ESSAYS ON CORPORATE FINANCE

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Abstract

My dissertation consists of three chapters, focusing on two main areas. First, I analyze the boundaries of firms and how a firm's organizational structure affects decisions and operations. I study firm boundary choices and their impact on operations, strategic decisions, and overall performance. Second, I evaluate the impact and effectiveness of monitoring and oversight by various firm stakeholders and examine how these stakeholders impact corporate governance outcomes and, consequently, affect firm performance and decision-making processes.

In the first chapter, I study how corporations leverage voluntary disclosure to illuminate the murk arising from business complexity. I find that conglomerates compensate for their business complexity by strategically disclosing more information voluntarily. This finding becomes more pronounced under heightened information demands from stakeholders and analysts or when the pay-performance sensitivity is higher. The enhanced transparency serves as a strategic move, yielding tangible benefits in the form of improved firm valuation and decreased capital costs. Overall, my study illustrates that multi-segment firms tactically deploy voluntary disclosure to offset the potential detriments of their business complexity.

In the second chapter, I study the efficacy of environmental enforcement in powering down pollution and investigate how management in the US electricity sector navigates such enforcement. Analyzing data from power plants, I find that facilities targeted by the EPA tend to reduce pollution emissions and electricity production. Managerial responses to these challenges involve strategies, including installing scrubbers, enhancing pollution abatement efforts, investing in energy-efficient generators, and reducing coal-fired electricity production. These changes are facilitated by the organizational structure of utility firms and the economies of scale in fuel acquisition, the availability of financial resources, environmental agencies undertaking enforcement, and utility firms' regulatory status. While heightened regulatory compliance costs do not significantly impact the financial performance of firms, they ultimately result in higher electricity prices for consumers, reflecting a transfer of the financial burden.

In the third chapter, I aim to unveil the role of lobbying activities in creating a nexus between corporations and their institutional shareholders and trace the footprints of lobbyists in mutual funds voting. This chapter investigates whether mutual funds exhibit a preference for portfolio companies with which they have shared lobbyists and assesses how this preference impacts their voting behavior. I uncover that connected institutional shareholders exhibit a higher propensity to vote in concurrence with company man-

agement—especially when such votes carry significant managerial value. Following these voting events, I observe that higher connected mutual fund support is negatively associated with abnormal return. Overall, my findings indicate that management might strategically leverage shared lobbying relationships to influence shareholder voting patterns.

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Chapter 1

1. Illuminating the Murk: The Effect of Business Complexity on Voluntary Disclosure

1.1. Introduction

Businesses today are ever more complex as the advancement in technology and communications powered the expansions across borders, intensifying competition globally. These multi-segment businesses or conglomerates, with complex organizational structures, are highly opaque, making financial information processing more challenging. Given investors' limited processing and resource capacity, such business complexity can create frictions in information processing that not only significantly delay the impounding of information into firm values but also make processing information more costly (e.g., Hirshleifer and Teoh, 2003; Hong and Stein, 1999). For example, Cohen and Lou (2012) and Barinov, Park, and Yıldızhan (2019) find that information takes longer to be reflected in the stock price of conglomerates compared to standalone firms, attributing their findings to the information-processing complexity of conglomerates' complicated business models. Yet little research has examined whether such complicated firms attempt to mitigate this adverse consequence of their business complexity.[1] Thus, in this study, I examine whether managers of multi-segment firms strategically disclose more information to improve their firm's information environment and explore the financial consequences of their actions.

