, in 2004, the UFJ Bank announced that it had agreed to be acquired by the Bank of Tokyo-Mitsubishi to form the Mitsubishi UFJ Group (MUFG). Over 10 large national banks that existed before 1995 were regrouped into four.

To examine the impact of a common lender, we exploit these M&As of major banks in Japan that created common lender connections among firms. The bank mergers in Japan during the period were mainly triggered by the Japanese government's bailout policy, minimizing the endogeneity concern that firm-specific driving forces caused these mergers.

Figure 2.1: Major bank mergers in Japan between 1995 and 2004

This figure shows how large national banks merged from 1995 to 2004. We give the announcement years next to the arrows.



2.3. Empirical Analysis

2.3.1. Data

The dataset used in this study is combined from several sources. First, we obtain annual financial data of Japanese non-financial firms listed on the Tokyo Stock Exchange from 1980 to 2007 provided by the Development Bank of Japan. Second, detailed annual data on Japanese firms' bank loans are from the Nikkei Economic Electronic Databank System (NEEDS). This dataset provides information on the loan amounts firms borrow from major banks each year. As we use policy-driven mergers between large national banks,[16] our sample banks are *toshi-ginko* (city banks) that had wide networks of branches in Japan during the sample period.[17]

Next, we obtain annual data on firms' directors from Toyo Keizai. The data allow us to trace a director's employment history and identify if an executive director was affiliated with the relationship bank of the firm before sitting on the firm's board. We define a director with representative rights as an executive director.[18] In Japan, such a director has the highest authority and capacity to enter into business and sign legal contracts on behalf of the corporation. Using this dataset, we identify the presence of an executive director who was formerly affiliated with the firm's relationship bank. Finally, we collect data on market value and stock returns from Datastream. As one of the key variables of interest, we construct the variable of a firm's relationship bank as follows. Loosely speaking, a firm's relationship bank is a bank that can influence a firm's

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[16] There were some mergers between city banks at the beginning of the 1990s. For example, Taiyo-Kobe and Mitsui merged to form Sakura in 1990. We exclude these mergers because, unlike the mergers of our interest, they targeted market share gain or business synergies and they were not policy-driven.

[17] According to the definition by the Japanese Bankers Association, city banks are large in size, headquartered in major cities, and have a branch network that covers Tokyo, Osaka, other major cities, and their immediate suburbs. In addition to city banks, we include the Industrial Bank of Japan (IBJ) into our sample banks because it was involved in the merger between the two city banks that formed Mizuho Group. See Figure 1 for the details.

[18] We focus on a senior position of management to make sure that a director has enough power to affect a firm's policies.

policies. In our study, using bank loan data, we first identify the top lender for a firm, the one that lends the largest amount to the firm among the other sample banks in a given year, as the candidate of the firm's relationship bank. Some firms, however, may borrow a similar amount from more than one bank in a year, resulting in the absence of a single lead bank. Given this possibility, we define the top lender to a firm as the relationship bank only if the loan amount of any other bank is smaller than 75% of the amount lent by the top lender.[19] Once a firm's relationship bank in a given year has been established, we use the M&A information to identify whether the firm's relationship bank engaged in a merger with another bank. Figure 2.1 lists the mergers among our sample banks that are used in our analysis.

In our identification strategy, we define a treated firm as a firm having its relationship bank going through a *connection-creating* merger. A connection-creating bank merger occurs when the focal firm's relationship bank announces a merger with the relationship bank of at least one of its rivals. We define a firm's rivals as firms operating in the same sector as the focal firm. For this purpose, we use the industry classification provided by Nikkei NEEDS which categorizes firms into over 100 sectors.[20] We drop sectors that have at most four firms in any year as those sectors are more likely to form an all-inclusive cartel when the number of sector participants is small.[21] Figure 2.2 illustrates how we identify treated and control firms from a merger of relationship banks. When firms' relationship banks merge, the post-merger bank becomes a common lender of those firms, which establishes a novel connection between them. If a common lender has any impact on affected borrowers, we expect to observe this impact on treated firms. The first variable, also the

[19] Under our definition, each bank except for the relationship bank lends to the firm less than 75% of the amount lent by the relationship bank. Therefore, the relationship bank of each firm is less likely to change under our definition.
[20] We use the six-digit classification of industries, which is the finest possible categorization.
[21] The dropped sectors include the gas industry, all of whose members were accused of a cartel in 2011, and the construction industry, all of whose members were recently investigated by the Japan Fair Trade Commission for having formed a cartel in railroad bidding.

most important one, is Merger_Exp—the cumulative frequency of being affected by a connection-creating bank merger. This variable represents a firm's common lender connections with its rivals created by connection-creating bank mergers.

We next construct variables to explore a channel through which common lenders affect corporate outcomes. We examine one potential channel wherein banks exert their influence on borrowers through the advice of directors that have executive power and were formerly affiliated with the banks. The presence of such executive directors on the board may amplify the influence of a common lender on treated firms' policies. To evaluate this possibility, we construct Dir_Merger_Exp—the cumulative frequency of being affected by a connection-creating bank merger conditional on the presence of an executive director who was previously affiliated with either merging bank (*ex-banker director*). This variable enables us to examine the roles of ex-banker directors in facilitating common lender effects. We also construct Dir_Presence, a dummy variable equal to one if the focal firm has at least one executive director who was formerly affiliated with the firm's relationship bank.[22,23]

Although our main specifications use Merger_Exp, we also examine common lender effects using banks' loan shares in the credit market of a given industry, in the spirit of Saidi and Streitz (2021). If a bank has a significant share in the loan market of an industry, it should have incentives to internalize product market externalities. Specifically, we compute the proportion of each sample bank's total loan volume for each industry (market share) on annual basis. We use these market

[22] Because of data limitation, some firms in the sample do not have data on Dir_Presence for some years before 1992. For those firms, we impute missing values of Dir_Presence before 1992 as follows: (i) impute zero for firms that never hired an executive director formerly affiliated with its relationship bank and existed in our sample period for over 15 years; and (ii) impute one for firms that always had at least one executive director formerly affiliated with its relationship bank and existed in our sample period for over 15 years.
[23] Note that Dir_Merger_Exp is not equal to the interaction of Merger_Exp and Dir_Presence.

shares to compute a Bank-Industry Herfindahl-Hirschman Index (HHI), capturing credit concentration at the industry-year level.

Finally, we construct other variables including dependent and control variables. For the dependent variables, we focus on corporate investment (Capex), markup (Markup), and profitability ratio (EBITDA). Capex is measured as capital expenditure divided by total assets (as a percentage). Markup is the difference between revenue and cost of goods sold divided by revenue (as a percentage). EBITDA is earnings before extraordinary items, interest, taxes, depreciation, and amortization, divided by revenue (as a percentage). We use control variables similar to those in Akdoğu and MacKay (2008). Specifically, Tobin's Q is defined as the market value of equity plus the book value of liabilities and preferred stock minus deferred taxes, divided by total assets. Sales_Growth is the growth in current year sales compared with the previous year's sales (as a percentage). ROA is the ratio of net income to total assets (as a percentage). Cashflow is defined as earnings before extraordinary items plus depreciation minus dividends, divided by total assets (as a percentage). Size is the natural logarithm of total assets. Cash is the ratio of cash and deposits to total assets (as a percentage). Leverage is the ratio of the book value of total liabilities to the market value of equity plus the book value of total liabilities (as a percentage). Cashflow_Std is the standard deviation of Cashflow for the past 10 (with a minimum of four) annual observations (as a percentage). For firms with less than four observations in a given year, we use the mean Cashflow_Std of all firms in the same sector for that year. Diversification is one minus the HHI of sales across the firm's segments, which is measured as the sum of the squared ratios of segment sales to the firm's total sales. We occasionally represent the first four control variables (i.e., Tobin's Q, Sales Growth, ROA, and Cashflow) by Growth_Efficiency and the remaining five by Firm_Characteristics. In addition, RB_Loan_Growth is the growth in the loan the firm borrows from its top lender in the current year compared with the previous year (as a percentage).[24] This variable captures the adjustment in loan supply from the firm's relationship bank.[25] All potentially unbounded variables are winsorized at 0.5% and 99.5%.

Figure 2.2: Identification strategy for baseline analysis

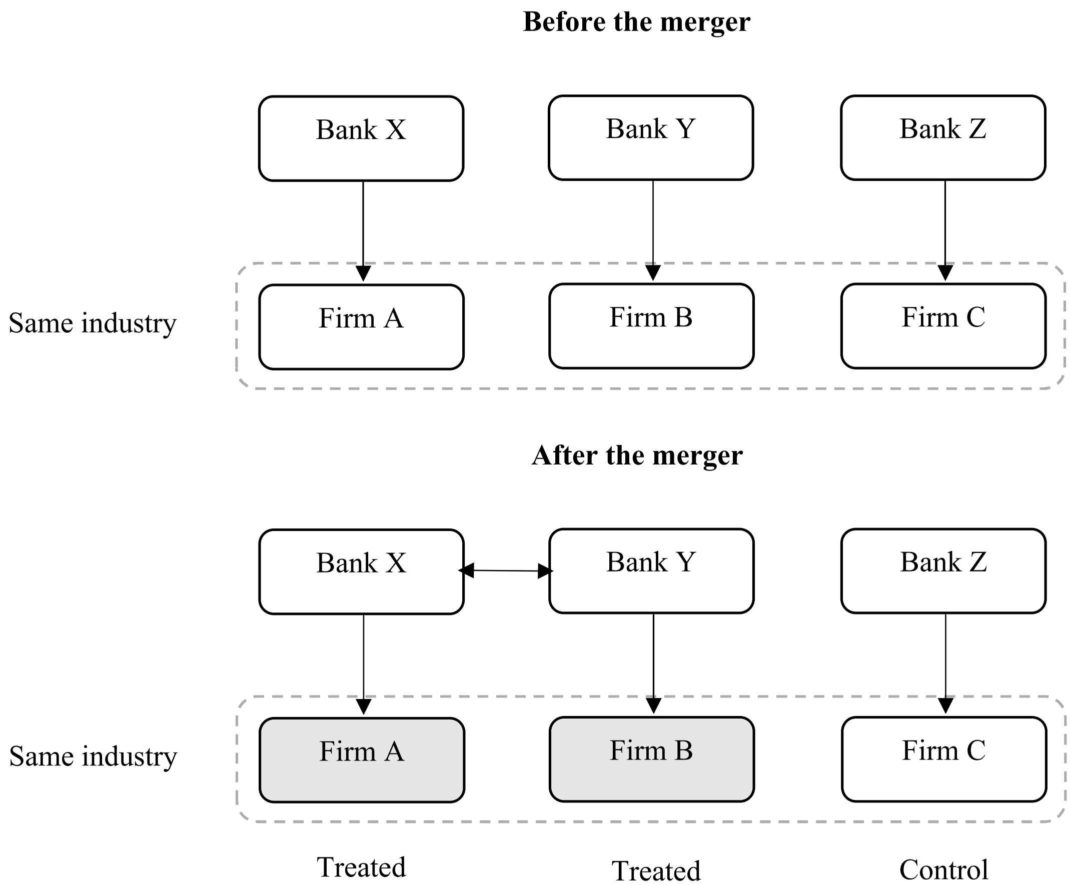

Table 2.1, Panel A, presents the descriptive statistics of the variables used in this study. The average Capex is 2.4, indicating that sample firms on average invest 2.4% of total assets.

[24] We compute the first difference of the natural logarithm of the loan the firm borrows from its top lender and multiply it by 100 so that it can be interpreted as a percentage change.
[25] The relationship bank is defined as the top lender only if the loan amount of any other sample bank is smaller than 75% of the loan amount of the top lender. In contrast, we allow RB_Loan_Growth to include all the largest loans to measure the loan growth of a top lender.

Merger_Exp has a maximum of two, suggesting that some firms have their relationship banks going through connection-creating mergers up to twice. Dir_Merger_Exp has a maximum of two, meaning that firms with ex-banker directors could also have their relationship banks going through connection-creating mergers up to twice. The average for Dir_Presence, a dummy variable, is neither large nor trivial, implying that firms with executive directors who were formerly affiliated with their relationship banks are not necessarily rare.[26] Our sample firms, on average, produce a markup of 22.79% and an EBITDA of 8.9% relative to the revenue. RB_Loan_Growth has a mean of almost zero, indicating that a relationship bank's loan supply, on average, did not grow as much during the sample period.

Regarding the control variables, our sample firms have an average Tobin's Q of 1.42, an average sales growth of 3.59%, and an average ROA of 1.83%. They yield an average cashflow of 7.55% relative to total assets. Firm size varies from 2.32 billion yen to 4.12 trillion yen with a mean of 154.95 billion yen. The average cash level is 12.73% relative to total assets, the average leverage is 46.96%, and the average cashflow volatility is 2.32% relative to total assets.[27] The mean diversification index of our sample firms is 0.38.[28]

Table 2.1, Panel B, reports the summary statistics of pre-merger control variables for the treated firms that had their relationship banks going through connection-creating mergers and the rest (control firms) for the years of bank merger announcements.[29] Overall, the mean pre-merger control variables are similar for both types of firms. Whereas the average pre-merger Tobin's Q,

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[26] Banker directors sit on the boards of directors in US companies, where around 6% of large firms have an executive of their main bank lender on the board (Kroszner and Strahan, 2001).

[27] Akdoğu and MacKay (2008) report that the average leverage of US firms that are comparable with our sample of Japanese firms is 23%. In the study by Chirinko and Elston (2006) about the influence of German banks, the average leverage of their sample of German firms exceeds 60%.

[28] The mean diversification index for the US firms, reported by Akdoğu and MacKay (2008), is a comparable 0.31.

[29] We report the summary statistics of one-year lagged control variables for the years of bank merger announcements we examine in Figure 1.

ROA, and cashflow are higher for control firms, the average pre-merger sales growth is higher for treated firms. Table 2.1, Panel C, reports the version where each variable is detrended by subtracting the average of the corresponding relationship-bank-year observations. The results show that the average detrended levels of growth opportunities and investment returns (Tobin's Q, sales growth, ROA, and cashflow) are higher for treated firms than for control firms. The result suggests that treated borrowers of a merging bank do not have fewer investment opportunities or receive lower investment returns than do control borrowers of the same bank. In the absence of effects specific to relationship banks, a treated firm is unlikely to face a more severe business environment than a control firm.

2.3.2. Empirical Model

2.3.2.1. Bank Mergers and Corporate Outcomes

In this section, we describe the empirical models that we use to examine the impact of a common lender on its borrowers. We predict that inter-competitor connections via a common lender may attenuate aggressive competition between the competitors in the product market. The state of weak competition is associated with lower production. Therefore, we first focus on corporate investment since it is a major input for firm production.

To capture the extent of common lending, Saidi and Streitz (2021) use a measure of bank concentration at the industry level—the HHI of banks' market shares in terms of loan volume for a given industry. We start our analysis with a model similar to Saidi and Streitz (2021):

$$Capex_{ijt} = \beta_1 Bank\_Industry\_HHI_{jt-1} + \beta_2 Z_{ijt-1} + \alpha_i + \delta_{bt} + \varepsilon_{ijt}. \quad (2.1)$$

The dependent variable is $Capex_{ijt}$, the capital expenditure of firm *i* in industry *j* in year *t*. The independent variable of interest is $Bank\_Industry\_HHI_{jt-1}$, which is the measure of bank concentration in the previous year. The variable, Z_{ijt-1}, stands for a set of one-year lagged control variables including Growth_Efficiency and Firm_Characteristics. We control for firm (α_i) and RB-year (δ_{bt}) fixed effects, where RB stands for relationship bank.

Table 2.1: Summary statistics

Capex is capital expenditure divided by total assets. Markup is the difference between revenue and cost of goods sold divided by revenue. EBITDA is earnings before extraordinary items, interest, taxes, depreciation, and amortization, divided by revenue. Bank-Industry_HHI is measured as the sum of the squared ratios of total loan volume each bank granted to the sector over the aggregate loan volume of the sector in a given year. Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger, i.e., a merger between the firm's relationship bank and the relationship bank of any of its rivals in the same sector. A relationship bank is defined as the top lender, i.e., our sample bank lending the largest loan to the firm in a given year, only if the loan amount lent by any other sample bank is smaller than 75% of the loan amount lent by the top lender. Dir_Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger conditional on the presence of an executive director who was previously affiliated with either merging bank. Dir_Presence is a dummy variable equal to one if there is at least one executive director of the firm who was previously affiliated with the firm's relationship bank. RB_Loan_Growth is the growth in the loan the firm borrows from its top lender in the current year compared with the previous year. TobinQ is defined as the market value of equity plus the book value of liabilities and preferred stock minus deferred taxes, all divided by total assets. Sales_Growth is the growth in current year sales compared with the previous year. ROA is the ratio of net income to total assets. Cashflow is defined as earnings before extraordinary items plus depreciation minus dividends, all divided by total assets. Size is total assets (in billion yen). Cash is the ratio of cash and deposits to total assets. Leverage is the ratio of the book value of total liabilities to the market value of equity plus the book value of total liabilities. Cashflow_Std is the standard deviation of Cashflow using up to the past 10 (minimum four) annual observations. Diversification is measured as one minus the Herfindahl-Hirschman index of sales across the firm's segments, which is measured as the sum of the squared ratios of segment sales to the firm's total sales. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Panel A provides descriptive statistics. Panels B and C compare pre-merger control variables between treatment and control groups in the years of bank mergers. Treated firms are firms affected by a connection-creating bank merger and control firms are the rest. Panel B shows the simple comparison whereas Panel C shows the comparison after controlling for relationship bank by year fixed effects.

Panel A:	**Summary statistics for variables used in the main analysis**					
	N	Mean	Std_Dev	Min	Median	Max
Capex (%)	45,626	2.40	5.13	-25.98	1.62	25.93
Markup (%)	46,625	22.79	14.70	1.00	19.46	82.27
EBITDA (%)	43,936	8.90	7.82	-9.78	7.32	49.44
Bank-Industry_HHI	46,777	0.18	0.08	0.00	0.14	1.00
Merger_Exp	46,777	0.16	0.39	0.00	0.00	2.00
Dir_Merger_Exp	46,777	0.01	0.12	0.00	0.00	2.00
Dir_Presence	46,777	0.03	0.17	0.00	0.00	1.00

Table 2.1 continued

	N	Mean	Std_Dev	Min	Median	Max
RB_Loan_Growth (%)	34,960	0.12	42.03	-172.28	0.00	194.59
TobinQ	40,697	1.42	0.76	0.52	1.21	6.41
Sales_Growth (%)	44,917	3.59	13.52	-41.66	2.74	74.30
ROA (%)	46,777	1.83	3.83	-20.97	1.79	14.96
Cashflow (%)	46,773	7.55	5.03	-6.55	6.96	27.07
Size (billion yen)	46,777	154.95	442.39	2.32	39.89	4119.69
Cash (%)	46,776	12.73	9.65	0.00	10.76	87.94
Leverage (%)	40,697	46.96	21.98	0.02	46.49	98.98
Cashflow_Std (%)	46,709	2.32	1.58	0.29	1.96	10.57
Diversification	46,767	0.38	0.34	0.00	0.48	0.89
Panel B:	**Means and standard deviations for pre-merger control variables by groups**					
	Control			Treated		
	N	Mean	Std_Dev	N	Mean	Std_Dev
TobinQ	8574	1.25	0.76	992	1.08	0.51
Sales_Growth (%)	8607	-0.63	12.85	999	-0.54	11.96
ROA (%)	8894	1.13	4.09	1029	0.89	4.16
Cashflow (%)	8894	6.82	5.00	1029	6.44	4.96
Size (billion yen)	8894	164.03	468.59	1029	106.61	245.97
Cash (%)	8894	11.64	9.77	1029	10.41	8.16
Leverage (%)	8574	51.20	23.21	992	58.94	20.51
Cashflow_Std (%)	8894	2.21	1.45	1029	2.26	1.48
Diversification	8893	0.37	0.33	1029	0.43	0.32
Panel C:	**Means and standard deviations for pre-merger control variables by groups (detrended)**					
	Control			Treated		
	N	Mean	Std_Dev	N	Mean	Std_Dev
TobinQ	8574	0.00	0.73	992	0.00	0.49
Sales_Growth (%)	8607	-0.01	12.48	999	0.11	11.73
ROA (%)	8894	-0.02	4.03	1029	0.14	4.12
Cashflow (%)	8894	-0.01	4.93	1029	0.10	4.90
Size (billion yen)	8894	3.22	465.07	1029	-27.81	252.34
Cash (%)	8894	-0.07	9.60	1029	0.60	8.11
Leverage (%)	8574	0.11	21.85	992	-0.94	20.08
Cashflow_Std (%)	8894	-0.01	1.44	1029	0.04	1.47
Diversification	8893	0.00	0.20	1029	0.00	0.21

Firm fixed effects capture unobservable time-invariant firm-specific characteristics. With fixed effects of each relationship bank interacted with year, we control for merger-specific effects other than common lender effects. For example, a bank merger may strengthen the bargaining power of a relationship bank against its borrowers by depriving them of an opportunity to borrow from other banks. As a result, the stronger the bargaining power of the relationship bank, its borrowers might reduce investment to minimize default risk. Alternatively, relationship banks that become common lenders may face restructuring pressures to improve the quality of their loans as mandated by the Japanese government, where the banks may try to force their borrowers to cut down investments. In either case, we may observe a negative correlation between bank concentration and investment. RB-year fixed effects capture the impacts of relationship banks uniformly exerted on their borrowers that might vary over time, such as the effects of stronger bargaining power and restructuring. After controlling for the fixed effects, any negative correlation between Bank-Industry_HHI and Capex is expected to reflect the reduction of investments by the borrowers due to the anti-competitive practices as a consequence of bank concentration.