Disclosure theories have modeled capital market valuation as a critical incentive for voluntary disclosure (e.g., Verrecchia, 1983; Verrecchia, 2001). For example, Diamond and Verrecchia (1991) show that disclosure leads to increased liquidity of securities, higher demand from large investors, and reduced information asymmetry and cost of capital. Similarly, Balakrishnan et al. (2014) document that increased voluntary disclosure can increase firm value by reducing information asymmetry. However, the revelation of information is curbed by the costs it imposes on firms, as firms may suffer losses in a competitive position when existing

[1] A contemporary paper by Baik, Johnson, Kim, and Yu (2023) examines how organizational complexity influences financial reporting complexity and the information environment. They focus on a firm's network of subsidiaries, hierarchical levels, and unique industries where a parent firm and its subsidiaries operate. They use these characteristics to construct the first principal component as a proxy for "organization complexity".

competitors use the revealed information to strategize competitive actions against the disclosing firms (Arya, Frimor, and Mittendorf, 2010; Heinle, Samuels, and Taylor, 2022). Indeed, Verrecchia (1983) demonstrates the role of proprietary costs in managers' discretion in information disclosure, while Ellis, Fee, and Thomas (2012) show that the threat of competition is an important factor affecting the firms' disclosure policy. For complex businesses, Berger and Hann (2007) highlight the proprietary costs of segment-relevant disclosure when high performing segments bring about more competition, as well as the agency costs associated with heightened external monitoring when information about an under-performing segment is revealed. I expect the tension between disclosure costs and benefits from business complexity to be particularly relevant in shaping managers' decisions in issuing voluntary disclosure. To explore this issue, I examine whether and how managers of complex firms exploit voluntary disclosure to improve their firm's information environment. If the benefits of voluntary disclosure help address the information processing costs and improve the information environment, I predict a positive relationship between business complexity and voluntary disclosure. However, if the proprietary and agency costs of revealing information outweigh the benefits and prohibit managers of complex firms from disclosing information, I expect a negative relationship between complexity and disclosure.

I empirically investigate the relationship between business complexity and voluntary disclosure on a sample of 8,307 unique publicly traded US firms between 1995 and 2020. Following the extant literature, I measure voluntary disclosure using the frequency of management forecasts (e.g., Balakrishnan et al., 2014) and business complexity based on a firm's organizational structure using a binary indicator to denote a conglomerate, the number of business segments the firm operates in, and one minus the firm's Herfindahl-Hirschman Index (e.g., Barinov, 2020). The results show a robust positive relationship between business complexity and voluntary disclosure. In economic terms, voluntary disclosure in conglomerates is 6% higher than that of the average standalone firm. Furthermore, I show that the increase in complicated firms' voluntary disclosure is not a response to the textual complexity of their financial statements, as documented in Guay, Samuels, and Taylor (2016). Instead, the effect of financial complexity, as measured by the readability of a firm's 10-K filing (Guay, Samuels, and Taylor, 2016), on voluntary disclosure becomes statistically insignificant in the presence of business complexity, suggesting that business complexity subsumes the role of financial complexity in explaining voluntary disclosure.

As the organizational structure of a firm is not determined randomly, and the decision of the segments in which a firm operates is made endogenously, the baseline findings may be contaminated by selection bias.

For instance, firms with higher voluntary disclosure may exploit a lower cost of capital to increase their investment in new segments (Frank and Shen, 2016). Furthermore, omitted factors, such as shareholders' monitoring and governance, that can influence both organizational structure and disclosure policy may interfere with a causal interpretation of the baseline results. To address these potential sources of endogeneity, I use two instrumental variables employed in prior studies to identify the baseline results. The first instrumental variable is an indicator variable that equals one for firms with non-zero minority interests (Dimitrov and Tice, 2006). Since minority interest may arise when firms acquire the majority stake in another firm, it relates to firms' organizational structure and the number of segments. The second instrument is the ratio of conglomerates in a given industry-year, indicating the attractiveness of an industry for conglomerates (Campa and Kedia, 2002). I also adopt another test that uses merger and acquisition activities as a quasi-exogenous shock to business complexity. Overall, the different approaches produce consistent evidence that the relationship between business complexity and voluntary disclosure is causal.

This study further conducts several robustness tests to establish the relationship between business complexity and voluntary disclosures. First, I examine the marginal effect of increasing the number of business segments on voluntary disclosure in different subsamples. The results suggest that conglomerates are more incentivized to disclose more information than an average standalone firm as their business gets more complex. Second, I also investigate the changes in voluntary disclosure for firms that switch from standalone firms to conglomerates and vice versa. I find a significant increase in voluntary disclosure as standalone firms evolve to conglomerates and a significant reduction as conglomerates become more focused. Finally, I test whether conglomerate' frequent disclosures are driven by the type of management earnings forecasts and find the effect of business complexity exists for management earnings forecasts that beat analysts' consensus (good news) and those with a shortfall (bad news), with a more pronounced effect for the latter.

I next explore several channels through which business complexity affects voluntary disclosure. The literature documents that institutional investors influence various corporate policies, including disclosure (Boone and White, 2015; Appel, Gormley, and Keim, 2016; Crane, Michenaud, and Weston, 2016; Bird and Karolyi, 2016). Higher voluntary disclosure in more complex firms may be a response to the information demand by institutional shareholders. Consistent with this argument, I find the effect of business complexity on voluntary disclosure to be more pronounced when firms have more institutional investors. Analysts are another market participant type that demands information. Unlike institutional investors who can exert both exit and voice strategies, analysts can influence firm disclosure policies through informal communications or by deciding whether to follow the firm. According to a survey by Graham, Harvey, and Rajgopal (2005), 50.8% of managers agreed or strongly agreed that they use voluntary disclosure to increase their analyst coverage, as it decreases the cost of information acquisition and increases the amount of information available to analysts. The impact of business complexity on voluntary disclosure is stronger when firms have higher analyst coverage, consistent with prior findings.

Another channel through which business complexity could impact voluntary disclosure is managers' intention to increase firm value. I argue that when the CEO's wealth is more sensitive to the changes in stock price (i.e., higher CEO portfolio delta), managers may be more motivated to react to the complexity arising from the organizational structure, indicating more alignment with shareholders' interests (Hui and Matsunaga, 2015). Similarly, managers may be likely to disclose more information when their firm experiences a better return on assets but less when it incurs a loss. These findings show that the effect of business complexity on voluntary disclosure is more robust in firms with higher CEO pay-performance sensitivity and when firms' return on assets is more significant, consistent with our expectations.

Finally, I investigate the financial consequences of increased voluntary disclosure in complex firms. Prior literature documents that firms have the incentive to increase disclosure to reduce information asymmetry, which subsequently leads to a lower cost of capital (Diamond and Verrecchia, 1991) and higher firm value (Balakrishnan et al., 2014). Drawn from the existing literature, I employ three different measures of a firm's information asymmetry: (1) *Turnover* is defined as the sum of share trading volume over the fiscal year divided by the number of shares outstanding at the beginning of the year; (2) *Analyst Forecast Error* is the analyst consensus minus actual earnings per share divided by the stock price; and (3) *Price Nonsynchonicity* is computed as one minus the correlation between the stock's return and the corresponding industry's return and the market's return. If *Price Nonsynchonicity* is high (i.e., a firm's stock return is less correlated with the market and industry returns), then the firm's stock price is likely to convey firm-specific information, valuable for managerial investment decisions (Chen, Goldstein, and Jiang, 2007). The results show that while increased voluntary disclosure helps improve the information environment of conglomerates, this enhanced benefit is no different from that of standalone firms. In other words, disclosing more information has the same impact on the information environment of complex businesses as it does on that of standalone firms. I also find that while conglomerates typically have a lower firm value and higher cost of capital than their standalone counterparts, their increased voluntary disclosure enables them to mitigate these adverse effects. Overall, it pays to disclose more – conglomerates enjoy an enhanced firm value and lower cost of equity and debt capital.