Next, we investigate the effect of a common lender on corporate markup and profitability ratio. We predict that firms connected through common lenders compete less aggressively. In this regard, we expect such coordination improves markup and profitability ratio. Using Markup and EBITDA as the dependent variables, we use a similar model as Equation (2.1). We expect a positive association between Bank-Industry_HHI and Markup as well as EBITDA, consistent with the anti-competitive effect of a common lender.

$$Markup_{ijt}(EBITDA_{ijt}) = \beta_1 Bank\_Industry\_HHI_{jt-1} + \beta_2 Z_{ijt-1} + \alpha_i + \delta_{bt} + \varepsilon_{ijt}. \quad (2.2)$$

Here, Z_{ijt-1} stands for a set of one-year lagged Firm_Characteristics.

As the specification of Equations (2.1) and (2.2) does not allow us to control for industry trends, we cannot rule out the possibility that both bank concentration and corporate outcomes in an industry are driven by industry-level time-varying factors. For instance, in low-growth industries, the loan market may become more concentrated because fewer banks are willing to lend to low-growth firms. In this case, we would observe a spurious correlation between firms' business activity and credit concentration. To rule out this possibility, we use a specification that uses our main variable Merger_Exp as follows:

$$Capex_{ijt} = \beta_1 Merger\_Exp_{ijt} + \beta_2 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}. \tag{2.3}$$

$$Markup_{ijt}(EBITDA_{ijt}) = \beta_1 Merger\_Exp_{ijt} + \beta_2 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}. \tag{2.4}$$

Both equations illustrate our main regression models to estimate common lender effects on corporate investment, markup, and profitability ratio, where Merger_Exp is a firm-level variable that captures the creation of a common lender by a connection-creating bank merger. Besides the firm and RB-year fixed effects, we control for industry-year (γ_{jt}) fixed effects to capture industry-specific business trends. Because we control for industry-year fixed effects, the coefficient of Merger_Exp represents the effect of a connection-creating bank merger on a treated firm relative to a control firm.[30] If horizontal coordination between treated firms occurs because of a connection-creating bank merger, it disproportionately shrinks the production of a treated firm relative to that of a control firm. In a homogeneous product market, non-treated rivals have fewer incentives to reduce production because the coordination increases the industry price (e.g., Salant, Switzer, and Reynolds, 1983; Heywood and McGinty, 2007; Perry and Porter, 1985). In a differentiated product market, non-treated rivals raise prices (and consequently shrink production) to a lesser extent because they do not internalize the positive externalities of their price hikes on other firms in the same industry (e.g., Deneckere and Davidson, 1985). We also predict, in both types of markets, treated firms increase markups and profits *per unit produced* more than non-treated rivals,[31] because lower production is associated with lower marginal and average cost or higher price.[32] As

[30] See Figure 2 for the definition of treated and control firms.
[31] Note that we examine markups and profitability ratios, which are mostly influenced by prices, and avoid using the absolute level of profits. Whether a treated firm increases the absolute level of profits more than a non-treated rival is ambiguous, because a non-treated rival takes a free ride on the high price charged by a treated firm. Indeed, if a non-treated rival's profitability ratio is lower than a treated firm's only by a small margin, its absolute level of profits should be higher because it produces more than a treated firm.
[32] In the Cournot competition model with constant marginal cost curves, marginal and average cost is constant and price is uniform across firms. A firm's markup and profitability ratio are therefore independent of its production level. However, this model is considered unsuitable for analyzing horizontal coordination, because it predicts that coordination is mostly unprofitable for the members of a coalition. Later models overcome this paradox by assuming

with Bank-Industry_HHI, we predict a negative association between Merger_Exp and Capex and a positive correlation between Merger_Exp and Markup as well as EBITDA.

2.3.2.2.Channel

In this section, we describe empirical models to explore a channel through which a connection-creating bank merger affects corporate outcomes. One potential channel is where merging banks may have a say in firm policies through executive directors formerly affiliated with them. To evaluate this director-channel, we use the variable Dir_Merger_Exp.

We use two models similar to Equations (2.3) and (2.4). First, we examine whether there are any differential effects on corporate investment, markup, and profitability ratio in the presence of an ex-banker director with Equations (2.5) and (2.6) as follows:

$$Capex_{ijt} = \beta_1 Merger\_Exp_{ijt} + \beta_2 Dir\_Merger\_Exp_{ijt} + \beta_3 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}, \quad (2.5)$$

$$Markup_{ijt}(EBITDA_{ijt}) = \beta_1 Merger\_Exp_{ijt} + \beta_2 Dir\_Merger\_Exp_{ijt} + \beta_3 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}\ . \quad (2.6)$$

While Merger_Exp captures the effect of a connection-creating bank merger, Dir_Merger_Exp captures the incremental effect of a connection-creating bank merger conditional on the presence of an ex-banker director. Controlling for both Merger_Exp and Dir_Merger_Exp allows us to investigate if an ex-banker director contributes to the influence of a common lender on the treated firm's policies. If an ex-banker director has a say in corporate policies and his advice

increasing marginal cost curves in the Cournot competition model or Bertrand competition in a differentiated product market.

serves the coordination purpose, we expect a negative (positive) coefficient of Dir_Merger_Exp in the Capex (Markup/EBITDA) regression, indicating an effect in line with that of Merger_Exp.

An alternative channel wherein a connection-creating bank merger can affect borrowers' policies is through a common lender's loan supply adjustment. One may argue that the role of ex-banker directors may lie in helping the relationship banks that become common lenders adjust loan supply instead of proactively advising a firm's management. If so, the impacts of Dir_Merger_Exp on corporate outcomes might reflect a more subtle channel of loan supply adjustment. To separate the director channel from the loan supply channel, we control for the growth of the loan supply from the relationship bank—RB_Loan_Growth—besides Dir_Merger_Exp as follows:

$$Capex_{ijt} = \beta_1 Merger\_Exp_{ijt} + \beta_2 Dir\_Merger\_Exp_{ijt} + \beta_3 RB\_Loan\_Growth_{ijt} + \beta_4 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}, \tag{2.7}$$

$$Markup_{ijt}(EBITDA_{ijt}) = \beta_1 Merger\_Exp_{ijt} + \beta_2 Dir\_Merger\_Exp_{ijt} + \beta_3 RB\_Loan\_Growth_{ijt} + \beta_4 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt} \ . \tag{2.8}$$

If a relationship bank that becomes a common lender curbs the growth of loan supply, it might act as another channel affecting corporate outcomes. If it is acting as another channel, we should observe a positive association between RB_Loan_Growth and Capex, and a negative association between RB_Loan_Growth and Markup as well as EBITDA.

To further examine if a common lender affects its borrowers through adjusting loan supply, we use Equation (2.9) where RB_Loan_Growth is the dependent variable. The independent variables of interest are Merger_Exp and Dir_Merger_Exp. Controlling for Merger_Exp allows us to investigate if a connection-creating bank merger changes the growth of credit from the relationship bank to the treated firm after the merger announcement; controlling for Dir_Merger_Exp allows us to examine if an ex-banker director contributes to the change in the loan supply.

$$\begin{aligned} &RB\_Loan\_Growth_{ijt} \\ &\quad = \beta_1 Merger\_Exp_{ijt} + \beta_2 Dir\_Merger\_Exp_{ijt} + \beta_3 Z_{ijt-1} + \alpha_i + \gamma_{jt} \\ &\quad + \delta_{bt} + \varepsilon_{ijt} \ . \end{aligned} \tag{2.9}$$

If the loan supply adjustment is a channel of the common lender effect induced by a connection-creating bank merger, we expect a negative correlation between RB_Loan_Growth and Merger_Exp. Furthermore, if an ex-banker director on the borrower's board contributes to the loan supply adjustment, we expect a negative correlation between RB_Loan_Growth and Dir_Merger_Exp, indicating an effect in line with that of Merger_Exp.

2.3.3. Results

This section presents our baseline results. Table 2.2 shows the effects of bank concentration on corporate outcomes. Bank concentration is captured by the two variables: Bank-Indsutry_HHI and Merger_Exp. Panel A shows the results for Bank-Indsutry_HHI (Equations (2.1) and (2.2)) and Panel B presents those for Merger_Exp (Equations (2.3) and (2.4)). The first two columns in each panel show the results for corporate investment and the last four show the results for markup and profitability ratio.

Panel A Columns (1) and (2) show a negative effect on Capex of Bank-Industry_HHI, a measure of bank concentration at industry level. In Column (1), the coefficient of -2.919 is statistically significant at the one percent level. In terms of economic significance, the coefficient indicates that one standard deviation increase in Bank-Indsutry_HHI is associated with a decrease of 9.7% in Capex of the sample mean. The effect is robust and even larger when we control for Firm_Characteristics in addition to Growth_Efficiency in Column (2). The Bank-Industry_HHI coefficient is -3.573 and statistically significant at the one percent level. The coefficient indicates that one standard deviation increase in Bank-Industry_HHI is associated with an investment reduction of 11.9% relative to the mean.

Table 2.2: Bank concentration and corporate outcomes

See Table 2.1 for the definition of variables. The dependent variables are Capex—capital expenditure divided by total assets; Markup—the difference between revenue and cost of goods sold divided by revenue; and EBITDA—earnings before extraordinary items, interest, taxes, depreciation, and amortization divided by revenue. The independent variables of interest are Bank-Industry_HHI in Panel A and Merger_Exp in Panel B. Growth_Efficiency includes TobinQ, Sales_Growth, ROA, and Cashflow. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Growth_Efficiency and Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Robust standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA
Panel A						
Bank-Industry_HHI	-2.919***	-3.573***	5.238**	5.015**	4.830**	5.825**
	(1.126)	(1.146)	(2.325)	(2.258)	(2.188)	(2.334)
TobinQ	0.255***	-0.225**				
	(0.088)	(0.100)				
Sales_Growth	0.013***	0.016***				
	(0.003)	(0.003)				
ROA	0.118***	0.098***				
	(0.016)	(0.016)				
Cashflow	0.111***	0.083***				
	(0.017)	(0.017)				
Size		-0.929***		-1.145***		1.175***
		(0.154)		(0.254)		(0.222)
Cash		0.046***		0.018		0.005
		(0.005)		(0.012)		(0.007)
Leverage		-0.043***		-0.084***		-0.085***
		(0.005)		(0.006)		(0.005)
Cashflow_Std		-0.088**		-0.137**		-0.158***
		(0.043)		(0.065)		(0.055)
Diversification		-0.242		-0.509		-0.954***
		(0.235)		(0.328)		(0.238)
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
N	36,544	36,503	43,634	37,721	41,179	35,740
R-squared	0.308	0.317	0.912	0.921	0.759	0.782

Table 2.2 continued

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA
Panel B						
Merger_Exp	-0.345**	-0.342**	0.526**	0.448*	0.387**	0.413**
	(0.149)	(0.150)	(0.257)	(0.251)	(0.194)	(0.189)
TobinQ	0.239***	-0.241**				
	(0.091)	(0.104)				
Sales_Growth	0.011***	0.015***				
	(0.003)	(0.003)				
ROA	0.109***	0.087***				
	(0.016)	(0.016)				
Cashflow	0.097***	0.067***				
	(0.017)	(0.018)				
Size		-0.841***		-0.874***		1.148***
		(0.167)		(0.263)		(0.227)
Cash		0.044***		0.016		0.004
		(0.006)		(0.013)		(0.008)
Leverage		-0.048***		-0.068***		-0.077***
		(0.005)		(0.006)		(0.006)
Cashflow_Std		-0.153***		-0.086		-0.114**
		(0.042)		(0.064)		(0.054)
Diversification		-0.417*		-0.409		-0.724***
		(0.237)		(0.359)		(0.259)
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y
N	36,505	36,466	46,610	37,690	43,902	35,697
R-squared	0.384	0.392	0.928	0.936	0.792	0.819

Panel B Columns (1) and (2) show a negative effect of a connection-creating bank merger on Capex. In Column (1), the Merger_Exp coefficient of -0.345 is statistically significant at the five percent level, indicating that firms affected by the merger reduce their investment by 14.4% compared with the mean Capex. The negative association between a connection-creating bank merger and investment barely changes when we control for Firm_Characteristics and Growth_Efficiency in Column (2). The Merger_Exp coefficient is -0.342 and is statistically significant at the five percent level, implying an investment reduction of 14.3% of the mean Capex.

Columns (3) and (4) of Table 2.2 display positive coefficients for Bank-Indsutry_HHI and Merger_Exp in the markup regressions. In Panel A, the coefficients of Bank-Indsutry_HHI are 5.238 and 5.015; both are statistically significant at the five percent level. They suggest that an increase of one standard deviation in Bank-Industry_HHI leads to an increase of around 2% in Markup compared to the mean. In Panel B, the coefficients of Merger_Exp are 0.526 and 0.448, which are statistically significant at the five and ten percent level, respectively. Similarly, these figures imply that a connection-creating bank merger is associated with an increase of around 2% in Markup relative to the mean.

Similarly, Columns (5) and (6) of Table 2.2 show a positive association between bank concentration and EBITDA. In Panel A, the coefficients of Bank-Indsutry_HHI are 4.830 and 5.825, which are statistically significant at the five percent level. They signify that an increase of one standard deviation in Bank-Industry_HHI leads to an increase in EBITDA ranging from 4% to 5% of the mean. In Panel B, the coefficients of Merger_Exp range from 0.387 to 0.413. Both estimates are statistically significant at the five percent level, showing that a connection-creating bank merger is associated with an increase in EBITDA ranging from 4% to 5% of the mean.

Overall, our findings support the conjecture that a common lender weakens the within-industry competition, which results in a reduction in investment and an improvement in the markup and profitability ratio of the involved firms. Also, we show that our results are robust to the subsample for the Post-Bubble period in Japan (1990-2007).[33]

[33] The results are not reported for brevity but available upon request.

Table 2.3: Relationship bank merger and corporate outcomes: channel

See Table 2.1 for the definition of variables. The dependent variables are Capex—capital expenditure divided by total assets; Markup—the difference between revenue and cost of goods sold divided by revenue; EBITDA—earnings before extraordinary items, interest, taxes, depreciation, and amortization divided by revenue; and RB_Loan_Growth—the growth in the loan the firm borrows from its top lender in the current year compared with the previous year. The independent variable of interest is Dir_Merger_Exp. Growth_Efficiency includes TobinQ, Sales_Growth, ROA, and Cashflow. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Growth_Efficiency and Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Robust standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA	(7) RB_Loan_Growth	(8) RB_Loan_Growth
Merger_Exp	-0.279*	0.110	0.431*	0.096	0.330*	0.070	-4.360***	-3.946***
	(0.154)	(0.170)	(0.259)	(0.278)	(0.192)	(0.209)	(1.349)	(1.367)
Dir_Merger_Exp	-0.620*	-0.677**	0.192	0.868*	0.834*	1.106**		-4.398*
	(0.349)	(0.343)	(0.501)	(0.520)	(0.488)	(0.497)		(2.529)
Dir_Presence	-0.097	-0.148	-0.407	-0.047	0.176	0.217		3.943**
	(0.205)	(0.218)	(0.305)	(0.253)	(0.245)	(0.247)		(1.666)
RB_Loan_Growth		0.015***		-0.004***		-0.005***		
		(0.001)		(0.001)		(0.001)		
TobinQ	-0.237**	-0.242					-5.618***	-5.620***
	(0.104)	(0.149)					(1.409)	(1.410)
Sales_Growth	0.015***	0.015***					0.026	0.026
	(0.003)	(0.004)					(0.031)	(0.031)
ROA	0.087***	0.073***					0.297**	0.299**
	(0.016)	(0.018)					(0.130)	(0.130)
Cashflow	0.067***	0.090***					-0.479***	-0.481***
	(0.018)	(0.022)					(0.151)	(0.151)
Size	-0.855***	-1.005***	-0.870***	-0.452	1.167***	1.526***	0.801	0.660
	(0.168)	(0.196)	(0.263)	(0.295)	(0.229)	(0.249)	(1.476)	(1.482)
Cash	0.044***	0.055***	0.015	0.031***	0.004	0.010	-0.268***	-0.263***
	(0.006)	(0.007)	(0.013)	(0.010)	(0.008)	(0.008)	(0.068)	(0.068)
Leverage	-0.048***	-0.048***	-0.068***	-0.066***	-0.077***	-0.071***	-0.406***	-0.406***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.047)	(0.047)
Cashflow_Std	-0.152***	-0.152***	-0.084	-0.110	-0.116**	-0.148**	0.022	-0.000
	(0.042)	(0.053)	(0.064)	(0.070)	(0.054)	(0.058)	(0.405)	(0.406)
Diversification	-0.431*	-0.350	-0.397	-0.644**	-0.706***	-0.940***	-0.500	-0.695
	(0.237)	(0.297)	(0.358)	(0.303)	(0.258)	(0.305)	(2.390)	(2.387)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	36,466	27,825	37,690	28,712	35,697	27,212	28,066	28,066
R-squared	0.392	0.431	0.936	0.936	0.819	0.831	0.193	0.194

The first six columns of Table 2.3 show the results of Equations (2.5) through (2.8), where we examine a channel through which a common lender affects corporate outcomes. The results for capital expenditure are presented in the first two columns and those for markup and profitability ratio in the next four. In odd columns, we report the regression results where we do not control for RB_Loan_Growth whereas in even columns we report the regression results in which we control for RB_Loan_Growth.

Columns (1) and (2) of Table 2.3 show a negative association between Dir_Merger_Exp and Capex. The coefficient in Column (1) is -0.620 and statistically significant at the ten percent level. The coefficient indicates a further reduction in the investment of a treated firm by 26% of the mean Capex when a treated firm has an ex-banker director on its board compared with a firm that does not. Our result shows that the board presence of an ex-banker director at the time of the merger contributes to the investment squeeze. When we control for RB_Loan_Growth in Column (2), Dir_Merger_Exp increases its explanatory power with a coefficient of -0.677, significant at the five percent level. Thus, our result suggests that an ex-banker director proactively advises the treated firm to cut investment, beyond coordinating the loan supply adjustment by the common lender. Interestingly, the coefficient of Merger_Exp in Column (2) switches its sign and becomes insignificant. This indicates that when we only control for the relationship bank's loan supply adjustment (one of the potential channels of common lender effects) the investment effect of a connection-creating bank merger is no longer significant in the absence of an ex-banker director. This result suggests that a common lender reduces its borrowers' investments mostly by the influence of an ex-banker director sitting on the firm's board, apart from by the adjustment of its loan supply.

We also find some evidence that Dir_Merger_Exp is positively associated with corporate markup and profitability ratio. Columns (3) and (4) present the result for Markup while Columns (5) and (6) show that for EBITDA. Regarding Markup, the coefficients of Dir_Merger_Exp range from 0.192 to 0.868, which are statistically significant at the ten percent level in Column (4). The reported coefficient in Column (4) implies that the markup of a treated firm further improves by around 4% of the mean in the presence of an ex-banker director compared with his absence. The result holds after controlling for the adjustment of loan supply by the relationship bank. We find similar results for EBITDA. Specifically, the coefficients of Dir_Merger_Exp in Columns (5) and (6) range from 0.834 to 1.106, significant at the ten and five percent level, respectively. They imply that EBITDA of a treated firm increases by around 10% of the mean in the presence of an ex-banker director on the board. Because the coefficients of Dir_Merger_Exp become even larger after controlling for the adjustment in the loan supply from the relationship bank, it highlights the importance of the director channel. The results are consistent with the active role of an ex-banker director in enhancing corporate markup and profitability ratio through directly advising the firm to cut investment.