This paper contributes to several strands of literature. First, I contribute to the literature that studies the determinants of voluntary disclosure (Cheng and Lo, 2006; Guay, Samuels, and Taylor, 2016; Pae, Song, and Yi, 2016; Bourveau and Schoenfeld, 2017; Bourveau, Lou, and Wang, 2018; Abramova, Core, and Sutherland, 2020). I find that firms use voluntary disclosure to partly offset the negative impact of business complexity on the information environment and to benefit from higher subsequent firm value and lower cost of capital. Importantly, this study differs from Guay, Samuels, and Taylor (2016) in that I measure complexity directly using the firms' organizational structure, allowing for a clear separation of business and financial statement complexity. This approach enables us to show that organizational complexity directly shapes voluntary disclosure practices, contributing to a deeper understanding of the determinants of disclosure behavior.

Second, this research is related to studies that examine the impact of institutional investors on firm policies, including information disclosure (Appel, Gormley, and Keim, 2016; Crane, Michenaud, and Weston, 2016; Boone and White, 2015; Bird and Karolyi, 2016). Expanding this strand of literature, I show that the demand for information from institutional investors acts as an underlying channel through which business complexity affects voluntary disclosure. Additionally, these analyses contribute to the existing literature that studies the effect of analyst coverage on information disclosure (Lang and Lundholm, 1996) in that I provide evidence that analysts' demand for information is another motivation for conglomerates issuing more disclosure.

Finally, this work expands the literature that examines the negative consequences of firm complexity on the information environment (Chemmanur and Liu, 2011; Cohen and Lou, 2012; Barinov, Park, and Yıldızhan, 2019). The latter two studies provide empirical evidence that complexity in information processing for conglomerates leads to significant delays in the impounding of information into asset prices. However, I show that these complicated firms compensate for the negative effect associated with their business complexity by strategically issuing more voluntary disclosures. While such disclosure may give rise to high proprietary costs, conglomerates benefit from improved firm value and lower cost of capital.

The remainder of the paper is organized as follows. Section **1.2** reviews the literature and develops the hypotheses. Section **1.3** describes the data and sample construction, and Section **1.4** provides the main empirical results. Section **1.5** discusses the underlying mechanisms. Section **1.6** explores the financial consequences of conglomerates' voluntary disclosure, and Section **1.7** concludes.

1.2. Background and Hypothesis Development

Prior research has shown that conglomeration increases firms' complexity and negatively affects the information environment. In their theoretical model, Chemmanur and Liu (2011) show that focus-increasing restructuring (i.e., when two firm divisions belong to different industry classifications) enhances information production by institutional investors. That is, dividing a conglomerate into segments having their own separate financial statements would reduce information production costs and enable institutions to specialize in information production and guide their investments toward industries within which they have an information production advantage. Furthermore, given the limited attention of investors, even disclosing non-aggregated financial information for different segments of conglomerates would not necessarily be helpful. Hirshleifer and Teoh (2003) theoretically show that failure to process all available information and using firm-level growth rates derived from aggregated financial data instead of individual segment growth rates induces a firm valuation bias and mispricing.

Moreover, specific useful attributes in conglomerates render analyzing them even more costly and challenging. For instance, due to the presence of coinsurance — imperfect correlation of cash flows — among business segments, conglomerates can benefit from a lower default risk (Lewellen, 1971) and cost of capital (Hann, Ogneva, and Ozbas, 2013). Conglomerates can also make use of an internal capital market in which cash-poor segments can be financed by cash-rich ones (Stein, 1997; Hubbard and Palia, 1999; Khanna and Tice, 2001; Billett and Mauer, 2003; Dimitrov and Tice, 2006). They can leverage the internal information market (Anjos and Fracassi, 2015) and internal labor market (Tate and Yang, 2015), allowing them to exploit no information friction within the firm to shift funds and human capital toward the most valuable projects.