To further investigate the contribution of an ex-banker director in improving the markup and profitability ratio of a treated firm, we re-run Equation (2.8) while restricting our sample firms to those whose loan from the top lender accounts for greater than a certain fraction of total interest-bearing debt. The results of these analyses are reported in Table 2.4. The estimated coefficients on Dir_Merger_Exp are all positive and statistically significant. The reported coefficients in markup regressions vary from 0.941 to 1.388, which correspond to the range between around 4% and 6% of the mean markup. Similarly, the reported coefficients in EBITDA regressions vary from 1.262 to 1.576, which correspond to the range between around 14% and 18% of the mean EBITDA. These coefficients are larger than their counterparts in Table 2.3. The results imply that the role of an ex-banker director in improving the treated firm's markup and profitability ratio becomes more pronounced when the stake of the relationship bank in its borrower is larger.

Further, to highlight the difference between an executive from a non-executive director, where the former has representative rights whereas the latter does not. We re-run Equations (2.5) through (2.8) while controlling for the variable associated with the presence of a non-executive director formerly affiliated with either merging bank, Non_Executive_Dir_Merger_Exp, which we define analogously to Dir_Merger_Exp. Specifically, Non_Executive_Dir_Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger conditional on the presence of a non-executive director but the absence of an executive director formerly affiliated with either merging bank. Because we use the presence of an executive director formerly affiliated with either merging bank to construct Dir_Merger_Exp, the connection-creating bank mergers counted by Non_Executive_Dir_Merger_Exp and Dir_Merger_Exp are mutually exclusive. Whereas Dir_Merger_Exp captures the influence of an executive ex-banker on the treated firm's outcome, Non_Executive_Dir_Merger_Exp captures that of a non-executive one. Controlling for both allows us to examine conditions under which an ex-banker can exert his influence on the treated firm's outcome.[34]

[34] Dir_Presence = 1 implies Non_Executive_Dir_Presence = 0. Therefore, imputing Dir_Presence allows us to impute Non_Executive_Dir_Presence automatically. After this imputation, we impute missing values of Non_Executive_Dir_Presence before 1992 as follows: (i) impute zero for firms if their Non_Executive_Dir_Presence was always zero and they existed in our sample period for over 15 years; and (ii) impute one for firms if their Non_Executive_Dir_Presence was always one and they existed in our sample period for over 15 years.

Table 2.4: Relationship bank merger and markup/profitability ratio: channel (alternative specification)

See Table 2.1 for the definition of variables. The dependent variables are Markup—the difference between revenue and cost of goods sold divided by revenue and EBITDA—earnings before extraordinary items, interest, taxes, depreciation, and amortization divided by revenue. The independent variable of interest is Dir_Merger_Exp. Columns (1), (2), (5), and (6) present the results for firms whose loan from the top lender (RB_Loan) accounts for greater than 10% of total interest-bearing debt. Columns (3), (4), (7), and (8) show the results for firms whose RB_Loan accounts for greater than 20% of total interest-bearing debt. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Robust standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	RB_Loan >= 10%		RB_Loan >= 20%		RB_Loan >= 10%		RB_Loan >= 20%	
	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA	(7) EBITDA	(8) EBITDA
Merger_Exp	0.266	0.239	-0.006	-0.080	0.057	0.036	-0.077	-0.128
	(0.278)	(0.286)	(0.311)	(0.314)	(0.210)	(0.215)	(0.235)	(0.241)
Dir_Merger_Exp	0.941*	1.011*	1.251**	1.388**	1.262**	1.321***	1.468***	1.576***
	(0.520)	(0.524)	(0.589)	(0.593)	(0.494)	(0.500)	(0.532)	(0.540)
Dir_Presence	-0.160	-0.165	-0.083	-0.102	0.131	0.131	0.143	0.091
	(0.234)	(0.235)	(0.253)	(0.251)	(0.246)	(0.248)	(0.276)	(0.279)
RB_Loan_Growth		-0.004***		-0.003***		-0.006***		-0.005***
		(0.001)		(0.001)		(0.001)		(0.001)
Size	-0.719**	-0.690**	-0.854**	-0.878**	1.391***	1.451***	1.185***	1.185***
	(0.291)	(0.291)	(0.361)	(0.360)	(0.250)	(0.256)	(0.315)	(0.322)
Cash	0.036***	0.032***	0.033***	0.029**	0.016*	0.012	0.014	0.007
	(0.010)	(0.010)	(0.012)	(0.013)	(0.009)	(0.009)	(0.010)	(0.010)
Leverage	-0.066***	-0.068***	-0.068***	-0.068***	-0.068***	-0.070***	-0.070***	-0.070***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.006)
Cashflow_Std	-0.161**	-0.159**	-0.144*	-0.138*	-0.186***	-0.198***	-0.183***	-0.200***
	(0.063)	(0.064)	(0.075)	(0.074)	(0.054)	(0.056)	(0.061)	(0.062)
Diversification	-0.613**	-0.752**	-0.518	-0.632*	-0.844***	-0.900***	-0.929***	-0.916***
	(0.300)	(0.303)	(0.350)	(0.354)	(0.293)	(0.303)	(0.315)	(0.324)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y	Y	Y
N	26,530	25,848	17,439	16,882	25,148	24,490	16,581	16,045
R-squared	0.938	0.939	0.944	0.944	0.816	0.818	0.827	0.832

The results are presented in Table 2.5. The coefficients on Non_Executive_Dir_Merger_Exp are negative in Column (1) and positive in Column (2); both are insignificant. Notice that these coefficients are much smaller than those of Dir_Merger_Exp in magnitude, implying a trivial incremental effect of having a non-executive ex-banker on the board on the treated firm's investment. Similarly, the coefficients in Columns (3)-(6) are positive, though insignificant, suggesting some incremental effect of having a non-executive ex-banker on the firm's board on the treated firm's markup and profitability ratio. However, their magnitudes are much smaller than those of Dir_Merger_Exp. The results imply that a common lender hardly affects corporate policies through a non-executive ex-banker. Conversely, Dir_Merger_Exp maintains its effects on corporate outcomes as its coefficients are quite similar to the corresponding estimates in Table 2.3. For example, if a treated firm has two ex-bankers on the board, one executive and one non-executive, the impact of a common lender on the firm is predominantly channeled via the executive one. The result suggests that a non-executive ex-banker might not have sufficient power to affect management and does not significantly contribute to the investment shrinkage or the improvement in the treated firm's markup and profitability ratio.

In general, our results are consistent with the debate over the influence of an ex-banker on a firm's management. Though Kaplan and Minton (1994) emphasize the importance of an ex-banker in the monitoring and disciplinary role of the relationship bank, Miwa and Ramseyer (2006) doubt the contribution of an ex-banker to the relationship bank's control over the management of the borrower firm. Our results are consistent with both in the sense that an ex-banker is important only if he has representative rights that allow him to exert influence on firm policies.

In summary, we find compelling evidence that an ex-banker director with sufficient power to affect a firm's management contributes to the effects of a connection-creating bank merger on corporate outcomes. Our results suggest that the ex-banker director plays a significant role beyond the role in coordinating the loan supply adjustment of the relationship bank after the announcement of its merger. A common lender can affect a borrower's investment through the inclusion of investment restriction covenants in loan contracts. In that case, an ex-banker director may play an active role in advising the firm to include those covenants and in monitoring the firm to ensure covenant compliance. However, this does not mean we reject the possibility that the loan supply adjustment by a relationship bank contributes to common lender effects. Consistent with this possibility, the estimated coefficient on RB_Loan_Growth in the investment regression (Table 2.3, Column (2)) is positive and that in the markup and profitability ratio regressions (Table 2.3, Columns (4) and (6)) is negative, suggesting that a decrease in the growth of credit from the firm's relationship bank may reduce its investment and improve its markup and profitability ratio.

Table 2.5: Relationship bank merger and corporate outcomes: channel (non-executive versus executive directors)

See Table 2.1 for the definition of variables. The dependent variables are Capex—capital expenditure divided by total assets; Markup—the difference between revenue and cost of goods sold divided by revenue; and EBITDA—earnings before extraordinary items, interest, taxes, depreciation, and amortization divided by revenue. The independent variables of interest are Dir_Merger_Exp and Non_Executive_Dir_Merger_Exp. Non_Executive_Dir_Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger conditional on the presence of a non-executive director but the absence of an executive one formerly affiliated with either merging bank. Non_Executive_Dir_Presence is a dummy equal to one conditional on the presence of a non-executive director but the absence of an executive one formerly affiliated with the firm's relationship bank. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Growth_Efficiency and Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Standard errors clustered at the firm level are in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA
Merger_Exp	-0.313*	0.079	0.247	-0.027	0.170	-0.034
	(0.172)	(0.187)	(0.274)	(0.305)	(0.201)	(0.213)
Non_Executive_Dir_Merger_Exp	-0.018	0.037	0.297	0.313	0.316	0.317
	(0.213)	(0.215)	(0.402)	(0.360)	(0.266)	(0.267)
Non_Exuective_Dir_Presence	0.038	0.076	-0.065	0.103	0.056	0.144
	(0.149)	(0.158)	(0.190)	(0.189)	(0.154)	(0.157)
Dir_Merger_Exp	-0.546	-0.627*	0.355	1.225**	0.934*	1.237**
	(0.376)	(0.373)	(0.537)	(0.533)	(0.512)	(0.518)
Dir_Presence	-0.067	-0.130	-0.235	0.333	0.444	0.565**
	(0.244)	(0.267)	(0.385)	(0.304)	(0.274)	(0.281)
RB_Loan_Growth		0.015***		-0.004***		-0.005***
		(0.001)		(0.001)		(0.001)
TobinQ	-0.185*	-0.134				
	(0.111)	(0.170)				

Table 2.5 continued

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA
Sales_Growth	0.014***	0.014***				
	(0.003)	(0.004)				
ROA	0.077***	0.065***				
	(0.016)	(0.019)				
Cashflow	0.058***	0.078***				
	(0.018)	(0.023)				
Size	-0.924***	-1.205***	-1.124***	-0.638*	0.919***	1.260***
	(0.195)	(0.236)	(0.307)	(0.344)	(0.251)	(0.293)
Cash	0.049***	0.064***	0.015	0.034***	0.009	0.010
	(0.006)	(0.008)	(0.016)	(0.011)	(0.009)	(0.009)
Leverage	-0.052***	-0.049***	-0.070***	-0.066***	-0.081***	-0.073***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Cashflow_Std	-0.151***	-0.144**	-0.027	-0.030	-0.086	-0.098
	(0.046)	(0.059)	(0.067)	(0.077)	(0.059)	(0.063)
Diversification	-0.388	-0.277	-0.348	-0.655**	-0.660**	-0.933***
	(0.240)	(0.305)	(0.357)	(0.312)	(0.262)	(0.312)
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y
N	32,215	24,002	33,305	24,768	31,558	23,478
R-squared	0.387	0.426	0.938	0.939	0.825	0.836

Finally, to fully examine this loan supply channel, we run Equation (2.9) in which RB_Loan_Growth is the dependent variable to examine the adjustment in the loan supply from the firm's relationship bank after the announcement of its merger. Table 2.3, Columns (7) and (8) report the regression results. Both columns show that the coefficients of Merger_Exp are negative and statistically significant at the one percent level. The coefficient of Dir_Merger_Exp in Column (8) is negative and statistically significant at the ten percent level. This result suggests that the growth of credit from the relationship bank not only decreases after the merger announcement but also decreases further in the presence of an ex-banker director compared with his absence. Taken together, our results are consistent with the possibility that an ex-banker director is involved in the relationship bank's loan supply, which ultimately squeezes investment and improves the markup and profitability ratio of the treated firm.[35] We thus suggest that an ex-banker director can strengthen the common lender effects on corporate investment, markup, and profitability not only through his direct advice to the treated firm's management but also through his influence on the loan supply adjustment by the common lender.

2.4. Additional Analysis

2.4.1. Common Lender or Confounding Common Owner?

In Japan, relationship banks are often the owners of borrowers. Firms may have a common owner in addition to a common lender when their relationship banks merge. This dual-holding practice has been declining since the 1990s because of the globalization of financial markets, but relationship banks often held their borrowers' stocks during our sample period. Although bank ownership is heavily regulated,[36] we investigate the possibility that confounding common ownership might explain the effects of a shared lender we identified in the previous section.

For this purpose, we assess the impacts of bank concentration on research and development (R&D) expenses and cash holding. If bank concentration exerts a common owner effect instead of a common lender effect, treated firms should use resources saved from reduced investments for the interests of shareholders. Because shareholders are residual claimants, they prefer to capture upsides from innovation rather than allow firms to accumulate cash. On the other hand, lenders want borrowers to have cash cushions to protect themselves against defaults. We therefore predict

[35] We also find that the coefficient of Dir_Presence is positive and statistically significant at the five percent level. The presence of an ex-banker director is therefore positively associated with the growth of credit from the relationship bank unless a connection-creating bank merger occurs. This result is consistent with the view that an ex-banker director helps a firm maintain a good relationship with its lead bank to keep receiving credit.

[36] Bank share ownership is mainly regulated by the Antitrust Law and the Banking Act which set the upper limit of 5% of outstanding shares (with exceptions such as the ownership of venture firms). It is also regulated based on the size of bank capital by the Large Credit Supply Regulation (under the Banking Act) and the Act on Limitation on Shareholding by Banks and Other Financial Institutions. Because of these regulations, confounding impacts of common ownership may be limited.

that treated firms would increase R&D, instead of Cash, in response to a connection-creating bank merger, if it exerted a common owner effect.[37] Analogously, R&D, instead of Cash, should be positively associated with bank concentration at the industry. The opposite would occur if it exerted a common lender effect.

Keeping the same covariates, we estimate Equations (2.1) and (2.3), while replacing the dependent variable by R&D, and Equations (2.2) and (2.4), while replacing the outcome by Cash. Here, R&D is measured as research and development expenses divided by total assets (as a percentage).[38] Table 2.6 reports the results for our models of R&D and Cash in the first two and last two columns, respectively. Panel A reports the results with the industry-level bank concentration and Panel B shows the results with the connection-creating bank mergers. We find that the estimated coefficients of Bank-Industry_HHI and Merger_Exp in the R&D regressions are all negative. Particularly, the estimated coefficients of Bank-Industry_HHI in Columns (1) and (2) of Panel A are around -1.16 and statistically significant at the one percent level, implying that one standard deviation increase in Bank-Industry_HHI is associated with a decrease in R&D by around 4% of the mean. We also find that the estimated coefficients of Bank-Industry_HHI and Merger_Exp in the Cash regressions are all positive. Particularly, we find that the estimated coefficient of Merger_Exp in Column (4) of Panel B, where we control for industry by year fixed effects as well as firm characteristics, is 0.301 and statistically significant at the five percent level. This result implies that after a connection-creating bank merger, treated firms increase their cash holdings by 2.4% of the mean. Overall, our results suggest that firms use saved resources from anti-

[37] This prediction is also consistent with López and Vives (2019).

[38] The mean and standard deviation of the variable are 2.02 and 2.24, respectively.

competitive practices for the interests of debt holders and our estimates for the impacts of shared lending are driven by common lenders rather than common owners.[39]

Table 2.6: Relationship bank merger and other corporate outcomes

See Table 2.1 for the definition of variables. The dependent variables are R&D— research and development expenses divided by total assets and Cash— the ratio of cash and deposits to total assets. The independent variables of interest are Bank-Industry_HHI in Panel A and Merger_Exp in Panel B. Growth_Efficiency includes TobinQ, Sales_Growth, ROA, and Cashflow. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Growth_Efficiency and Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Robust standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) R&D	(2) R&D	(3) Cash	(4) Cash
Panel A				
Bank-Industry_HHI	-1.165***	-1.163***	1.159	0.365
	(0.362)	(0.357)	(1.851)	(0.875)
TobinQ	-0.091**	-0.115**		
	(0.041)	(0.049)		
Sales_Growth	0.001	0.001		
	(0.001)	(0.001)		
ROA	-0.000	-0.002		
	(0.003)	(0.003)		
Cashflow	0.014***	0.013**		
	(0.005)	(0.005)		
Size		0.030		-1.015***
		(0.082)		(0.160)
Cash		-0.002		0.620***
		(0.003)		(0.010)
Leverage		-0.003		0.002
		(0.002)		(0.003)
Cashflow_Std		-0.008		0.055
		(0.015)		(0.037)
Diversification		-0.009		0.495**
		(0.082)		(0.251)
Firm FE	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y
N	10,901	10,901	43,758	37,829
R-squared	0.938	0.938	0.641	0.797
Panel B				
Merger_Exp	-0.033	-0.029	0.489	0.301**
	(0.089)	(0.090)	(0.307)	(0.137)
TobinQ	-0.096**	-0.133**		
	(0.047)	(0.054)		
Sales_Growth	0.001*	0.002*		
	(0.001)	(0.001)		

[39] Another test for common owner effects is to control for the existence of common ownership in baseline models. The results are quantitatively similar when we control for whether a relationship bank also hold shares of its borrowers.

Table 2.6 continued

	(1) R&D	(2) R&D	(3) Cash	(4) Cash
ROA	-0.000	-0.002		
	(0.003)	(0.003)		
Cashflow	0.014**	0.012**		
	(0.006)	(0.006)		
Size		-0.020		-1.135***
		(0.091)		(0.180)
Cash		-0.003		0.609***
		(0.003)		(0.010)
Leverage		-0.004**		-0.002
		(0.002)		(0.004)
Cashflow_Std		-0.021		0.053
		(0.015)		(0.042)
Diversification		-0.016		0.446
		(0.092)		(0.284)
Firm FE	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y
N	10,855	10,855	46,760	37,798
R-squared	0.942	0.942	0.667	0.814

2.4.2. Financially Distressed Firms

A common lender is distinct from a common owner in that its incentive to coordinate its investees becomes stronger when the investees are financially distressed. If a common lender's borrowers are distressed, the values of loans granted to them become more sensitive to their fundamentals. The common lender, therefore, benefits more from the coordination of its distressed borrowers than from its healthy ones. We expect the common lender promotes anti-competitive practices across distressed firms more aggressively. Specifically, we anticipate that common lender effects on investment, markup, and profitability ratio become more pronounced for financially distressed firms.

To examine this premise, we first estimate models that are similar to Equations (2.1) and (2.2) while adding the interaction Bank_Industry_HHI * Distress where Distress is a dummy that equals one if, in the previous year, the debt-to-EBITDA ratio of the firm was in the top sector tercile.[40] Debt is measured as the total of long- and short-term debt obligations. The coefficient on the interaction indicates the incremental impact of the industry-level bank concentration on the outcome of a distressed firm relative to that of a healthy one.

Second, we estimate models that are similar to Equations (2.5) and (2.6) while replacing Dir_Merger_Exp with Distress_Merger_Exp and Dir_Presence with Distress, respectively. Distress_Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger conditional on being financially distressed in the previous year (Distress = 1).[41] This variable captures the incremental effect of a connection-creating bank merger on the outcome of a distressed firm relative to that of a healthy one.

As a common lender has a stronger incentive to coordinate its borrowers that are closer to default, we expect stronger common lender effects on distressed firms' investment, markup, and profitability ratio. In particular, regarding the investment regressions, we expect negative coefficients on the interaction Bank_Industry_HHI * Distress and Distress_Merger_Exp. For the markup and profitability ratio regressions, we expect positive coefficients on the interaction Bank_Industry_HHI * Distress and Distress_Merger_Exp.

Table 2.7 presents the regression results. Panel A depicts the results with the industry-level bank concentration and Panel B shows the results with the connection-creating bank mergers. We report the results for our models of investment, markup, and profitability ratio in the first two, middle two, and last two columns, respectively. In Columns (1) and (2) of Panel A, the coefficients of Bank_Industry_HHI * Distress vary from -3.302 to -3.236 and are statistically significant at the

[40] Chava et al. (2019) used the similar definition of financial distress. The mean and standard deviation of the debt-to-EBITDA ratio are 5.90 and 10.86, respectively, after being winsorized at 0.5% and 99.5%.
[41] The mean and standard deviation of Distress_Merger_Exp are 0.07 and 0.26, respectively. The mean of Distress_Merger_Exp is 44% of that of Merger_Exp.

one percent level. When firms face one standard deviation increase in Bank_Industry_HHI, distressed ones reduce their investments by around 11% of the sample mean more than healthy firms do, indicating an incremental negative effect of bank concentration on corporate investment for distressed firms. Similarly, in Panel B, the coefficients of Distress_Merger_Exp range from -0.385 to -0.384 and are statistically significant at the five or ten percent level. The coefficients imply that, after being affected by a connection-creating bank merger, distressed firms squeeze their investments by around 16% of the sample mean more than healthy ones. In the next four columns of Panel A, the coefficients of the interaction Bank_Industry_HHI * Distress are all positive and statistically significant at the one percent level. When Bank_Industry_HHI increases by one standard deviation, Markup of distressed firms improves by around 2% of the sample mean, and their EBITDA increases by at least 5% of the sample mean, relative to that of healthy ones. In Panel B, the coefficients of Distress_Merger_Exp are all positive, which is consistent with the positive coefficients of Bank_Industry_HHI * Distress, although they are overall weaker than corresponding coefficients in Panel A.[42] The coefficient of Distress_Merger_Exp in the last column is 0.483 and still statistically significant at the five percent level, implying that, after a connection-creating bank merger, treated firms witness a further increase of EBITDA, which is around 5% of the sample mean, if they are financially distressed.

These results demonstrate that the effects of bank concentration at the industry level and a connection-creating bank merger on corporate investment, markup, and profitability ratio are greater for financially distressed firms than for healthy ones. The results in Table 2.7 are consistent

[42] Note that we control for industry by year fixed effects in Panel B, but we do not in Panel A. The difference in the statistical significance of Bank_Industry_HHI * Distress and Distress_Merger_Exp suggests that cross-industry variations substantively contribute to the identification of Bank_Industry_HHI * Distress.

with our prediction that common lender effects become more pronounced in financially distressed firms.

Table 2.7: Bank concentration and corporate outcomes: financial distress

See Table 2.1 for the definition of variables. The dependent variables are Capex—capital expenditure divided by total assets; Markup—the difference between revenue and cost of goods sold divided by revenue; and EBITDA—earnings before extraordinary items, interest, taxes, depreciation, and amortization divided by revenue. The independent variables of interest are the interaction Bank-Industry_HHI*Distress in Panel A and Distress_Merger_Exp in Panel B. Distress_Merger_Exp is the cumulative frequency of being affected by a connection-creating bank merger conditional on being financially distressed in the previous year. Distress is a dummy variable equal to one if, in the previous year, the debt-to-EBITDA ratio of a firm was in the top sector tercile where debt is measured as the total of long- and short-term debt obligations. Growth_Efficiency includes TobinQ, Sales_Growth, ROA, and Cashflow. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Growth_Efficiency and Firm_Characteristics are one-year lagged values. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Robust standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

	(1) Capex	(2) Capex	(3) Markup	(4) Markup	(5) EBITDA	(6) EBITDA
Panel A						
Bank-Industry_HHI	-2.149*	-2.954**	2.901	2.433	2.389	2.611
	(1.148)	(1.165)	(2.125)	(2.047)	(1.894)	(1.960)
Bank-Industry_HHI * Distress	-3.302***	-3.236***	5.656***	6.299***	6.357***	8.630***
	(0.993)	(0.995)	(1.881)	(1.889)	(1.699)	(1.766)
Distress	0.210	0.522***	-2.385***	-1.715***	-2.648***	-2.371***
	(0.180)	(0.183)	(0.298)	(0.310)	(0.278)	(0.295)
Growth_Efficiency	Y	Y	N	N	N	N
Firm_Characteristics	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
N	35,390	35,349	42,277	36,515	39,856	34,564
R-squared	0.315	0.323	0.918	0.925	0.775	0.792
Panel B						
Merger_Exp	-0.151	-0.162	0.388	0.321	0.354*	0.259
	(0.163)	(0.165)	(0.243)	(0.239)	(0.211)	(0.205)
Distress_Merger_Exp	-0.384**	-0.385*	0.159	0.208	0.147	0.483**
	(0.195)	(0.200)	(0.373)	(0.353)	(0.252)	(0.242)
Distress	-0.368***	-0.019	-1.190***	-0.563***	-1.359***	-0.793***
	(0.088)	(0.088)	(0.113)	(0.125)	(0.101)	(0.112)
Growth_Efficiency	Y	Y	N	N	N	N
Firm_Characteristics	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y
N	35,340	35,301	42,275	36,473	39,847	34,509
R-squared	0.392	0.398	0.934	0.939	0.812	0.827

2.4.3. Heterogeneous Investment Effect

We next examine whether the investment effect is heterogeneous across firms in different business environments. For this purpose, we concentrate on the interaction between Merger_Exp and the indicator for the presence of growth opportunities. We create an indicator variable Proxy based on whether the variable of interest that reflects the firm's growth opportunities is above the sector median. We use Tobin's Q, ROA, and Sales_Growth as the variables that signify growth opportunities. For each of these variables, we estimate:

$$Capex_{ijt} = \beta_1 Merger\_Exp_{ijt} + \beta_2 Merger\_Exp_{ijt} * Proxy_{ijt-1} + \beta_3 Proxy_{ijt-1} + \beta_4 Z_{ijt-1} + \alpha_i + \gamma_{jt} + \delta_{bt} + \varepsilon_{ijt}. \tag{2.10}$$

Under this setting, the coefficient of the interaction between Merger_Exp and the indicator (Merger_Exp*Proxy) captures the incremental effect of a connection-creating bank merger on the firm's investment when the firm has growth opportunities.

Table 2.8 reports the estimates from equation (10). Columns (1) and (2) present the results when we use Tobin's Q for the proxy, Columns (3) and (4) use ROA, and Columns (5) and (6) use Sales_Growth. We find that the estimated coefficients of Merger_Exp * Proxy range from -0.203 to 0.156 across proxies and specifications; none of them are statistically significant at the ten percent level. This result suggests that a connection-creating bank merger does not disproportionately increase the investment of a treated firm with greater growth opportunities. Instead, the investment reduction by a common lender seems uniform in magnitude across firms facing various levels of growth opportunities.

Table 2.8: Relationship bank merger and corporate investment sensitivity to growth opportunities

See Table 2.1 for the definition of variables. The dependent variable is Capex—capital expenditure divided by total assets. The independent variable of interest is the interaction between Merger_Exp and an indicator for growth opportunities (Proxy). Growth_Efficiency includes TobinQ, Sales_Growth, ROA, and Cashflow. Firm_Characteristics includes Size, Cash, Leverage, Cashflow_Std, and Diversification. Proxy is the indicator for TobinQ, ROA, and Sales_Growth being greater than the sector median in the first two, the middle two, and the last two columns, respectively. Growth_Efficiency and Firm_Characteristics are one-year lagged. All potentially unbounded variables are winsorized at 0.5% and 99.5%. Standard errors clustered at the firm level are reported in parentheses. The number of observations and R-squared are given in the last two rows. Statistical significance (two-sided) at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Proxy:	TobinQ > Sector Median		ROA > Sector Median		Sales_Growth > Sector Median	
	(1) Capex	(2) Capex	(3) Capex	(4) Capex	(5) Capex	(6) Capex
Merger_Exp	-0.311**	-0.296*	-0.398**	-0.382**	-0.348**	-0.359**
	(0.157)	(0.157)	(0.168)	(0.168)	(0.166)	(0.166)
Merger_Exp * Proxy	-0.134	-0.203	0.156	0.113	0.008	0.041
	(0.195)	(0.198)	(0.164)	(0.163)	(0.156)	(0.156)
Proxy	0.168*	-0.216**	0.305***	0.134	0.441***	0.418***
	(0.086)	(0.092)	(0.083)	(0.083)	(0.078)	(0.078)
Growth_Efficiency	Y	Y	Y	Y	Y	Y
Firm_Characteristics	N	Y	N	Y	N	Y
Firm FE	Y	Y	Y	Y	Y	Y
RB x Year FE	Y	Y	Y	Y	Y	Y
Industry x Year FE	Y	Y	Y	Y	Y	Y
N	36,505	36,466	36,505	36,466	36,505	36,466
R-squared	0.384	0.392	0.384	0.392	0.385	0.392

2.5.Conclusion

We present results that show a common lender weakens within-industry competition. A common lender brings involved firms a reduction in investment and improved markup and profitability ratio. We provide evidence that an ex-banker director on the board facilitates the common lender effect on corporate investment.

Our study suggests that a series of connection-creating bank mergers has induced new coordinating relationships between firms in Japan since the end of the 1990s. These relationships were also observable from alliances and merger talks between newly connected firms in the same industry. For example, a chemical giant in Japan, Sumitomo Chemical, attempted to merge with another giant, Mitsui Chemical, following the merger between their relationship banks (Sumitomo and Sakura) forming SMBC (Sumitomo Mitsui Banking Corporation), although the merger did not go through. In the steel industry, NKK whose relationship bank was Fuji, and Kawasaki Steel whose relationship bank was DKB formed a strategic alliance, following the merger of their relationship banks forming Mizuho.[43]

Thus, new relationships arising from post-merger bank relations might be surprising for commentators who suspected that bank mergers dissolved business groups (i.e., keiretsu) that had traditionally bound lead banks, trading houses, and industrial firms into loosely linked conglomerates in Japan.[44] It is, however, also important to recognize that, during the late 1990s and 2000s, Japanese companies — many of which competed in capital-intensive businesses that suffered from severe overcapacity — were slowly reinventing themselves by selecting and concentrating on a few core businesses (Economist, 2000). Under such a business environment and due to the consolidation of the Japanese banking sector, we consider newly merged banks to play a crucial role in the horizontal coordination of firms in an industry, revealing the importance of their role even if the traditional business groups might have lost their power.

[43] See Economist (2000) for more detail.
[44] For example. Lincoln and Shimotani (2010) argue that keiretsu no longer constitutes a significant topographic feature of the Japanese economic landscape, although it was influential until the early 2000s.

3. Chapter 3: Polarized Corporate Boards

3.1. Introduction

Even a cursory glance at the evolution of politics in the United States (U.S.) over the past few decades reveals a significant increase in polarization—the views of the members of the Democratic and Republican parties in Congress have become increasingly divergent. At the same time, polarization of the elites has spilled over into the general public, impacting how individuals view and evaluate people affiliated with the opposing political party. Media reports suggest that polarization has penetrated social networks in a significant way, with almost half of the Americans polled reporting that they had an argument with someone in their social circle (family, friend, co-worker, etc.) in the lead up to the 2016 presidential election.[45] The result has been a breakdown in communication and growing animosity toward people from the opposite side of the political spectrum, a phenomenon known as *affective* polarization (e.g., Iyengar, Sood, and Lelkes, 2012; Iyengar, Lelkes, Levedusky, Malhotra, and Westwood, 2019; Mason, 2013; 2015).

An important body of literature has emerged to provide understanding of the causes and consequences of polarization.[46] While the effects of polarization in Congress are well documented—policy gridlock, government shutdowns and so on—we know much less about how *mass* polarization of the general public can influence economic outcomes. Anecdotal evidence suggests that the economic impact of polarization may be large. For example, data from Pew Research (2016) show that more than half of the American public are frustrated, angry, or afraid of

[45] See Edwards-Levy (2016).

[46] For example, increasing polarization has been attributed to media bias (Bernhardt, Krasa, and Polborn, 2008; Martin and Yurukoglu, 2017), the internet (Praiser, 2011; Farrell, 2012; Gabler, 2016; Haidt, 2016; Sunstein, 2001; 2009; 2017), trade (Dorn, Hanson, and Majlesi, 2020), and income inequality (McCarty, Poole, and Rosenthal, 2003) among other things. On the consequences, papers have shown, for example, that polarization influences the size of government (Linqvist and Ostling, 2010), overall economic performance (Frye, 2002) and more recently, the effectiveness of government social distancing rules during the COVID-19 pandemic (Makridis and Rothwell, 2020).

individuals affiliated with the opposing party. Even worse, 45% of Republicans and 41% of Democrats think the other party is so dangerous that it is a threat to the nation.

In this paper, we add to the debate on the economic costs associated with polarization by examining the interplay between directors of a board in public firms. The corporate board is an ideal setting to examine the economic costs associated with political polarization for at least two reasons. First, directors, as a group, are influential individuals with significant exposure to the political environment. For example, many are current CEOs of large firms themselves or former government officials (Kang and Zhang, 2018). Thus, any polarization observed in the general public is likely amplified in this group, with potentially greater consequences, due to the significant resources they control.

Second, board members perform their fiduciary duties as a team, which involves collective interaction with the management and, importantly, collective decision making. Thus, frictions due to differing political views will manifest in how the boards of directors carry out their monitoring and advising roles (e.g., Adams and Ferreira, 2007; Adams, Hermalain, and Weisbach, 2010). Moreover, how well these functions are performed can have significant implications for corporate policy and performance (e.g., Masulis, Wang and Xie, 2009; Field, Lowry, and Mkrtchyan, 2013; Hauser, 2018; Bernile, Bhagwat, and Yonker, 2018; Liu, Masulis, Low, and Zhang, 2020).

To provide evidence on the effectiveness of a board of directors, we focus on an important decision made by the board: the decision to retain or fire a CEO. Not only is removing the top executive considered one of the most aggressive actions taken, but it is also one of the few observable measures of the effectiveness of corporate governance (Weisbach, 1988; Hermalin, 2005; Hermalin, and Weisbach, 2003; Jenter and Kanaan, 2015; Guo and Masulis, 2015; You, Zhang, and Zhang, 2018).

The theoretical prediction for the relation between polarization and the turnover–performance sensitivity is unclear. On the one hand, the literature argues that given a set of facts, political polarization leads not only to differences in opinion, but also to differences in the perception of these facts or even differing beliefs about the facts themselves (Alesina, Miano, and Stantcheva, 2020; Bartels, 2002; Conover, Feldman, and Knight, 1987; Jerit and Barabas, 2012). As a result, polarization increases the degree of divergent views and chance of conflict among board members which inhibit the collective decision-making process of the board and hinder its advisory and monitoring functions. This, in turn, slows the responsiveness of the board to remove an underperforming CEO: a *reduction* in the CEO turnover–performance sensitivity. This mechanism is consistent with what we have witnessed in American politics in recent history—polarization leading to a breakdown in bi-partisanship in Congress (McCarty, 2011) and stagnation in policy making (Kelly, 2020). We refer to this prediction as the *boardroom stalemate hypothesis*.

An alternative hypothesis is that the polarization generates a source of distrust or dislike among board members and between the board and the CEO (e.g., Iyengar et al., 2012), leading to a breakdown in communication and flow of soft information in the boardroom (Adams and Ferreira, 2007). Consistent with this, survey evidence from the American Psychological Association (2016) cites that in the lead up to the 2016 election, one-quarter of workers reported being stressed, argumentative, and less productive because of political discussions on the job. Similarly, a poll conducted by the Society for Human Resources (HR) Management reports that a quarter of HR managers surveyed cited tension, hostility, or arguments among co-workers because of political affiliation in 2016.[47] More precisely, polarization can have two (non-mutually

[47] As reported in "Politics at the office: How to manage the conversation", by Richard Sine, October 3, 2016, Forbes. Available at https://www.forbes.com/sites/adp/2016/10/03/politics-at-the-office-how-to-manage-the-conversation/?sh=71124593707b (accessed December 15, 2021).

exclusive) effects on the flow of information in the boardroom. First, the CEO may share less soft information with board and vice-versa. Likewise, board members may share less soft information with each other. Second, when receiving information from the CEO or from another board member who has differing political views, directors may discount or simply ignore this information. Since a less friendly boardroom hinders the production of soft information, when the board is required to make a decision about the CEO, it must rely more on hard information such as stock market or accounting performance. As a consequence, the turnover–performance sensitivity will be *higher* in firms with more polarized boards. We refer to this hypothesis as the *information destruction hypothesis*.

To measure polarization between board members, that is, the distance between their individual political views, we need to know where they sit on the political spectrum beyond simply knowing whether they vote red or blue. We therefore use data on personal contributions to *individual* members of Congress to measure the political ideology of individual members of the board, including the CEO.[48] To construct a firm-level measure of polarization, we calculate the standard deviation across individual board members' political ideology.

We examine the link between polarization and CEO turnover–performance sensitivity and find robust evidence that polarization in the boardroom significantly reduces turnover–performance sensitivity. The economic magnitude of the effect is large. Our results show that a 1% fall in industry-adjusted returns in the prior year increases the likelihood of CEO turnover by approximately 125% relative to the sample mean turnover rate of 2%. In other words, the forced turnover rate increases from 2% to approximately 4.5%. However, a one-standard-deviation increase in polarization of the board reduces this sensitivity by 1.3%—the same 1% fall in industry

[48] Our results are not sensitive to the exclusion of the CEO as shown and discussed in Table 3.

adjusted returns now only increases the likelihood of forced turnover by 1.2%. These findings suggest that political frictions introduce inefficiencies into board governance.

To alleviate endogeneity concerns, we apply two approaches. First, prior work establishes that the local supply of directors has significant effects on board structure and independent director representation (Knyazeva, Knyazeva, and Masulis, 2013; Kang et al., 2018). Since board polarization is a function of the political views of board members (i.e., board composition), we argue that the supply of local directors also has a direct impact on firm polarization. We construct instruments to capture the degree of local polarization based on the local director pool (i.e., the number of local nonfinancial firms). Specifically, we instrument for polarization using the average polarization of local firms and perform an instrumental variable analysis. The results from this analysis confirm our main finding, though the economic magnitude of the effect is smaller than the Ordinary Least Squares (OLS) estimates.

In our second approach, we use the introduction of the Sarbanes-Oxley (SOX) Act to generate exogenous variation in polarization at the firm level. The SOX Act (along with exchange listing rules) required all firms to have the majority of the board directors be independent, which, interestingly, resulted in noncompliant and most compliant firms changing their board structure (Dah, Frye, and Hurst, 2014). The SOX Act was thus an event that led to a general reshuffling of corporate boards in the US. As individual directors have different political ideologies, a by-product of the SOX Act was to cause a shift in the degree of polarization in the board. Crucially, we show that firms are as likely to experience an increase in polarization as they are a decrease around SOX and that this variation is not predictable by firm or board characteristics. These patterns suggest that new directors are not selected based on their ideology. We implement short window tests around the introduction of SOX by estimating heterogeneous treatment effects in a difference-in-difference framework and confirm our main finding.

In the cross-section, we find that the link between polarization and CEO turnover–performance sensitivity is driven by presidential elections but not mid-term elections and does not differ between periods of high versus low political uncertainty. This evidence suggests that polarization in the boardroom matters most during salient political events when people talk more about politics, and our finding is orthogonal to political uncertainty. We also find that the link between political polarization and CEO turnover–performance sensitivity is more pronounced in more complex firms, suggesting that the inefficiency introduced by political polarization is higher when firms have more monitoring and advising needs.

We investigate how polarization influences future board composition by examining director departures. We find that polarization increases the likelihood of director departure, but only for polarized directors (i.e., those who are ideologically far from the group). Thus, over time, polarized boards likely become more politically homogenous. This self-selection based on political preferences—that are unobserved at appointment and only revealed over time—is consistent with work by Westphal and Zajac (1995) who argue that boards tend to select new directors who are demographically similar. This result also supports the findings of Fos, Kempf, and Tsoutsoura (2021) who find that executive teams in the US have become increasingly politically homogeneous over time as well as Colonnelli, Neto, and Teso (2021) who document significant labor market matching based on political preferences in Brazil.

Next, since polarization leads to boardroom dysfunction and a slowing of decision-making process, we investigate the real consequences of polarization by examining how responsive firm investment is to changing investment opportunities. We show that polarization reduces firms' investment–Q sensitivity by 6.7%, suggesting that firms with polarized boards have lower investment efficiency.

Finally, we examine firms' environmental performance. It is well documented that climate change views in the US are highly polarized: Liberal and Democrat beliefs about climate change are more in line with mainstream climate science compared to the views of Conservative and Republican supporters (e.g., Hamilton and Keim, 2009; Malka, Krosnick, and Langer, 2009; Borick and Rabe, 2010; Hamilton 2011; McCright and Dunlap 2011; Hamilton and Saito, 2015). Thus, polarized boardrooms will find it much harder to overcome corporate inertia (Hoppmann, Naegele, and Girod, 2019) and respond to climate risks by making more environmentally friendly investments. We find that polarization reduces firms' environmental performance, driven mainly by greater number of environmental concerns. These results are consistent with the idea that polarization leads firms to be less responsive to growing public concerns over climate change, which in turn, leads to growing concerns over these firms' own environmental practices.