However, Cohen and Lou (2012) report that analyzing these firms requires more information processing and cognitive resources. For instance, Figure **1.1** shows different business segments of General Electric Co. and their corresponding share in the firm's total sales. The quantity and diversity of business segments make analyzing the firm more complicated. For example, it would be easier to incorporate an oil-price shock into the price of a firm that operates solely in the oil & gas industry compared to General Electric Co., which operates in several other sectors besides the oil & gas industry. Cohen and Lou (2012) document that the return of each conglomerate can be predicted using the return of a portfolio of single-segment firms mimicking that firm, attributing this predictability to the delay in incorporating complicated information processing of industry-specific shocks into stock prices. In a related study, Barinov, Park, and Yıldızhan

(2019) attribute the more considerable post-earnings announcement drift (PEAD) of conglomerates to their complex information processing, compared with standalone firms, resulting in an under-reaction to earning surprises.

Voluntary disclosure is among internally-determined firm policies that can ameliorate the negative impact of business complexity. In their theoretical study, Diamond and Verrecchia (1991) show that firms disclose more information to reduce information asymmetry and, in turn, experience increased attention from large investors and a lower cost of capital. Using the plausibly exogenous closure of research operations in several brokerage firms and the exogenous reduction in analyst coverage as quasi-natural experiments, Balakrishnan et al. (2014) show that firms shape their information environment and improve their liquidity by increasing voluntary disclosure and subsequently, benefit from a higher firm value. Guay, Samuels, and Taylor (2016) study the effect of financial statement's textual complexity on firms' voluntary disclosure. Using several readability indices to measure the complexity, they find that textual complexity is positively associated with voluntary disclosure. They attribute this finding to managers' intention to mitigate the negative effect of textual complexity and the management's desire to help investors better understand their financial information. Therefore, to the degree that conglomeration increases complexity, I hypothesize that more complex firms disclose more voluntary information, as stated below.

H1: Conglomerates with greater business complexity have higher voluntary disclosure than standalone firms.

However, certain factors prevent firms from being in a fully unraveling equilibrium (Grossman and Hart, 1980; Milgrom, 1981). Given the multi-segment nature of conglomerates and their exposure to competition in different industries, complexity exacerbates the proprietary cost of information disclosure (Verrecchia, 1983; Ellis, Fee, and Thomas, 2012). In a theoretical model, Arya, Frimor, and Mittendorf (2010) show that when firms face competition across multiple segments, in the equilibrium, disclosing aggregated firm-level information, as opposed to segment-level information, could help them maintain their competitive advantage.

Conglomeration can further exacerbate agency problems since managers may find it easier to opportunistically determine the level, timing, and quality of information disclosures (Berger and Hann, 2007). Li (2008) suggests that managers engage in obfuscation by shaping the linguistic complexity of financial statements. Pae, Song, and Yi (2016) suggest that managers with more career concerns are more conservative and likely to provide downward earnings forecasts to increase the likelihood of meeting or beating expectations. Baginski et al. (2018) show that career concerns encourage managers to withhold and delay bad news. Managers may also try to control voluntary disclosure to maximize the profit of their opportunistic insider trading. Cheng and Lo (2006) find that managers increase bad news disclosure before purchasing the shares to reduce the stock price, a finding that Rogers (2008) later corroborated using disclosure quality. In addition to the timing of information disclosure, Cheng, Luo, and Yue (2013) show that managers also strategically set the precision of their forecasts to increase the stock price before their sales and decrease it before their purchases. Finally, Kothari, Shu, and Wysocki (2009) demonstrate that managers are incentivized to prevent stock price declines by withholding unfavorable news as much as possible. Therefore, the costs associated with voluntary disclosure may prevent managers of conglomerate firms from addressing the business complexity via increased information dissemination. Hence, I propose an alternative hypothesis to **H1** as follows:

H1a: Conglomerates with greater business complexity have a similar level of voluntary disclosure to standalone firms.