Taken all together, our results are in line with the *boardroom stalemate hypothesis*: polarization increases the chance of conflict among board members and inhibits the collective decision-making process of the board, in turn, hindering its advisory and monitoring functions.

We contribute to the literature by studying the consequences of polarization, especially affective polarization. Most studies on the economic consequences of polarization rely on experimental or survey evidence. For example, Iyengar et al. (2012) report that the fraction of survey respondents stating that they would be displeased if their child married outside their political party increased from 5% in 1960 to 50% (30%) in 2010 for Republicans (Democrats). On the economic costs, McConnell, Margalit, Malhotra, and Levendusky (2018) run a series of experiments to show that individuals are willing to make themselves worse off to avoid repeatedly dealing with or benefiting someone from the opposing political party. For example, in one experiment, they find that people are willing to work for less money to avoid having a boss from the opposing political party.

There are two recent exceptions to the use of survey and experimental data. First, Fos et al. (2021) examine political partisanship within the executive team in U.S. firms and document that although there is significant heterogeneity across party lines, executive teams have displayed a trend toward political party harmonization over time. Second, Colonnelli et al. (2021) examine the role of politics in the Brazilian labor market and document significant matching based on political preferences. They also document a significant political wage premium whereby workers from the same political party of the business owner are paid more. Our paper differs from these in two important ways. First, these two papers examine the influence of partisanship (i.e., which party one belongs to) and not political polarization per se (i.e., the distance in political views). This distinction is important, as politically moderate individuals can come from either side of the political spectrum: a high degree of heterogeneity across party lines does not imply a high degree of polarization. Likewise, individuals who support the same party can still have significantly different political ideologies. For example, Republican Senator for Maine, Susan M. Collins, only voted in-line with President Trump 44% of the time in the 116th Congress and was often criticized by President Trump. In particular, our paper examines the consequences of increasing polarization, that is, the increasing distance in political views across individuals. Second, we are the first to examine the economic impact of polarization in the boardroom and show that polarization leads to a breakdown in the board advisory and monitoring functions which generate inefficiency in various outcomes, including turnover–performance sensitivity, investment–Q sensitivity, and environmental policies.

We also contribute to the literature on corporate boards. Prior studies have shown that independent directors (e.g., Harris and Raviv, 2008; Masulis and Mobbs, 2011; Guo and Masulis, 2015), busy directors (Field et al., 2013; Hauser, 2018), board diversity (Adams and Ferreira, 2009; Bernile et al., 2018), and shareholder oversight (Liu et al., 2020) are important determinants of how well boards function, which ultimately impacts firm performance and value. Our paper is particularly related to the literature on board diversity. While the benefits and costs of diversity are debated,[49] our results show that political polarization influences board decision making while controlling for traditional measures of diversity such as the gender, race, and age composition of the board. Our findings are consistent with the recent theoretical work of Donalson, Malenko, and Piacentino (2020) who show that board diversity can create board "deadlock" and lead directors to retain an underperforming CEO. Indeed, we identify a new dimension of diversity—political polarization—that can inhibit board functioning, resulting in a decrease in CEO turnover–performance sensitivity and firm investment efficiency.

Finally, our paper is related to the broader literature on the political economy of finance. Recent papers study the relation between political uncertainty and corporate investment (Julio and Yook, 2012) and dividend policy (Huang, Wu, Yu, and Zhang, 2015), the politics of privatization (Dinc and Gupta, 2011), political interference in banking (Brown and Dinc, 2005; Duchin and Sosyura, 2012; Liu and Ngo, 2014), political considerations in the allocation of credit (Dinc, 2005; Khwaja and Mian, 2005), and the asset pricing implications of politics (Pastor and Veronesi, 2012; 2013; Belo, Gala, and Li, 2013; Boutchkova, Doshi, Durnev, and Molchanov; 2012; Brogaard, Dai, Ngo, and Zhang, 2020). We contribute by being the first paper to examine how polarization, one of the most defining features of modern politics, influences the efficacy of corporate boards.

[49] See Ferreira (2010) for a review.

3.2. Variable Construction, Data, and Descriptive Statistics

3.2.1. Data, main variable construction, and sample formation

We construct our main sample by linking several databases. Firm accounting and stock return data are from the Compustat and CRSP databases, respectively. We collect information on CEOs from the Execucomp database and information on board structure and director characteristics (such as name, gender, ethnicity, age, tenure, and directorship) from the RiskMetrics (formerly IRRC) database.

Our dependent variable is forced CEO turnover (i.e., *Forced Turnover*), which is a dummy variable equal to one if the CEO leaves the job involuntarily. The true nature of CEO turnover is not straightforward, as firms rarely disclose the fact that a CEO has been fired. We follow the literature to identify such cases based on press coverage along with an age criterion (e.g., Parrino, 1997; Peters and Wagner, 2014; Jenter and Kanaan, 2015).[50] Specifically, departures are classified as forced if press coverage states that the CEO was fired, forced out, retired, or resigned due to policy differences or pressure. In addition, for CEOs under the age of 60, turnovers that have not been classified as forced by the press criterion are classified as forced if the articles do not report the reason to be death, poor health, or acceptance of another position; or the articles report that the CEO is retiring but the company does not announce the retirement date at least six months before departure.

To construct our firm-level political polarization measure, we begin by measuring the political ideology of the CEO and each director of the board. Recent work by Fos et al. (2021) and Kempf and Tsoutsoura (2021) use voter registration records to identify individuals' party

[50] We thank Florian Peters and Alexander Wagner for providing us with their forced CEO turnover data, part of which was collected by Chritian Dezso, Dirk Jenter, Greg Nini, Bob Parrino, and Luke Taylor.

affiliation; however, since polarization is a measure of distance between individual political ideologies, what we are after is a continuous measure of ideology rather than a simple classification as red or blue. That is, ideological distance can be relatively close between Democrat and Republican supporters if both are politically moderate. Likewise, individuals supporting the same party may still have quite different political views. For example, many Republican supporters do not support Donald Trump.

Accordingly, to construct our measure, it is necessary to focus on *personal* contributions made by directors and CEOs to *individual* members of Congress, for whom we are able to observe their political ideology based on congressional voting records. We do *not* use contributions made by directors/CEOs to political action committees (PACs), which tend to be made to a political party and can be distributed to multiple candidates running for office who are not necessarily known to the contributors at the time they contribute. As such, assigning precise ideology based on PAC donations is not possible, and we are left with a coarse partisan classification. Moreover, directors and CEOs who take the time and effort to make personal contributions to individual congressional candidates are the most politically engaged and thus have a greater vested interest in electoral outcomes compared to, say, someone who donates to a partisan PAC or simply votes for a particular party.

The ideological positions of congressional members are estimated using roll call voting records following Poole and Rosenthal's (1985) seminal work (i.e., DW-NOMINATE scores). DW-NOMINATE estimates assume that members occupy a static ideological position across the course of their career. We make use of the first dimension (often interpreted as economic liberalism-conservatism) of the score, which is a scaled index ranging from -1 (left or liberal) to +1 (right or conservative). The most recent update of these ideological scores is available from the website *voteview.com*.

The source for individual contribution information is the Federal Election Commission (www.fec.gov). Law requires that candidates receiving campaign contributions from individuals of more than $200 file Form 3A detailing information about each contributor.[51] This form contains information such as name (first, last, middle, and initial), gender, address, employer, occupation, and contributing amount. Bonica (2016) produces the Dataset on Ideology, Money in Politics, and Elections (DIME), where he collates information on individual contributions from these filings into a database for the period 1979 to 2014 covering almost 15 million unique individual contributors. The DIME dataset also provides a unique contributor identification number such that contributors can be easily tracked over time.

We match contributors from DIME with our sample of firm directors and CEOs. We first match on full name and gender, keeping only 100% matches. Since information regarding employer and occupation of the contributors can be missing, misspelt, or entered in nonstandard ways (e.g., a CEO can appear as "CEO", "executive", "chief executive", etc., and "Citi Group" can also appear as "Citi" or "Citibank", among other things), we manually check our matches from the first stage match against the information provided. That is, for the matches that we obtain in the first stage, we eliminate any match where we can see it is clearly not a CEO or director of a company (e.g., if the contributor lists their occupation as an anaesthesiologist or a farmer). From our sample of 4,055 CEOs and 21,149 directors, we are able to match 728 (17.95%) CEOs and 2, 2,376 (11.23%) company directors who contributed at least once between 1996 and 2014. The percentage of

[51] Individual contributions (just like all contributions) are subject to federal limits. For current limits see: https://www.fec.gov/help-candidates-and-committees/candidate-taking-receipts/contribution-limits/

matched directors is in line with the fact that only approximately 0.25% to 0.5% of the general public in the U.S. make political contributions greater than $200 during our sample period (see Center for Responsive Politics: www.opensecrets.org) and that individual contributions tend to increase with age, education, and income (Pew Research, 2017).

To construct CEO and director political ideologies' scores, we then take the weighted average of the contribution recipient (i.e., congressional candidate) DW-Nominate scores, where the weights are based on the fraction of total contributions made to all candidates. For example, if director A donates $1000 to one congressional candidate with an ideological score of -1 in the 2000 election cycle, then we assign director A an ideological score of -1 for the year 2000. However, if the same director donates a total of $1000 in the 2004 election, but this time evenly splits across two different candidates, with ideological scores of -1 and +0.5, then we assign the director a score of $-0.25 = (0.5 \times (-1) + 0.5 \times (0.5))$ for 2004. Thus, director and CEO ideology can vary over time, depending on who they contribute to and the relative amounts that they contribute. In situations where we cannot match a director/CEO to a contributor in the DIME database, we consider the individual politically neutral (i.e., a score of zero).[52]

Finally, to capture the political distance within the board at the firm level, we calculate the standardized ideological distance between each of the board members. We treat the CEO as simply another board member. In other words, our main measure is the standard deviation of ideological scores across the board members.

[52] Our empirical results are not sensitive to this treatment of missing matches. For example, we have similar findings if assigning noncontributing directors with the industry-year median value of ideologies' scores.

$$Polarization_{i,t} = \sqrt{\frac{\sum\left(Director\ Ideology_{d,i,t} - Mean\ Ideology_{i,t}\right)^2}{N}} \tag{3.1}$$

That is, polarization for firm *i* in year *t* is a function of the sum of squared differences in score between each of firm *i*'s board members, *d*, and the mean board, scaled by the number of board members, *N*. Thus, variation in *Polarization* is driven by variation in directors' relative contribution amounts to various congressional candidates as well as variation in the composition of the board.

We also construct two alternative measures in robustness tests: the maximum ideological distance between the any two board members (*Polarization Max*), and the mean of the ideological distance between each of the director pairs (*Polarization Mean*).

3.2.2. Descriptive statistics

Table 3.1 provides summary statistics for our key variables. Appendix A2 defines the variables. We winsorise all the continuous variables at the 1% and 99% levels. Panel A of Table 3.1 compares the characteristics of directors and CEOs who make individual campaign contributions with those who do not. We find that CEOs and directors who contribute are younger, have longer tenures, and are more likely to be females. Under the condition of making individual campaign contributions, we find that CEOs and directors who contribute to left leaning candidates are younger with shorter tenure and are more likely to be females. CEOs who contribute to left leaning candidates are also less likely to hold the chairman position on the board, suggesting they may have less power.

Table 3.1: Summary Statistics

Panel A compares the characteristics of directors and CEOs who make individual campaign contributions with those who do not. Further, conditional on making individual campaign contributions, Panel A compares the characteristics of left vs. right leaning directors and CEOs. Panel B presents the summary statistics for the main variables used in our analysis. All variable definitions are in Appendix A2.

Panel A: Contributors		**Contribute**	**Do Not Contribute**	**Diff (t-statistic)**	**Left**	**Right**	**Diff (t-statistic)**
CEOs	Age	55.84	56.11	-2.21	55.50	55.90	-1.40
	Gender	0.77	0.81	-5.55	0.65	0.81	-9.85
	Tenure	5.07	4.80	4.38	4.57	5.27	-5.75
	White	0.66	0.63	3.81	0.58	0.69	-6.33
	Duality	0.41	0.45	-4.42	0.36	0.43	-3.92
Directors	Age	60.43	61.46	-18.03	59.81	60.79	-8.44
	Gender	0.72	0.76	-13.80	0.63	0.77	-22.96
	Tenure	4.97	4.85	-53.91	4.95	4.96	-0.24
	White	0.59	0.56	9.15	0.50	0.64	-20.45

Panel B: Summary Statistics		**Obs**	**Mean**	**Std. Dev.**	**Min**	**Median**	**Max**
Ideology	CEO Ideology	2,238	0.10	0.23	-0.56	0.10	0.75
	Director Ideology	12,014	0.08	0.27	-0.62	0.08	0.88
Polarization	Polarization	16,964	0.04	0.06	0.00	0.00	0.36
	Polarization Max	16,966	0.13	0.18	0.00	0.00	1.12
	Polarization Mean	16,966	0.03	0.04	0.00	0.00	0.24
Dependent and control variables	Forced Turnover	16,966	0.02	0.15	0.00	0.00	1.00
	Return	16,941	0.14	0.42	-0.72	0.11	1.70
	Adjusted Return	16,941	-0.00	0.35	-1.57	-0.03	1.78
	Size (in billion)	16,960	7.99	17.17	0.11	2.07	118.06
	Q	16,953	1.95	1.20	0.79	1.55	7.61
	Leverage	16,899	0.23	0.17	0.00	0.23	0.69
	Risk	14,655	0.39	0.18	0.14	0.34	1.06
	Growth	16,954	0.10	0.22	-0.45	0.07	1.08
	Board Size	16,966	9.51	2.36	1.00	9.00	23.00
	Board Independence	16,966	0.72	0.16	0.00	0.75	0.94
	New Director	15,326	0.87	1.17	0.00	1.00	16.00
	Gender	16,966	0.77	0.23	0.00	0.85	1.00
	Age Dispersion	16,963	7.76	2.45	0.89	7.42	26.50
	Ethnicity	16,966	0.76	0.19	0.28	0.78	1.00
	Director Busyness	16,966	0.31	0.22	0.00	0.29	1.00
	CEO Age Dummy	16,966	0.30	0.46	0.00	0.00	1.00
	CEO Tenure	16,966	4.29	3.24	1.00	3.00	19.00
	Duality	16,966	0.45	0.50	0.00	0.00	1.00
Director	Director Departure	40,392	0.07	0.25	0.00	0.00	1.00
	Against Voting	41,569	0.05	0.08	0.00	0.02	1.00

We report summary statistics of the main variables in Panel B of Table 3.1. We first report summary statistics of ideology score for directors and CEOs who make contributions (i.e., only those whom we can match to DIME). We can see that the mean ideology scores for directors and CEOs are 0.10 and 0.08, respectively, suggesting that executives and directors of public firms are on average slightly right leaning. Importantly, we see large variation in ideology scores for directors and CEOs. For example, the range of scores for directors and CEOs is [-0.56, 0.75] and [-0.62, 0.88], respectively, which highlights that board members can have very different political views. The summary statistics for our polarization measure confirm this. The average firm is slightly polarized with a mean value of 0.04 and a standard deviation of 0.06. However, the median firm is not polarized, whereas the most polarized firm has a value of 0.36, suggesting that the distribution across firms is skewed. Figure 3.1 plots the time series pattern of corporate board polarization over our sample period. Two important patterns emerge. First, there is a slight upward drift in polarization over time, consistent with the pattern observed in Congress and the general public. Second, polarization tends to increase sharply during election years when politics is at the forefront of people's minds.

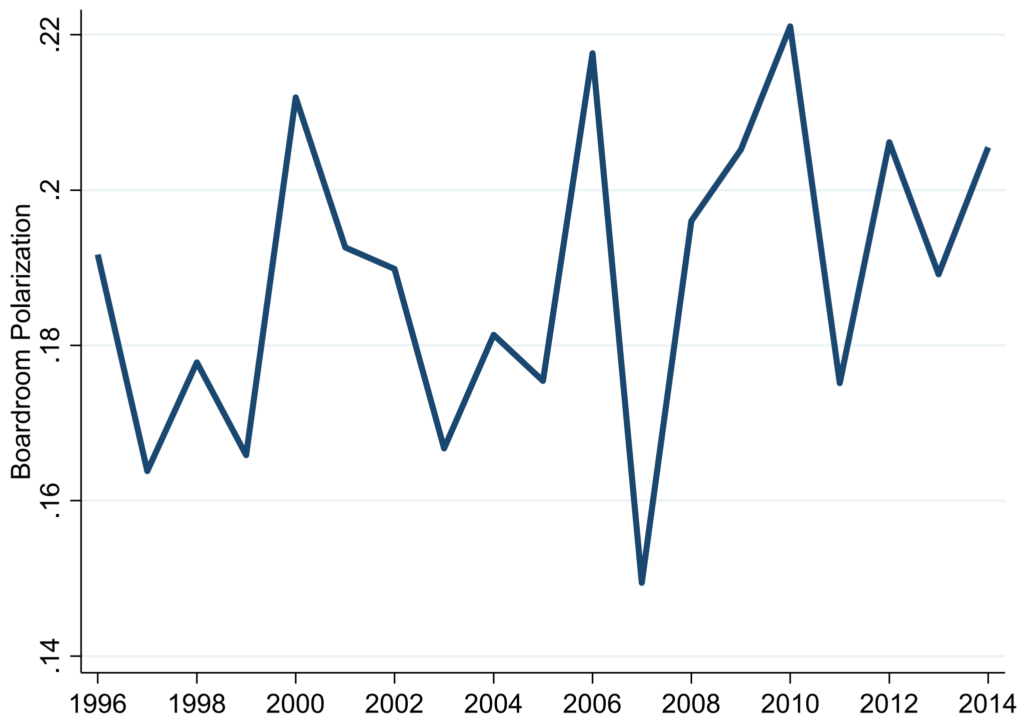
We find that our key dependent variable, *Forced Turnover*, has a mean value of approximately 0.02, indicating a relatively small likelihood of CEOs leaving the job involuntarily, which is not surprising given that firing the CEO is one of the most dramatic actions a board can take. The distribution of the forced turnover measure is also consistent with Peters and Wagner (2014).

We also report the distribution of our control variables, including financial, board, director, and CEO characteristics. We find that the average firm in our sample has an annual return of 14%, total assets of 7.99 billion dollars, and a Tobin's Q of 1.95. A typical board in our sample has approximately 9 directors, with 1 director newly appointed. For the CEO characteristics, we find that on average, the CEO is 56 years old and has been in the job for more than 4 years. We also find that less than half of the CEOs serve as the chairman of the board. The distribution of the control variables is in line with other studies using the *Riskmetrics* database, such as Liu et al. (2020).

Figure 3.1

Polarization of corporate boards over time and in the cross-section

This figure graphs our main measure of polarization of corporate boards over time.



3.3.Empirical Approach and Results

Our empirical approach comprises three parts. First, we examine how polarization alters CEO turnover–performance sensitivity using standard panel data methods. Second, to ameliorate concerns about endogeneity, we apply an instrument variable approach and exploit exogenous variation in polarization induced by the introduction of the SOX Act. Third, we investigate the underlying mechanisms linking polarization to turnover–performance sensitivity as well as the consequences of polarization in the boardroom for firm investment efficiency.

We examine the likelihood of top executive forced turnover in the following regression:

$$Forced\ Turnover_{i,t} = \gamma_1 Adjusted\ Return_{i,t-1} \times Polarization_{it} + \gamma_2 Adjusted\ Return_{i,t-1} + \gamma_3 Polarization_{it} + \boldsymbol{\beta}'\boldsymbol{X_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \quad (3.2)$$

Our dependent variable is *Forced Turnover,* defined above as an indicator equal to one if the CEO leaves the job involuntarily. The variable *Adjusted Return* is the industry-adjusted past stock market performance for firm *i*. We use contemporaneous value of polarization for two reasons. First, there is no direct link between forced turnovers and polarization, which minimizes the possibility that polarization is a consequence of CEO forced turnover. Specifically, any difficulty in finding a desired CEO does not mean the board would tend to be more or less polarized. In fact, when we compare polarization change around turnovers, the difference between forced turnovers and routine turnovers are insignificant. Second, forced turnover is measured in the last year that CEO stays in office and polarization is measured among directors in the board at the same year. Therefore, polarization is not a consequence of the reshuffle due to a CEO forced turnover. If we use lagged polarization, we may include directors that do not involve in monitoring and voting for firing the CEO. Furthermore, we control for new directors to address the impact of reshuffle after a CEO turnover.