Prior literature has established the role of institutional investors in various corporate policies, such as governance and dividend payments (Appel, Gormley, and Keim, 2016; Crane, Michenaud, and Weston, 2016). Institutional shareholders' monitoring can limit managers' autonomy and enhance corporate governance. In related studies, Boone and White (2015) and Bird and Karolyi (2016) show that institutional ownership has a positive causal effect on the level of voluntary disclosure. As a component of governance, voluntary disclosure provides investors with decision-relevant information. Additionally, the increase in transparency, consequently reducing information asymmetry, enhancing liquidity, and decreasing the overall transaction costs, will benefit institutional investors. Similarly, Abramova, Core, and Sutherland (2020) report that passive institutional investors' attention significantly increases voluntary disclosure.

Analysts are also market participants that rely on the information provided by firms. A series of studies document the complementary nature of voluntary disclosure and analyst coverage (e.g., Lang and Lundholm, 1996; Graham, Harvey, and Rajgopal, 2005). Frequent voluntary disclosures can reduce analysts' information acquisition costs and increase their forecasts' informativeness. Therefore, to the degree that analyst coverage benefits firms, managers are incentivized to increase voluntary disclosure to enhance their analyst coverage. Supporting this notion, and according to a survey by Graham, Harvey, and Rajgopal (2005), 50.8% of managers agreed or strongly agreed that they use voluntary disclosure to increase their analyst coverage. Furthermore, Chapman and Green (2018) find that managers are more likely to disclose the information asked by analysts in a conference call in subsequent calls or earnings announcements, suggesting that analysts influence firms' disclosure decisions by requesting important information or informally guiding them toward better disclosure. Put together, I hypothesize that the effect of business complexity on disclosure is stronger when firms have more institutional owners or are covered by more analysts. Drawn from these findings, I test the following hypothesis:

H2: The increase in voluntary disclosure in more complex firms is more pronounced when the demand for information is higher.

Managerial intention to improve the information environment may be another reason for the higher voluntary disclosure in more complex firms (Hui and Matsunaga, 2015). The higher sensitivity of CEO pay performance results in further alignment between the interests of the CEO and shareholders, incentivizing additional communication, especially if the firm has favorable operating performance. Accordingly, managers may rely on increased voluntary disclosure when their interests are aligned with shareholders, suggesting a stronger relationship between business complexity and voluntary disclosure. We, therefore, expect this relationship to be more robust when firms have better operating performance but weaker when firms experience a loss, leading to the hypothesis below.

H3: The increase in voluntary disclosure in more complex firms is more pronounced in firms with higher CEO pay-performance sensitivity and stronger operating performance.

1.3. Data and Sample Construction

In this study, I construct the sample using data from different sources: (1) firm financial variables are obtained from Compustat, (2) management forecast data and analyst information are from I/B/E/S, (3) stock price information is from CRSP, (4) M&A data is from SDC, (5) the institutional ownership measure is from Thomson-Reuters' Institutional (13f) Holdings database, (6) the texts for 10-K filings and master dictionary for textual complexity indices are downloaded from Bill McDonald's website,[2] (7) the CEO's portfolio delta measure (i.e., a measure of pay-performance sensitivity) is obtained from Lalitha Naveen's website and extended to 2020,[3] and (8) cost of capital measures are from Lee, So, and Wang (2021).[4]

[2] https://sraf.nd.edu/data/stage-one-10-x-parse-data/
[3] https://sites.temple.edu/lnaveen/data/
[4] https://leesowang2021.github.io/data/

1.3.1. Business Complexity

Researchers face the challenge of separating the business and the financial statement when they use readability measures (Loughran and McDonald, 2016). While managers may use complex language to better convey technical information about their business, they may also use language complexity to reduce informativeness. Using several readability indices to measure complexity, Guay, Samuels, and Taylor (2016) find that managers increase voluntary disclosure to mitigate the negative impact of financial statement complexity. Li (2008), however, demonstrates contrary evidence, showing the managers' inclination to obfuscate information and reduce the informativeness of disclosures by using more complex language in financial statements.