The literature establishes $\gamma_2 < 0$ as turnover–performance sensitivity: a drop in past performance increases the likelihood of the CEO being fired. Our variable of interest is the *Polarization* × *Adjusted Return* interaction term, which measures how turnover–performance sensitivity varies with polarization in the boardroom. Our primary argument is that polarization dampens turnover–performance sensitivity (i.e., *boardroom stalemate hypothesis*) implying that $\gamma_1 > 0$, while the *information destruction hypothesis* predicts that $\gamma_1 < 0$.

We include a vector of firm and board characteristics, $\boldsymbol{X}$, to control for time-varying observable factors known to influence CEO turnover. Specifically, we control for total assets (*Size*), investment opportunities (*Tobin's Q*), capital structure (*Leverage*), stock return volatility (*Risk*), sales growth (*Growth*), age of the CEO (*CEO Age Dummy*), tenure of the CEO (*CEO Tenure*), and whether the CEO is also the chairperson (*Duality*). Ideally, we could also control for institutional ownership. When institutional investors take into account board polarization in their investment decisions, institutional ownership would affect CEO turnover. However, constrained by data availability, we are unable to include in the model institutional ownership. While acknowledging this data limitation, we attempt to control for as many governance variables as possible in this test. In particular, we control for number of board members (*Board Size*), percentage of independent directors (*Board Independence*), number of newly appointed directors *(New Director*), ratio of directors serving on multiple boards (*Director Business*), percentage of male directors (*Gender*), age dispersion across board members (*Age Dispersion*), ethnicity diversity of the board (*Ethnicity*), Firm characteristics are one-year lagged, whereas CEO and board characteristics are contemporaneous. The term α_i is a firm fixed effect that captures time invariant heterogeneity, and α_t is a year fixed effect that accounts for common shocks across all firms. We follow the literature (e.g., Guo and Masulis, 2015) and estimate Equation (3.2) using a linear probability model (LPM). Our regression sample contains 12,529 observations between 1996 and 2014. We cluster standard errors at the 2-digit SIC code industry level.[53]

[53] Our results are similar if we instead cluster at the firm level.

3.3.1. Baseline results and robustness

We estimate Equation (3.2) and present our main results in Table 3.2 Model (1). Consistent with the literature, we find a negative and significant coefficient on *Adjusted Return*: a drop in industry-adjusted returns increases the likelihood of forced CEO turnover. The point estimate implies that a 1% fall in industry-adjusted returns in the prior year increases the likelihood of CEO turnover by 2.5% or 125% relative to the sample mean turnover rate of 0.02. In other words, the forced turnover rate increases from 2% to approximately 4.5%.

Next, we find that the coefficient on *Polarization* is negative but not significant in explaining turnover, suggesting that political polarization does not alter the turnover probabilities per se. However, and importantly, we find a positive and significant coefficient on our variable of interest *Polarization* × *Adjusted Return*. The point estimate of 0.22 implies that polarization in the boardroom has a large economic impact on turnover–performance sensitivity. Previously, we established that a 1% fall in industry-adjusted performance leads to a 2.5% rise in the forced turnover rate; however, a one-standard-deviation increase in polarization (0.06) of the board reduces this sensitivity by 1.3% (i.e., 0.22 × 0.06). Specifically, the same 1% fall in industry-adjusted returns now only increases the likelihood of turnover by 1.2%. Thus, given a 1% fall in industry-adjusted performance, a one-standard-deviation increase in polarization reduces the turnover–performance sensitivity by roughly one-half. This result is consistent with the *boardroom stalemate hypothesis*: polarization inhibits the collective decision making and hinders the advisory and monitoring functions of the board.

One potential concern is the possibility that new director appointments occur at a similar time to a CEO departure following poor performance. If this is the case, CEO turnover may be the cause of a reshuffling of the board and therefore polarization. To address this concern, we decompose the board members into two groups according to their tenure. The first group, new directors, are those who have been newly appointed in the current year. The second group, existing directors, are those who have been on the board for more than one year. We are therefore able to identify the cohort of board members that contribute most to the link between polarization and CEO turnover–performance sensitivity. In Model (2), we modify Equation (3.2) by decomposing *Polarization* × *Adjusted Return* into *Polarization* (*Existing Directors*) × *Adjusted Return* and *Polarization* (*New Directors*) × *Adjusted Return* and find similar effects for both new and existing directors which are inconsistent with the idea that new director appointments are driven by the CEO's departure. We next perform a series of robustness tests of the main result. The results are presented in Table 3.3.

First, although the literature typically uses the LPM for its simplicity and ease of interpretation, since Equation (3.2) is a binary dependent variable, estimation using OLS is problematic since the error term of an LPM has a binomial distribution instead of a normal distribution, which implies that the traditional *t*-tests for individual significance and *F*-tests for overall significance are invalid. Moreover, predictions from an LPM are not bound between zero and one, which makes interpreting predictions as probabilities challenging.

Table 3.2: Polarization and CEO performance-turnover sensitivity

This table presents the results from estimating Equation (3.2) using Linear Probability Model. The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Polarization* × *Adjusted Return* where *Polarization* is the standard deviation of board members' ideology and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. The definitions of all other variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)
Polarization	-0.028	
	(0.031)	
Polarization × Adjusted Return	0.217***	
	(0.050)	
Polarization (Existing Directors)		-0.024
		(0.032)
Polarization (New Directors)		-0.013
		(0.036)
Polarization (Existing Directors) × Adjusted Return		0.180***
		(0.050)
Polarization (New Directors) × Adjusted Return		0.259*
		(0.141)
Adjusted Return	-0.025***	-0.024***
	(0.005)	(0.006)
New Director	0.001	0.001
	(0.001)	(0.002)
Size	0.007*	0.007*
	(0.004)	(0.004)
Q	-0.002	-0.002
	(0.002)	(0.002)
Leverage	0.025	0.026
	(0.023)	(0.023)
Risk	0.007	0.007
	(0.014)	(0.014)
Growth	-0.006	-0.007
	(0.014)	(0.014)
Board Size	0.001	0.001
	(0.001)	(0.001)
Board Independence	-0.001	-0.001
	(0.017)	(0.017)
Gender	-0.046**	-0.045**
	(0.020)	(0.020)
Age Dispersion	0.000	0.000
	(0.001)	(0.001)
Ethnicity	0.004	0.005
	(0.009)	(0.009)
Director Busyness	-0.001	-0.001
	(0.014)	(0.014)
CEO Age Dummy	-0.013***	-0.013***
	(0.004)	(0.004)
CEO Tenure	0.004***	0.004***
	(0.001)	(0.001)

Table 3.2 continued

	(1)	(2)
Duality	-0.007	-0.007*
	(0.005)	(0.004)
Firm FE	Y	Y
Year FE	Y	Y
N/R^2	12,529/0.01	12,525/0.01

Thus, we alternatively estimate Equation (3.2) using a probit model. However, estimating α_i in nonlinear models leads to the incidental variables problem, resulting in a biased estimate of γ_1 (see, e.g., Chamberlain 1982; Chamberlain 1984; Lancaster, 2000). We therefore account for cross-sectional heterogeneity by estimating a probit model allowing for correlated random effects rather than estimating α_i directly (see Chamberlain, 1982; Chamberlain, 1984; Mundlak, 1978; Woodridge, 2018). This approach yields a consistent within-estimate of γ_1.

The outcome from this exercise is presented in Model (1) of Table 3.3. We find a similar result: polarization reduces the turnover–performance sensitivity. The point estimate on *Adjusted Return* implies that a 1% fall in industry-adjusted returns in the prior year increases the likelihood of CEO turnover by approximately 67% (i.e., exp[0.51]). At the same time, the estimate on *Polarization* × *Adjusted Return* indicates that, for the same 1% reduction in *Adjusted Return,* a one-standard-deviation increase in *Polarization* reduces the sensitivity by more than half. Specifically, the same 1% fall in industry-adjusted returns now only increases the likelihood of turnover by 28% (i.e., exp[0.51 – 4.34 × 0.06]). Thus, we find that the dampening effect of polarization is approximately the same regardless of the choice of estimation technique.

Second, we add a control for the ratio of non-contributing directors on the board and find similar results (Model 2). Third, we check the robustness of our results for the treatment of non-contributing directors and CEOs. Recall that in our main analysis, we treat directors and CEOs who do not make any personal political contributions as politically neutral, assigning them an ideology score of zero. An alternative is to assign non-contributing directors and CEOs the industry-year median of ideology score. Estimating Equation (3.2) using this approach yields similar results (Model (3)).

Fourth, we check the robustness of our results to alternative measures of polarization, namely, the maximum ideological distance between board members (*Polarization Max*) and the mean of the ideological distance between each of the director pairs (*Polarization Mean*). In the former measure, we first calculate the absolute ideological distance between each unique pair of directors and then take the maximum ideological distance as the main measure. In the latter, we calculate the absolute ideological distance between each unique pair of directors and then calculate the average across all director pairs. The results using these alternative proxies, presented in Models (4) and (5), respectively, show qualitatively similar results. In Model (6) we recalculate our polarization measure excluding the CEO. This new measure has a correlation of 0.91 with our main measure which treats the CEO as another board member. The results using this measure is virtually identical to our main result presented in Table 3.2. Finally, in Model (7), to construct our polarization measure, we replace the DW-NOMINATE ideology score with a new measure of political ideology developed in Bonica (2014) known as the *CF Score*. We again find similar results.

Table 3.3: Polarization and CEO performance-turnover sensitivity: Robustness

This table presents the results from performing a series of robustness tests estimating Equation (3.2). The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Polarization* × *Adjusted Return* where *Polarization* is the standard deviation of board members' political ideologies and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. Model (1) estimates a non-linear Probit model with Correlated Random Effects (CRE) instead of firm fixed effects. Model (2) controls for the ratio of non-contributors in the board. Model (3) assigns board members who do not contribute the industry-year median political ideology (instead of assigning them to be neutral); Model (4) measures *Polarization* as the maximum absolute difference between board members' ideology; Model (5) measures *Polarization* as the mean of the absolute deviation between board members' ideology; Model (6) measures *Polarization* as the standard deviation of directors' political ideologies (excluding CEO); and Model (7) uses an alternative proxy for political ideology (i.e., CF Score) to construct *Polarization*. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5 and 1% levels, respectively.

	(1) *Probit with CRE*	(2) *Non-contributor*	(3) *Median Ideology*	(4) *Polarization Max*	(5) *Polarization Mean*	(6) *CEO excluded*	(7) *CF Score*
Polarization	-0.183	-0.018	-0.044	-0.009	-0.027	-0.022	-0.012
	(0.634)	(0.030)	(0.035)	(0.009)	(0.051)	(0.031)	(0.017)
Polarization × Adjusted Return	4.335***	0.218***	0.176***	0.067***	0.326***	0.208***	0.067***
	(1.407)	(0.050)	(0.060)	(0.021)	(0.065)	(0.061)	(0.019)
Adjusted Return	-0.505***	-0.025***	-0.023***	-0.024***	-0.024***	-0.023***	-0.023***
	(0.114)	(0.005)	(0.006)	(0.006)	(0.005)	(0.114)	(0.006)
Non-contributors		0.016					
		(0.019)					
Other controls in Table 3.2	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
N/ R^2	12,529/-	12,529/0.01	12,508/0.01	12,529/0.01	12,529/0.01	12,529/0.01	12,529/0.01

Our baseline results show strong evidence that polarization in the boardroom dampens CEO turnover–performance sensitivity. Of course, these results are subject to endogeneity concerns. To ameliorate these concerns, we next present our results using the instrumental variables approach as well as using the SOX Act as a natural experiment that generates plausibly exogenous variation in polarization in corporate boards.

3.3.2. Identification

Since polarization of the board is a function of board composition, it is likely endogenous to CEO turnover and firm performance. For example, it could be the case that the boards appoint new directors who are politically like-minded. In this case, board polarization will tend to be lower than what would otherwise be observed. Alternatively, there could be omitted variables that are correlated with CEO turnover, firm performance, and polarization, which can drive a spurious association between these variables.

To address this issue, we exploit two approaches. In the first setting, we employ instruments related to the supply of local directors. In the second setting, we exploit variation in board composition due to the introduction of the SOX Act in 2002.

a) Instrumental Variables Analysis

Prior work establishes that the local supply of directors has significant effects on board structure and director appointments (Knyazeva et al., 2013; Kang et al., 2018). The argument is that local directors are more likely to sit on the board of a firm due to geographic proximity and better information about the firm. Furthermore, when a firm decides to hire a director, the firm is more likely to look for a local candidate. We assume that prospective directors holding director positions at other firms are generally concentrated at a firm's headquarters. Therefore, we define the local pool of prospective directors in the firm's vicinity is the density of nonfinancial firms located in the same area as the sample firm. To the extent that board polarization is a function of the political views of board members (i.e., board composition), we argue that the average polarization of local firms has a direct impact on firm polarization. Specifically, if the local pool of directors is more polarized, when a firm chooses a set of directors from the local pool, it is more likely that the firm will have a more polarized board. At the same time, it is unlikely that the average polarization of local firms will have an impact on CEO performance-turnover sensitivity, except through its impact on the polarization of the focal firm, thus satisfying the exclusion restriction.

Using firm headquarter locations from historical SEC filings, we define a local firm as one that is in the same 2-digit zip code area as the focal firm (Kang et al., 2018). To construct our instrument, *Local Firm Polarization*, we calculate the mean polarization across all local nonfinancial firms. Since Equation (2) contains two endogenous variables (i.e., *Polarization* and *Polarization* × *Adjusted Return*), we require two instruments to exactly identify the system. Consequently, we employ *Local Firm Polarization* × *Adjusted Return* as our second instrument.

We also construct two alternative sets of instrument variables following this method. First, when determining the number of local firms, we exclude firms in the same 2-digit SIC code industry since executives of direct competitors are unlikely to join the board due to competitive concerns. Second, instead of calculating the mean polarization of local firms using a simple average, we calculate the board size weighted mean across all local firms.

We estimate the system of three equations using two-stage least squares. In the first stage, we regress *Polarization* and *Polarization* × *Adjusted Return* on the two instruments *Local Firm Polarization* and *Local Firm Polarization* × *Adjusted Return* along with the set on controls in Equation (3.2) as well as industry and year fixed effects. In the second stage, the predicted values from the two first-stage regressions, $\widehat{\boldsymbol{Polarization}}$ and $\widehat{\boldsymbol{Polarization \times Adjusted\ Return}}$, replace their original counterparts in Equation (3.2).

Table 3.4: Instrumental variables analysis

This table presents the results from two-stage-least-squares estimation of Equation (3.2). The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Polarization* × *Adjusted Return* where *Polarization* is the standard deviation of board members' ideology and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. We instrument *Polarization* × *Adjusted Return* and *Polarization* using the mean polarization of local (same 2-digit zip code) firms (*Local Firm Polarization*) as well as the interaction of this instrument with *Adjusted Return* (i.e., *Local Firm Polarization* × *Adjusted Return*). Model 1 is the first stage regression for *Polarization*, Model 2 is the first stage regression for *Polarization* × *Adjusted Return*, and Model 3 is the second stage regression. Panel A calculates the simple mean of all local firms' polarization, Panel B excludes local firms in the same industry in a simple mean calculation, Panel C calculates the board size weighted mean of all local firms' polarization. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

Panel A: Mean Polarization	(1) Polarization	(2) Polarization × Adjusted Return	(3) Forced Turnover
Local Firm Polarization	0.147***	-0.003	
	(0.037)	(-0.008)	
Local Firm Polarization × Adjusted	-0.056	0.417***	
	(0.060)	(0.064)	
$\widehat{\text{Polarization}}$			0.312
			(0.448)
$\widehat{\text{Polarization} \times \text{Adjusted Return}}$			0.828***
			(0.252)
Adjusted Return			-0.055***
			(0.012)
Other controls in Table 3.2	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
N	12,529	12,529	12,529
Cragg-Donald Wald F statistic	-	-	18.115

Table 3.4 continued

Panel B: Excluding Firms in Same Industry	(1) Polarization	(2) Polarization × Adjusted Return	(3) Forced Turnover
Local Firm Polarization	0.127***	-0.005	
	(0.043)	(-0.007)	
Local Firm Polarization × Adjusted Return	-0.059	0.399***	
	(0.061)	(0.066)	
$\widehat{\text{Polarization}}$			0.098
			(0.503)
Polarization $\widehat{\times \text{ Adjusted}}$ Return			0.917***
			(0.280)
Adjusted Return			-0.060***
			(0.014)
Other controls in Table 3.2	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
N	12,529	12,529	12,529
Cragg-Donald Wald F statistic			14.445

Panel C: Board Size Weighted Mean Polarization	(1) Polarization	(2) Polarization × Adjusted Return	(3) Forced Turnover
Local Firm Polarization	0.161***	-0.001	
	(0.039)	(0.008)	
Local Firm Polarization × Adjusted Return	-0.049	0.435***	
	(0.058)	(0.069)	
$\widehat{\text{Polarization}}$			0.395
			(0.437)
Polarization $\widehat{\times \text{ Adjusted}}$ Return			0.692***
			(0.255)
Adjusted Return			-0.049***
			(0.013)
Other controls in Table 3.2	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
N	12,529	12,529	12,529
Cragg-Donald Wald F statistic			20.335

The results from this analysis are presented in Table 3.4 across three separate panels: Panel A is the full sample of local firms, Panel B excludes firms in the same 2-digit SIC code industry as the focal firm, and Panel C uses the board size weighted mean instead of the simple average. In each panel, there are three columns. Model (1) is the first-stage regression for *Polarization*, Model (2) is the first-stage regression for *Polarization* × *Adjusted return,* and Model (3) presents the second-stage results.

There are several points of note. First, the instruments are significant and strong shifters for *Polarization* and *Polarization* × *Adjusted Return*: across all panels, *Local Firm Polarization* is significantly related to *Polarization,* and *Local Firm Polarization* × *Adjusted Return* significantly predicts *Polarization* × *Adjusted Return*. Second, the robust *F*-statistic is greater than the threshold of 10 for a weak instrument test in all three panels, suggesting that our instruments are valid. Third, and importantly, we find that the second-stage results are consistent with the OLS results in Table 2. That is, while polarization does not have an impact on CEO turnover per se, higher levels of board polarization lead to a reduction in CEO turnover–performance sensitivity.

b) Using the introduction of the Sarbanes-Oxley Act for Identification

The SOX Act imposed significant reforms on corporate governance, especially board composition, as a result of the major accounting scandals related to Enron and World.com; thus, its passage was unrelated to political variables in general and polarization of the board in particular. The passage of SOX, in conjunction with exchange listing requirements, mandated corporations to have a majority of independent directors serving on their boards. Consequently, any firm that did not already comply with this rule had until 2005 to change their board structures and become compliant (Dah et al.,2014; Guo and Masulis, 2015).

Although the SOX Act did not target political polarization directly, a by-product of shifting the composition of the board is to also change the political orientation of the board. Incoming new independent board members may have different political ideologies, leading to a shift in the degree of polarization of the board.

In principle, the SOX Act affected only noncompliant firms (i.e., those firms for which the ratio of independent directors was less than 50% in 2002), leaving compliant firms with no compositional (and therefore polarization) changes to the board around SOX. However, Dah et al. (2014) point out that 56% of compliant firms also added independent directors, and a further 26% of compliant firms reduced the number of independent directors and moved closer to the 50% target ratio. Thus, the SOX Act was a salient event that led almost all firms—either compulsorily or voluntarily—to change their board structure. Accordingly, defining treatment and control based on pre-SOX compliance is misleading. Instead, given our interest in identifying shifts in polarization and not board composition per se, we define treatment firms based on whether firms experience a change in polarization around SOX. Control firms are those experiencing no change in polarization around SOX.[54]

To implement our test, we first restrict our sample to the three-year period before the introduction of SOX (1999—2001) and the three-year period post-SOX (2003—2005). Short window tests reduce the likelihood of other confounding factors that may weaken our interpretation. We then calculate the change in *Polarization* for each firm between the pre-SOX period and the post-SOX period and create a variable $\Delta Polarization$ to capture this change in polarization. We estimate heterogeneous treatment effects in a difference-in-difference (DID) regression of the form:

$$Forced\ Turnover_{i,t} = \emptyset_1 Adjusted\ Return_{i,t-1} \times Post_t \times \Delta Polarization_i$$

$$+\boldsymbol{\delta Z_{i,t}} + \boldsymbol{\beta' X_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \tag{3.3}$$

[54] The results are similar if we define treated firms as firms that were non-compliant before the SOX and experienced a change in polarization around SOX.

where *Post* is an indicator equal to one in the post-SOX period (2003–2005) and the vector $\boldsymbol{Z}$ contains a full expansion of interaction terms. All other variables have previously been defined in Equation (3.2). We expect that treated firms in the post-SOX period that also experience an increase in polarization to experience dampened turnover–performance sensitivity, implying that $\emptyset_1 > 0$. We again estimate the model using an LPM, clustering standard errors at the 2-digit SIC code industry level.