Bushee, Gow, and Taylor (2018) propose an empirical method to disentangle these two components of textual complexity — information versus obfuscation. Comparing managers' linguistic complexity with that of analysts in conference calls and using analysts' linguistic complexity as a benchmark, they extract the part of linguistic complexity that stems from managers' obfuscation intention. Based on their findings, textual complexity is not an appropriate way to measure firms' underlying business complexity. To alleviate this issue, in this paper, I measure firm complexity directly using the firms' organizational structure and examine whether firms increase voluntary disclosure as their complexity increases.

I construct the measures of business complexity using the historical segment information from the Compustat database. As firms retroactively update their previous segment disclosure in 10-K filings for three years, I only keep the first reporting for each year.[5] Following Barinov, Park, and Yıldızhan (2019), I employ three measures to proxy for the business complexity of firms. The first business complexity measure is the indicator variable *Conglo*, which equals one if the firm reports more than one business segment and zero otherwise. The second measure, *#Seg*, equals the number of business segments a firm operates in. The third measure, *Comp*, is defined as 1-HHI, where HHI is the Herfindahl-Hirschman Index computed as the sum of the squares of each segment's sales as a fraction of total firm sales. According to this definition, a standalone firm would have the *Comp* equal to zero, and to the degree that the number of segments increases and total sales spread across different segments, *Comp* increases to the limit of one.

[5] Firms are required to provide updated segment information for three consecutive years using the most recent segment definition to ensure the comparability of their financial information with previous years.

1.3.2. Voluntary Disclosure

My main measure of voluntary disclosure is management earnings forecasts. Managers can share their expectations of their firm's future operations and earnings by issuing guidance, an essential source of communication between managers and shareholders. Such earnings guidance allows the stock market and analysts to adjust their expectations when valuing the firm and helps prevent overvaluation. Prior research has established the importance of management forecasts for firms' shareholders (e.g., Bourveau and Schoenfeld, 2017; Bourveau, Lou, and Wang, 2018; Park et al., 2019; Abramova, Core, and Sutherland, 2020). Throughout the paper, I focus on management earnings guidance since it is among the most critical sources of forward-looking information that directly affects investors' valuation of the firm and reflects the managers' overall evaluation of the firm's economic environment and future outcomes. Following prior literature and due to the skewness in the number of EPS guidance across firms, my measure of voluntary disclosure (*VolDisc*) is calculated as the natural logarithm of one plus the number of management earnings forecasts during a firm-year.

1.3.3. Control Variables

This study employs several control variables commonly used in prior literature. *ReadIndex* is a measure of textual complexity, calculated following Loughran and McDonald (2011) and using the first principal component of six readability indices, namely Flesch Kincaid, Fog Index, LIX, RIX, ARI, and SMOG. Guay, Samuels, and Taylor (2016) provide a detailed description of these readability measures. *Size* equals the natural logarithm of one plus the book value of assets. *MB* equals the market value of equity over the firm's book value. *Loss* is a dummy variable equal to one when the firm has negative net income and zero otherwise. *Leverage* is calculated as long-term debt plus short-term debt scaled by total assets. *ROA* is the ratio of income before extraordinary items over assets. *SpecialItems* is defined as special items over assets. *Volatility* equals the standard deviation of monthly returns over the fiscal year, and *Return* is the sum of monthly returns during the fiscal year. All variable definitions and their sources are contained in Appendix A. The results are not sensitive to the choice of control variables and remain robust when I omit certain variables. All variables are winsorized at 1% and 99% levels to account for the effect of outliers in the data.