We argue that this approach is justified because changes in polarization, as a by-product of SOX-induced board compositional changes, are unlikely to be predictable. One concern is that newly appointed directors may be appointed on the grounds of their political ideology. In particular, it may be the case that firms choose independent directors who are ideologically similar, implying that polarization should fall after SOX. We argue that this is unlikely given that a firm's choices of new independent directors were constrained within a short period after SOX was imposed.

Nevertheless, to reassure the readers, we perform two analyses. First, we plot the distribution of $\Delta Polarization$ in Figure 3.2. We can see that treated firms appear to be likely to experience an increase in polarization as they are to experience a decrease in polarization. The mean, median, and skewness of the distribution are 0.005, 0.004, and 0.28, respectively. Second, we investigate whether firm and board characteristics can predict the directional change in polarization for our sample of firms. If it were possible to select independent directors based on political ideology, then we would expect firm and board characteristics to be significantly correlated with the directional change in polarization (i.e., firm and board characteristics can predict treatment).

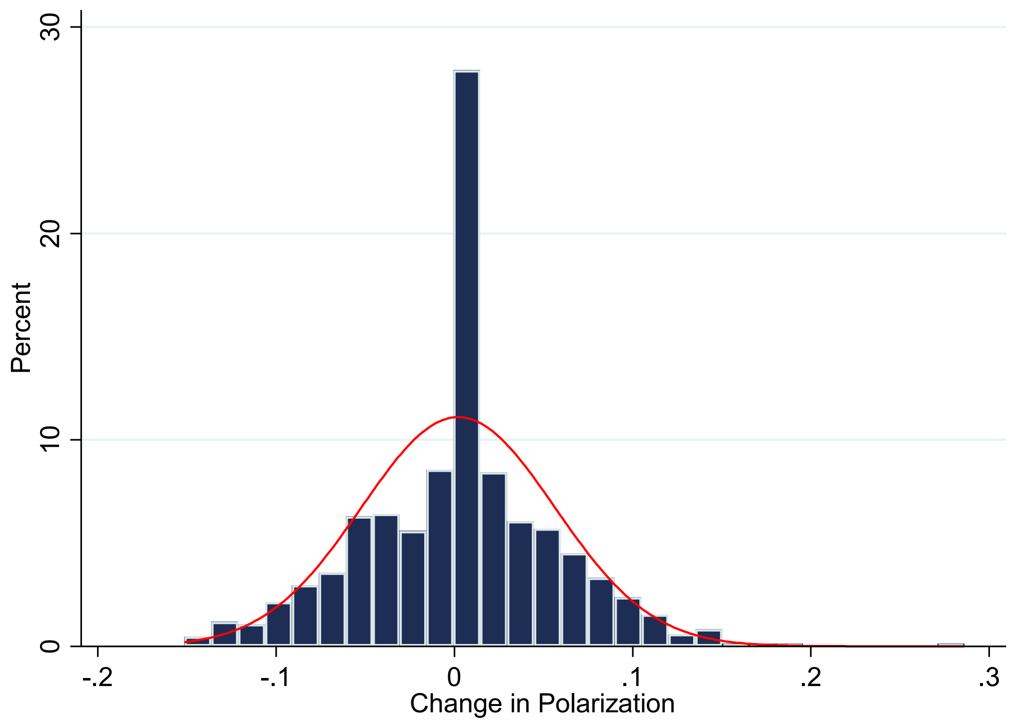
To implement the test, we construct an indicator for the change in mean polarization (Δ*Polarization*) between the pre-SOX period (1999–2001) and the post-SOX period (2003–2005).

This indicator takes the value of 0, 1, or 2 for no change, decrease, and increase, respectively. Using a multinomial logistic model (with a base case of no change in polarization), we regress this indicator on firm and board characteristics in vector $\boldsymbol{X}$ and present the results in Table 3.5. Models (1) and (2) differ in the timing of the variables $\boldsymbol{X}$. Model (1) uses the mean value of the characteristics for the entire pre-SOX period (i.e., 1999–2001), whereas Model (2) uses the characteristic values in the year immediately before the introduction of SOX (i.e., 2001).

Figure 3.2

The distribution of $\Delta \boldsymbol{Polarization}$ around the Sarbanes-Oxley Act

This figure plots the change in the mean *Polarization* between the pre-SOX period (1999-2001) and the post-SOX period (2003-2005) for all firms.



We can see that across both specifications, there is little evidence that firm and board characteristics individually predict the directional change in polarization around SOX. Since the firm and board characteristics are correlated, we also perform a joint test of significance for each model. We perform the likelihood ratio and Wald test for each model and in each case fail to reject the null that firm and board characteristics do not jointly predict the change in polarization around SOX. In Panel B, we present the confusion matrix associated with the two models. Overall, the models perform poorly, only correctly predicting treatment in 16% of *in-sample* cases with type II errors (i.e., the models fail to predict treatment when treatment has occurred) being the most common occurrence.

Collectively, these results show that the SOX-induced change in polarization is plausibly exogenous. Specifically, treated firms are equally likely to experience increases or decreases in polarization around SOX and that this change is not predictable using observable firm and board characteristics, which implies that independent directors are not solely selected based on their political views.

We therefore exploit plausible exogenous variation in firm-level polarization induced by the SOX Act for identification by estimating Equation (3.3). The result is presented in Table 3.6 Model (1). The coefficient on our variable of interest, $Adjusted\ Return_{i,t-1} \times Post_t \times \Delta Polarization_i$, is positive and significant as expected: firms that experience an increase in polarization around SOX also experience a dampening in turnover–performance sensitivity. This finding is consistent with our baseline results.

Table 3.5: The predictability of SOX-induced polarization changes

This table comprises two panels. Panel A tests whether firm and board characteristics can predict the change in polarization for treated firms (i.e., firms with a change in polarization) following the introduction of the SOX Act using Multinomial Logistic Regression. The dependent variable is an indicator for the change (increase, decrease, or constant) in mean polarization (Δ*Polarization*) between the pre-SOX period (1999-2001) and the post-SOX period (2003-2005). The base model is when there is no change in polarization. Model (1) regresses the indicator for Δ*Polarization* on the mean of firm controls over the pre-SOX period and Model (2) regresses the indicator for Δ*Polarization* on controls in 2001. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively. Panel B presents the confusion matrix associated with the estimated models.

Panel A: Regression	(1)		(2)	
	Pre-SOX Mean (1999-2001)		Pre-SOX (2001)	
	Decrease	Increase	Decrease	Increase
Adjusted return	-0.334	0.464	-0.159	0.103
	(0.585)	(0.593)	(0.266)	(0.288)
Size	0.041	0.093	0.037	0.167
	(0.111)	(0.109)	(0.111)	(0.108)
Q	-0.095	-0.007	-0.064	-0.010
	(0.077)	(0.060)	(0.083)	(0.072)
Leverage	0.673	0.229	1.102	0.361
	(0.860)	(0.971)	(0.811)	(1.054)
Risk	0.806	0.570	1.099*	0.942*
	(0.738)	(0.721)	(0.582)	(0.558)
Growth	0.767	0.740	0.403	-0.184
	(0.568)	(0.689)	(0.450)	(0.373)
New Director	0.105	-0.033	0.047	0.026
	(0.149)	(0.187)	(0.092)	(0.101)
Board Size	0.053	0.106	0.075	0.083
	(0.068)	(0.075)	(0.065)	(0.065)
Board Independence	-1.285**	-0.929*	-0.951*	-0.776
	(0.633)	(0.540)	(0.563)	(0.530)
Gender	-1.181	0.515	-1.548	0.463
	(1.222)	(1.412)	(1.102)	(1.218)
Age Dispersion	0.013	0.026	-0.033	0.015
	(0.045)	(0.046)	(0.043)	(0.046)
Ethnicity	-0.905	0.151	-0.789	0.244
	(0.653)	(0.583)	(0.549)	(0.465)
Director Busyness	0.508	0.527	0.287	0.274
	(0.694)	(0.713)	(0.613)	(0.550)
CEO Age Dummy	-0.180	-0.138	-0.167	-0.226
	(0.249)	(0.352)	(0.225)	(0.306)
CEO Tenure	-0.176	-0.004	-0.147**	-0.020
	(0.110)	(0.090)	(0.071)	(0.072)
Duality	0.427	0.181	0.266	-0.022
	(0.263)	(0.215)	(0.234)	(0.217)
N/ *pseudo* R^2	665/0.03		651/0.03	
Ho: All coefficients are simultaneously zero.				
	Likelihood-ratio test	Wald test	Likelihood-ratio	Wald test
Chi-squared	38.53	36.383	38.060	35.922
df	32	32	32	32
Pr > Chi-squared	0.198	0.272	0.213	0.290

Table 3.5 continued

Panel B: Confusion Matrix

Model (1)	Correct	Type I Error	Type II Error
Decrease	58	13	247
	18%	4%	77%
Increase	45	13	273
	14%	4%	82%
Overall	103	26	520
	16%	4%	80%

Model (2)	Correct	Type I Error	Type II Error
Decrease	56	12	246
	18%	4%	78%
Increase	49	12	269
	15%	4%	81%
Overall	105	24	515
	16%	4%	80%

Finally, to ensure that unobserved differences between treatment firms (i.e., firms experiencing a change in polarization around SOX) and control firms are not contaminating our findings, we use propensity score matching to select the most comparable group of firms for our tests. Specifically, we employ a matching process with replacement to match each treated firm with a control firm based on observable characteristics just before SOX (i.e., 2001). These observable characteristics include firm, board, and CEO characteristics as described in the baseline analysis. Panel A of Table 3.7 shows a comparison between the treatment and control groups before and after SOX for the full sample, while Panel B presents a similar comparison for the propensity score matched sample. Although the comparison before the matching does not show that the treated firms, overall, were considerably different from the control firms, the matching further eliminates significant differences between the two groups.

We then estimate Equation (3.3) using the matched sample. The result is presented in Table 3.6 Model (2). We find similar results: CEO turnover–performance sensitivity is dampened post-

SOX if firms also experience an increase in polarization. Overall, the results in this section show robust evidence that polarization of corporate boards leads to a reduction in CEO turnover–performance sensitivity and that this relation is likely causal.

Table 3.6: Polarization and CEO performance-turnover sensitivity: Evidence from the SOX Act

This table presents the results from estimating Equation (3.3) using Linear Probability Model. The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Adjusted return* × *Post* × Δ*Polarization* where *Post* is an indicator for the post-SOX period (2003-2005); Δ*Polarization* is the change in mean *Polarization* between the pre-SOX period (1999-2001) and the post-SOX period (2003-2005); and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. Model (1) uses the full sample and Model (2) uses the propensity score matched sample. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)
	Full sample	Propensity score matched sample
Adjusted return × Post × ΔPolarization	0.844*	0.707*
	(0.440)	(0.366)
Adjusted return × ΔPolarization	-0.310**	-0.283*
	(0.138)	(0.145)
ΔPolarization × Post	0.119	0.093
	(0.175)	(0.181)
Adjusted return × Post	-0.015	-0.016
	(0.017)	(0.016)
Adjusted return	0.844*	0.707*
	(0.440)	(0.366)
Other controls in Table 3.2	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
N/ R^2	3,476/0.03	2,970/0.03

3.4.Economic Mechanisms and Consequences for Future Board Composition

Up to this point, we have presented robust evidence that political polarization in the boardroom dampens CEO turnover–performance sensitivity. The final section of the paper investigates the underlying mechanism driving this finding as well as the broader economic consequences of a reduction in turnover–performance sensitivity.

3.4.1. Evidence across the political cycle

We begin by assessing how the effect we document varies over the political cycle. As the events surrounding recent elections show us, political polarization tends to be most pronounced during election years when everyone is thinking and talking about who to vote for. In particular, presidential elections are salient events that bring politics to the forefront of people's minds, which can lead to sharp increases in polarization, probably due to election campaign road shows and election media coverage. For example, the first debate between Hillary Clinton and Donald Trump in the 2016 Presidential race was the most watched event in American TV history (Stelter, 2016).

Therefore, we expect that the impact of polarization in the boardroom on the turnover–performance sensitivity will be more pronounced during presidential election years. To test this conjecture, we divide our sample into three subsamples, presidential election years, mid-term election years, and nonelection years, and re-estimate Equation (3.2). The results are presented in Table 3.8 Models (1) to (3).

We find that among these time periods, our results are only significant during the presidential election years. Moreover, we test the difference in the coefficients on *Polarization* × *Adjusted Return* across subsamples and find that the coefficient during presidential election years is significantly different from that of the nonelection years and that mid-term election years are not significantly different from nonelection years. Thus, polarization in the board room matters most during presidential election years when politics is at the forefront of people's minds and is a likely topic of conversation in the workplace.

There may be concerns that what we are documenting is related to political uncertainty. In Models (4) and (5), we divide our sample into periods of high and low political uncertainty based on the Economic Policy Uncertainty Index constructed by Baker, Bloom, and Davis (2016). We find that the coefficient $Polarization \times Adjusted\ Return$ is significantly positive in both subsamples. We also find that the difference in this coefficient across the political uncertainty subsamples is not statistically significant, suggesting that our result is not driven by political uncertainty.

Taken together, these results suggest that politically polarized discussions in the boardroom harm board function and lead to a dampening of the turnover–performance sensitivity. Indeed, several recent surveys report a growing trend in heated workplace political discussions leading to increased coworker hostility and worker stress and a decline in worker quality and productivity (e.g., American Psychological Association, 2016).

3.4.2. Firms' monitoring and advising needs

We argue that the dampening of CEO turnover–performance sensitivity is due to compromised board monitoring and advising function. To the extent that complex firms have greater monitoring and advising needs (Linck, Netter, and Yang, 2008), we expect the link between political polarization and CEO turnover–performance sensitivity to be stronger in complex firms. To test this conjecture, we divide the sample into above- and below-median values for three measures of complexity. The first measure we use is sales, as large firms tend to have more external contracting relationships and thus more monitoring and advisory requirements (Coles, Daniel, and Naveen, 2008). The second measure is R&D expenditure. R&D-intensive firms can benefit more from board advising given higher project verification costs (Raheja, 2005). Large and R&D-intensive firms are also expected to incur high monitoring costs (Linck et al., 2008; Linn and Park, 2005). The third measure we use is the leverage ratio, as firms with high leverage depend more on external resources and could require greater board monitoring and advising (Klein, 1998; Doan and Nguyen, 2018).

We re-estimate Equation (3.2) for each subsample. Table 3.9 shows the results of subsample analyses. Overall, we find that the coefficients of *Polarization* × *Adjusted Return* are positive across the six columns. However, for more complex firms (i.e., larger, more innovative, and highly levered firms), the coefficients of the interaction are larger in magnitude and more statistically significant. Tests for the difference between subsample coefficients are significant for subsamples based on firm size and leverage. These findings show that the link between political polarization of the board and CEO turnover–performance sensitivity is more pronounced in firms with greater advising and monitoring needs.

Table 3.7: Pre- and post-SOX characteristics of treated and control firms

This table compares the firm, board, and CEO characteristics for treated and control firms in the pre- and post-SOX for the full and the Propensity Score Matched (PSM) samples (Panels A and B, respectively). The definitions of all variables are contained in Appendix A2.

Panel A: Full Sample	*Before SOX (2001)*						*After SOX (2003)*					
	N	Treated	Control	Difference	*t*-statistic	*p*-value	N	Treated	Control	Difference	*t*-statistic	*p*-value
Forced Turnover	842	0.02	0.01	-0.01	-1.41	0.158	848	0.02	0.01	-0.01	-0.61	0.541
New Director	792	0.89	0.84	-0.05	-0.52	0.604	847	0.96	0.81	-0.16	-1.82	0.070
Adjusted Return	841	-0.01	0.05	0.06	1.80	0.074	847	-0.01	0.01	0.02	0.50	0.615
Size	842	7.68	7.40	-0.28	-2.20	0.029	848	7.84	7.53	-0.31	-2.43	0.016
Q	842	2.04	2.17	0.13	1.10	0.271	848	1.86	2.11	0.25	2.35	0.020
Leverage	839	0.26	0.24	-0.02	-1.52	0.130	847	0.24	0.22	-0.02	-1.38	0.170
Risk	756	0.48	0.48	0.00	0.24	0.810	762	0.36	0.35	-0.01	-0.57	0.567
Growth	842	0.08	0.04	-0.03	-1.78	0.076	848	0.11	0.11	0.00	0.10	0.920
Board Size	842	9.56	8.97	-0.59	-2.83	0.005	848	9.54	9.19	-0.35	-1.67	0.097
Board Independence	842	0.65	0.67	0.02	1.53	0.128	848	0.69	0.71	0.02	1.33	0.184
Gender	842	0.90	0.91	0.01	1.42	0.157	848	0.89	0.89	0.00	-0.08	0.935
Age Dispersion	842	8.00	8.04	0.04	0.17	0.863	848	7.83	8.06	0.23	1.04	0.299
Ethnicity	842	0.71	0.72	0.01	0.32	0.747	848	0.68	0.70	0.02	1.23	0.220
Director Busyness	842	0.33	0.31	-0.02	-1.02	0.307	848	0.34	0.30	-0.04	-2.05	0.041
CEO Age Dummy	842	0.23	0.29	0.07	1.68	0.094	848	0.24	0.32	0.08	1.90	0.059
CEO Tenure	842	3.51	3.59	0.09	0.54	0.586	848	4.47	4.75	0.28	1.41	0.159
Duality	842	0.68	0.66	-0.02	-0.58	0.564	848	0.65	0.65	0.00	-0.09	0.927

Table 3.7 continued

Panel B: PSM Sample	*Before SOX (2001)*						*After SOX (2003)*					
	N	Treated	Control	Difference	*t*-statistic	*p*-value	N	Treated	Control	Difference	*t*-statistic	*p*-value
Forced Turnover	647	0.01	0.01	0.00	-0.33	0.741	626	0.02	0.01	-0.02	-1.40	0.163
New Director	647	0.88	0.89	0.01	0.10	0.923	626	0.95	0.79	-0.16	-1.65	0.101
Adjusted Return	647	0.01	0.03	0.02	0.61	0.544	626	-0.02	-0.03	-0.01	-0.28	0.781
Size	647	7.84	7.66	-0.18	-1.29	0.198	626	8.01	7.81	-0.20	-1.42	0.159
Q	647	2.06	2.10	0.04	0.31	0.759	626	1.89	2.06	0.16	1.32	0.188
Leverage	647	0.27	0.26	-0.01	-0.50	0.619	626	0.25	0.24	0.00	-0.18	0.858
Risk	647	0.46	0.46	0.00	-0.07	0.941	626	0.34	0.34	0.00	-0.30	0.766
Growth	647	0.08	0.05	-0.02	-1.12	0.266	626	0.11	0.11	0.00	-0.09	0.930
Board Size	647	9.79	9.53	-0.26	-1.14	0.255	626	9.74	9.79	0.05	0.21	0.833
Board Independence	647	0.66	0.67	0.01	0.59	0.556	626	0.70	0.71	0.01	0.91	0.363
Gender	647	0.90	0.90	0.00	0.60	0.551	626	0.89	0.88	-0.01	-0.81	0.418
Age Dispersion	647	7.79	7.95	0.16	0.64	0.523	626	7.59	8.00	0.41	1.59	0.115
Ethnicity	647	0.70	0.71	0.01	0.75	0.454	626	0.68	0.70	0.02	1.27	0.205
Director Busyness	647	0.35	0.33	-0.02	-0.83	0.405	626	0.37	0.33	-0.04	-1.60	0.112
CEO Age Dummy	647	0.24	0.27	0.03	0.66	0.512	626	0.25	0.32	0.07	1.52	0.130
CEO Tenure	647	3.75	3.82	0.07	0.40	0.689	626	4.77	5.00	0.23	0.98	0.327
Duality	647	0.69	0.71	0.02	0.37	0.715	626	0.66	0.73	0.07	1.46	0.146

Table 3.8: Polarization and CEO performance-turnover sensitivity: Across the political cycle

This table presents the results from estimating Equation (3.2) using Linear Probability Model for sub-samples based on political variables. The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Polarization* × *Adjusted Return* where *Polarization* is the standard deviation of board members' ideology and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. Models (1), (2) and (3) are estimates based on presidential election years, mid-term election years, and non-election years respectively. Models (4) and (5) provide estimates for periods of high (above sample median) and low political uncertainty based on the Economic Policy Uncertainty Index by Baker, Bloom, and Davis (2016). All regressions include the same set of controls as in Table 3.2. The definitions of all other variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Presidential Election	*Mid-term Election*	*Non-Election*	*High Political Uncertainty*	*Low Political Uncertainty*
Polarization	0.060	-0.034	-0.048	-0.023	-0.060
	(0.055)	(0.049)	(0.058)	(0.040)	(0.052)
Polarization × Adjusted Return	0.446***	0.123	0.094	0.158**	0.206**
	(0.154)	(0.145)	(0.108)	(0.062)	(0.095)
Adjusted Return	-0.033*	-0.018	-0.032***	-0.020***	-0.032***
	(0.017)	(0.013)	(0.009)	(0.006)	(0.009)
β(Polarization × Adjusted Return)					
Difference of coefficients	(1)-(3) = 0.352	(2)-(3) = 0.029		(4)-(5) = -0.048	
Z-statistic	3.74***	0.32		-0.85	
Other controls in Table 3.2	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N/R^2	2,815/0.02	3,489/0.02	6,225/0.01	7,041/0.01	5,488/0.02

Table 3.9

Polarization and CEO performance-turnover sensitivity: Firm complexity

This table presents the results from estimating Equation (3.2) using Linear Probability Model for sub-samples split based on proxies for firm complexity. The dependent variable is *Forced Turnover*, an indicator equal to one if a CEO turnover in year *t* is forced and zero otherwise. The main dependent variable of interest is the interaction term *Polarization* × *Adjusted Return* where *Polarization* is the standard deviation of board members' ideology and *Adjusted Return* is the annualized stock return adjusted by 2-digit SIC code industry mean for year *t*-1. Models (1) and (2) split the sample by firm size (Log(sales)). Models (3) and (4) split the sample by R&D intensity. Models (5) and (6) split the sample by leverage. "High" and "Low" refer to above and below median samples based on the characteristic in question. Large firms, firms with high R&D and high leverage are considered more complex. All regressions include the same set of controls as in Table 3.2. The definitions of all other variables are contained in Appendix A2. Robust standard errors clustered at 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Size		*R&D*		*Leverage*	
	High	Low	High	Low	High	Low
Polarization	0.028	-0.064	-0.043	-0.009	0.019	-0.080*
	(0.047)	(0.050)	(0.053)	(0.048)	(0.040)	(0.046)
Polarization × Adjusted Return	0.314**	0.158**	0.259***	0.163*	0.408**	0.109*
	(0.122)	(0.066)	(0.067)	(0.087)	(0.160)	(0.062)
Adjusted Return	-0.026***	-0.024***	-0.026***	-0.025***	-0.033***	-0.017***
	(0.007)	(0.007)	(0.005)	(0.008)	(0.009)	(0.005)
β(Polarization × Adjusted Return)						
Difference of coefficients	(1)-(2) = 0.156		(3)-(4) = 0.096		(5)-(6) = 0.299	
Z-statistic	2.25***		1.75		3.49***	
Other controls in Table 3.2	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
N/R^2	6,812/0.01	5,717/0.02	5,878/0.02	6,651/0.01	6,606/0.02	5,923/0.01

3.4.3. Director departure future board composition

A natural question to ask is how polarization influences individual directors' decisions to stay on or leave the board. We argue that since polarization creates a divisive boardroom and can also generate dislike and distrust among directors with different political views, polarized directors (i.e., those who are ideologically far from the group) have strong incentives to vacate their positions and leave the board.

We investigate how polarization influences future board composition by examining director departures in the following regression.

$$Depart_{d,i,t+1} = \alpha_1 Polarization_{it} \times Director\ Polarization_{d,t} +$$

$$\alpha_2 Polarization_{it} + \alpha_3 Director\ Polarization_{d,t}$$

$$+\boldsymbol{\beta}'\boldsymbol{X}_{\boldsymbol{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \qquad (3.4)$$

The dependent variable, *Depart*, is an indicator equal to one if director *d* leaves the board of firm *i* in the following year (*t*+1). The variables of interest are (i) *Director Polarization* which is the absolute value of director ideology; and (ii) *Polarization* which is the firm level measure of polarization defined previously. To understand which types of directors respond to polarization in the boardroom, we also include the interaction term *Polarization* × *Director Polarization.* Finally, the vector ***X*** contains the same set of controls as in Equation (3.2) except that we add the following director-level controls: *Against Vote* which is the ratio of "against" and "abstain" shareholder votes to total number of votes cast for director *d* in director election occurring in year *t; Director Age* which is the director's age in years; *New Director Dummy* which is an indicator equal to one if director *d* is new to the board in year *t*; and *Non-Contributor* which is an indicator equal to one if director *d* does not make personal contributions to individual candidates (i.e., they are not matched to the contribution data and thus have an ideology score of zero). All other variables are the same as in Equation (3.2).

We estimate Equation (3.4) using an LPM and report the results in Table 3.10 Model (1). We find that while *Polarization* is insignificant in explaining director departure, *Director Polarization* is significantly and negatively related to director departure. That is, directors who have strong political leanings—whether right or left—are less likely to depart the board. Interestingly, the interaction term *Polarization* × *Director Polarization* is significantly positive, suggesting that although firm level polarization does not determine director departure per se, when firm polarization is high then polarized directors—those with political views far from the rest of the board—are more likely to leave, as expected. To aid interpretation, in Model (2), we replace the continuous polarization measure with an indicator equal to one if firm *i* is above median polarization. We find similar results. Economically, from Model (2), if the polarization is above the median, a one-standard-deviation increase in *Director Polarization* (i.e., politically more extreme) leads to a 3% rise in the probability (or 43% increase relative to the sample mean departure rate) that a director departs the board.

In summary, we find that polarization increases the likelihood of director departure, but only for directors whose political views are far from the average of the rest of the board. Thus, over time, polarized boards likely become more politically homogenous. This self-selection based on political preferences—that are unobserved at appointment and only revealed over time—is consistent with work by Westphal and Zajac (1995) who argue that boards tend to select new directors who are demographically similar. The difference in our setting is that the selection on political views is made by the directors themselves through departure and not by the board at the time of appointment. This result is also in line with the findings of Fos et al. (2021) who find that *executive teams* in the US have become increasingly politically homogeneous over time.

3.5.The Economic Consequences of Politically Polarized Boards

The decline of board effectiveness due to political polarization can also manifest itself in corporate outcomes. Our results support the *boardroom stalemate hypothesis* that polarization makes collective decision making more difficult and therefore reduces the effectiveness of the board. In line with this hypothesis, we expect that corporate investment decisions to be less responsive to external shocks. We test this conjecture in two settings. First, we examine how political polarization affects firms' investment efficiency in the following regression:

$$Investment_{i,t} = \mu_1 Q_{i,t-1} \times Polarization_{it} + \mu_2 Q_{i,t-1} + \mu_3 Polarization_{it}$$

$$+\boldsymbol{\beta}'\boldsymbol{X_{i,t}} + \alpha_i + \alpha_t + \varepsilon_{i,t} \quad (3.5)$$

The dependent variable, *Investment*, is total investment (i.e., capital investment and R&D investment) scaled by total assets. The variable *Q* is Tobin's Q, which is a proxy for the marginal productivity of capital. The literature documents a significant and positive relation between investment and *Q*: firms should invest more when the marginal productivity of capital rises. To investigate how the firm responsiveness of investment to *Q* varies with polarization, we include the interaction term *Q* × *Polarization*. If polarization leads to compromised board functions, we expect the investment–Q sensitivity to be dampened, implying $\mu_1 < 0$. That is, firms with polarized boards are slower to respond to investment opportunities. All other variables are the same as in Equation (3.2).

Table 3.11 presents the results. In Model (1), we find that the coefficient of Q is significantly positive, suggesting that firms respond to increased investment opportunities by investing more.

Importantly, we find that the coefficient on *Q* × *Polarization* is significantly negative, suggesting that political polarization dampens the sensitivity of firm investment–Q sensitivity. We interpret this as a reduction in efficiency. Comparing the magnitudes of the coefficients μ_1 and μ_2, for a given change in *Q*, a one-standard-deviation increase in *Polarization* leads to a 6.7% reduction in investment–Q sensitivity. In Model (2), we repeat the analysis replacing the continuous *Polarization* variable with a dummy variable that equals one if *Polarization* is higher than the sample median and zero otherwise. We find similar results.

Second, we examine firms' environmental performance. Climate change is quite often cited as the most important global challenge at present. Yet, the climate debate—at all levels, from the causes to the solutions to even if global temperatures are indeed rising—is also one of the most divisive and politicized. In particular, recent research on climate change views in the US finds a strong effect of political orientation: Liberals and Democrats' beliefs about climate change are more in line with mainstream climate science and they express greater concerns about global warming than do their Conservative and Republican counterparts (e.g., Hamilton and Keim, 2009; Malka et al., 2009; Borick and Rabe, 2010; Hamilton, 2011; McCright and Dunlap 2011; Hamilton and Saito, 2015). Thus, polarized boardrooms will find it much harder to overcome corporate inertia (Hoppmann et al., 2019) and respond to climate risks by making more environmentally friendly investments.

We use the environmental scores from MSCI ESG Research (formerly KLD Research and Analytics) which have been used extensively in prior research (e.g., Pedersen, Fitzgibbons, and Pomorski, 2021; Christensen, Serafeim, and Sikochi, 2022), to examine firms' environmental performance in the following regression model:

$$Enviroment_{i,t} = \omega_1 Polarization_{it} + \boldsymbol{\beta}' \boldsymbol{X}_{\boldsymbol{i,t}} + \alpha_{j,t} + \varepsilon_{i,t} \tag{3.6}$$

The dependent variable, *Environment*, is one of three measures: (1) a score that captures the environmental strengths of the firm; (2) a score that captures the environmental weaknesses/concerns of a firm; and (3) a net score which is the difference between the firm's strengths and weaknesses. These scores are highly persistent: a regression of current on lagged values produces an AR(1) coefficient of 0.9 and R^2 of 0.8, thus including firm fixed-effects absorbs much of the variation we are interested in exploring. Instead, we include $\alpha_{j,t}$ which is an industry-by-year fixed effect to absorb all industry wide variation that may explain environmental scores. Identification therefore comes from comparing the environmental scores of similar firms in the same industry in a given year with differing levels of polarization. All other variables are the same as in Equation (3.2). Since polarization decreases firms' responsiveness to growing environmental concerns over climate change, we expect that it will be negatively related to firms' net score, implying $\omega_1 < 0$.

The results are presented in Table 3.12 across three columns. In Model (1) the dependent variable is the net score, whereas Models (2) and (3) unpack the net score into strengths and concerns, respectively. We can see, as expected, that the coefficient on *Polarization* is negative and significant in Model (1), suggesting that polarization reduces firms' environmental performance. Further, from Models (2) and (3), we can see that this result is largely driven by greater environmental concerns. These results are consistent with the idea that polarization leads firms to be less responsive to growing public concerns over climate change, which in turn, leads to growing concerns over these firms' own environmental practices.

Table 3.10: Polarization and director departure

This table presents the results from estimating Equation (3.4) using a Linear Probability Model. The dependent variable is an indicator equal to one if a director leaves the board in the following year. The independent variables of interest are (i) *Director Polarization* which is the absolute value of director ideology; and (ii) *Polarization* which is the standard deviation of board members' ideology. Models (1) and (2) use a continuous variable for *Polarization* whereas Models (3) and (4) use an indicator for above median *Polarization*. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the director level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5, and 1% levels, respectively.

	(1) Polarization: Continuous	(2) Polarization: Dummy variable
Director Polarization	-0.184***	-0.449**
	(0.071)	(0.177)
Polarization	0.033	0.006
	(0.037)	(0.004)
Director Polarization × Polarization	0.681*	0.375**
	(0.356)	(0.168)
Non-Contributor	-0.008	-0.004
	(0.010)	(0.009)
Against Voting	0.101***	0.102***
	(0.024)	(0.024)
Director Age	0.228***	0.228***
	(0.012)	(0.012)
New Director Dummy	-0.010***	-0.010***
	(0.002)	(0.002)
Staggered Board	-0.008	-0.008
	(0.006)	(0.006)
Other controls in Table 3.2	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
N/R^2	31,020/0.06	31,020/0.06

Table 3.11: Polarization and firm investment–Q sensitivity

This table presents the results from estimating Equation (3.5) using Ordinary Least Squares regressions. The dependent variable is total investment (i.e., capital investment and R&D investment) scaled by total assets. The independent variable of interest is the interaction term *Polarization* × *Q* where *Polarization* is the standard deviation of board members' ideology and *Q* is a firm's Tobin's Q. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5 and 1% levels, respectively.

	(1) Polarization: Continuous	(2) Polarization: Dummy variable
Polarization	0.021*	0.003*
	(0.012)	(0.002)
Polarization × *Q*	-0.010*	-0.002**
	(0.006)	(0.001)
Q	0.009***	0.009***
	(0.002)	(0.002)
Other controls in Table 3.2	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
N/R^2	12,526/0.16	12,526/0.16

Table 3.12: Polarization and firm environmental performance

This table presents the results from estimating Equation (3.6) using Ordinary Least Squares regressions. Models (1)-(3) use alternative measures of firm environmental performance based on data from MSCI ESG Research. The dependent variable in Model (1) is the net environmental score of the firm (i.e., strengths minus concerns). The dependent variable in Model (2) is a score that captures the environmental strengths of the firm. The dependent variable in Model (3) is a score that captures the environmental concerns of the firm. The independent variable of interest is the term *Polarization* which is the standard deviation of board members' ideology. All regressions include the same set of controls as in Table 3.2. The definitions of all variables are contained in Appendix A2. Robust standard errors clustered at the 2-digit SIC code industry level are reported in parentheses. *, **, *** represent statistical significance at the 10, 5 and 1% levels, respectively.

	(1)	(2)	(3)
		Environmental Score	
	Net	Strengths	Concerns
Polarization	-0.820***	-0.321	0.499***
	(0.291)	(0.220)	(0.174)
Other controls in Table 3.2	Y	Y	Y
Industry x Year FE	Y	Y	Y
N/R^2	8296/0.31	8296/0.43	8296/0.47

3.6.Conclusion

In this paper, we study the economic consequences of affective political polarization. Using the corporate board of directors as our experimental setting, we examine how polarization between the board members influences turnover–performance sensitivity. We find that polarized corporate boards are much less likely to fire a CEO following poor performance—a dampening of the turnover–performance sensitivity. These findings are more pronounced for firms with high monitoring and advising needs and during presidential election years when politics is at the forefront of people's minds.

Our results are consistent with the idea that polarized boards lead to a stalemate in decision making, thus hampering both the monitoring and advisory functions of the board. Further, we show that polarization increases the likelihood of director departure, but only for those directors who are ideologically far from the rest of the group. Thus, over time boards likely become politically homogeneous. Finally, we show that weakened board functions lead to a reduction in investment efficiency as measured by a reduction in firms' investment–Q sensitivity and environmental performance. Overall, our paper is among the first to document the significant impact that political polarization has on corporate America.

Appendix A2: Variable definitions

	Description
Dependent variable	
Forced Turnover	An indicator variable that equals one if a CEO turnover is forced, and zero otherwise
Polarization	
Polarization SD	The standard deviation of board members' ideology
Polarization Max	Maximum absolute difference between board members' ideology
Polarization Mean	The mean of absolute deviation of board members' ideology
Firm characteristics	
Adjusted Return	Annualized stock return adjusted by 2-digit SIC code industry mean
Size	The natural logarithm of total assets
Q	Market value of equity plus the book value of liabilities and preferred stock minus deferred taxes, all divided by total assets
Leverage	The ratio of total debt to total assets
Risk	Annualized variance of daily stock returns
Growth	Annual growth of sales
Board characteristics	
New Director	Number of newly appointed directors
Board Size	Number of directors in the board
Board Independence	The ratio of independent directors in the board using the ISS classification
Gender	The ratio of male directors in the board
Age Dispersion	The standard deviation of age across directors in the board
Ethnicity	Hirschman-Herfindahl Index of ethnicity concentration of five groups: White/Caucasian, African-American, Hispanic, Asian, and Other
Board Busyness	The ratio of directors serving on multiple boards
CEO characteristics	
CEO Age Dummy	An indicator variable that equals one if CEO age is greater than or equal to 60, and zero otherwise
CEO Tenure	The number of years a CEO has served
Duality	An indicator variable that equals one if a CEO is also the chairman, and zero otherwise
Director characteristics	
Director Polarization	The absolute value of director ideology
New Director Dummy	An indicator variable that equals one if a director is newly appointed
Director Age	The natural logarithm of director age
Non-Contributor	An indicator variable that equals one if a director does not contribute, and zero otherwise
Director Departure	An indicator variable that equals one if a director leaves in the following year, and zero otherwise
Against Voting	The ratio of "against" and "abstain" shareholder votes to total number of votes cast for a director

4. Concluding remarks

This thesis comprises three chapters examining three aspects that have not been fully addressed in corporate finance. In each aspect, the thesis attempts to explore the roles of key decision makers in corporate outcomes.

The first chapter focuses on the interactions within the top management team, examining the effects of an unexplored dimension of managerial risk-taking—heterogeneity in risk-taking incentives among top executives—on firm risk and performance. Despite many prior studies on risk-taking incentives of a firm's CEO, little is known about the incentives of all the firm's executives as a team. Since corporate policies result from collective decisions by top managers maximizing their own utility, divergent risk-taking incentives among them may introduce disagreements and conflicts of interest into the decision-making process. Consequently, these potential frictions could result in suboptimal corporate decisions. Consistent with this premise, the analysis demonstrates that firms run by top managers with more divergent risk-taking incentives are less willing to take risks and more likely to suffer inferior performance. The chapter also examines mechanisms through which managerial risk-taking incentive heterogeneity reduces risk and harms performance, finding that more divergent risk-taking incentives are associated with attenuated investment efficiency, lower R&D, and less likelihood of M&A transactions. The findings therefore provide important implications for how the risk-taking preferences of key decision-makers within a firm shape its corporate policies.

The second chapter investigates how common lenders can facilitate anti-competitive practices among their borrowers. Utilizing the government-driven mergers of large banks in Japan, the chapter shows that a common lender reduces corporate investment and improves corporate markup or profitability ratio. In addition, these effects are more pronounced on financially distressed firms whose values of loans granted are more sensitive to fundamentals. More importantly, we explore a channel of the common lender effect. Specifically, we document a further reduction in investment and higher improvement in markup/profitability ratio for a treated firm in the presence of an ex-banker director—an executive director who was formerly affiliated with either merging bank. This finding implies that a common lender can exercise their voice through former employees currently serving as their borrowers' executive directors. The finding also responds to the criticism against previously found common investor effects whose channels remain unclear. The findings suggest that common lenders, in an attempt to minimize the delinquency rate of their borrowers, may facilitate coordination strategies among their borrowers within the same industry. Overall, the chapter contributes to the literature by providing evidence on not only the anti-competitive effect but also the channel through which a common investor affects the management of its investees.

The third chapter concentrates on the interactions between directors due to differences in their political ideology. While political polarization has increased dramatically in recent decades, little is known about its economic consequences. The chapter fills this void by being the first to examine the impact of political polarization in a corporate board setting. As polarization increases the degree of divergent views and chance of conflict among board members, it could inhibit the collective decision-making process of the board and hinder its advisory and monitoring functions. This, in turn, may slow the responsiveness of the board to remove an underperforming CEO. To test this hypothesis, the chapter uses data on personal contributions to individual members of Congress to measure the political ideology of individual members and then polarization within the board. The analysis shows that political polarization between board members reduces the CEO turnover-performance sensitivity. Polarization also increases the departure likelihood for directors who are ideologically distant from the rest of the board, making boards more politically homogeneous over time. Finally, the finding shows that polarization in the boardroom lowers firms' investment–Q sensitivity and environmental performance. The chapter therefore puts forward novel evidence on the real economic cost of political polarization.

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