1.3.4. Descriptive Statistics

I start with the Compustat universe from 1995 to 2020 and keep all firm-year observations for which financial information is available. I use the Compustat Historical Segment database to create business complexity measures and drop all observations for firms in the finance and utility industries (corresponding to SIC codes in 6000-6900 and 4900-4999, respectively). I then match this data with the I/B/E/S database to get management forecast data and measures of the information environment. Aggregating the data from these sources, including information on control variables, and dropping observations with missing variables restricts the main sample to 73,331 firm-year observations during the 1995-2020 period. Table **1.1** provides the descriptive statistics of the main variables separately for the entire sample, conglomerates, and standalone firms. It also presents the differences in means of each variable between conglomerates and standalone firms.

As seen in the table, on average, conglomerates issue about 0.974 (=exp(0.68)-1) earnings forecasts in each fiscal year, standalone firms issue about 0.537 (=exp(0.43)-1) forecasts per year, and the entire sample of firms releases 0.699 (=exp(0.53)-1) forecasts per year. Hence, the issuance of management earnings forecasts is significantly more for conglomerates than their standalone counterparts. Univariate analysis shows statistics consistent with the hypothesis that conglomerates increase voluntary disclosure to mitigate the effect of conglomeration on the information environment. An average conglomerate in my sample has 2.94 different business segments and provides disclosures with more textual complexity. For example, the average ReadIndex of conglomerates is 0.06, compared to -0.03 for standalone firms. Moreover, conglomerates are larger, more leveraged, and more profitable. They also have a significantly lower market-to-book ratio and return volatility than standalone firms, and yet their mean return is statistically indifferent from the latter. Table **??** in the Internet Appendix shows the pairwise correlation between these variables.

1.4. Business Complexity and Voluntary Disclosures

1.4.1. Baseline Results

I examine how business complexity affects a manager's choice of voluntary disclosure by using the following regression model,

$$VolDisc_{i,t} = \alpha + \beta Business\ Complexity_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t}, \tag{1}$$

where the dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts; $Business\ Complexity_{i,t}$ denotes the business complexity of a firm; $Controls_{i,t}$ is a vector of firm-specific variables, including $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$; and θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. The measures of business complexity are: (1) $Conglo$, a dummy variable equals one for the conglomerate and zero otherwise; (2) $\#Seg$, the number of a firm's business segments; and (3) $Comp$, defined as 1-HHI, where HHI is the Herfindahl-Hirschman index computed as the sum of squares of segments' sales as a fraction of aggregate firm sales.

If complicated firms resort to disclosing more information voluntarily, I expect β to be positive. The results of the estimation of Model (1) are provided in Table **3.2**, with the business complexity measure used being $Conglo$ in columns (1) and (2), $\#Seg$ in columns (3) and (4), and $Comp$ in columns (5) and (6). The odd columns show the results without controlling for other covariates, whereas the even columns include the complete set of control variables. The relationship between business complexity and the number of management earnings forecasts is positive and statistically significant across all columns. This association is also economically meaningful. On average, a conglomerate increases voluntary disclosure by 6% (=0.026/0.43) relative to standalone firms, while adding one segment increases voluntary disclosure by 3.5% (=0.015/0.43). Furthermore, a one-standard-deviation increase in $Comp$, on average, results in a 5.2% (=0.094×0.24/0.43) rise in voluntary disclosure. Overall, the results indicate a robust positive relationship between business complexity and voluntary disclosure, consistent with hypothesis H1.

1.4.2. Identification Strategy

Conglomeration, firm boundaries, and the number of segments a firm chooses to operate in may not necessarily be randomly selected, as managers endogenously determine most of these factors based on their preferences and investment opportunities. Therefore, certain omitted variables may be simultaneously affecting both the organizational structure and information disclosure decisions and policies. Furthermore, firms with higher voluntary disclosure would have lower information asymmetry and cost of capital (Diamond, 1985; Diamond and Verrecchia, 1991), and thus might benefit from a cheaper expansion of their operation scopes by investing in new industries and segments, suggesting the possibility of reverse causality. In what follows, I employ instrumental variables and an exogenous shock to business complexity in the form of an M&A to alleviate the potential endogeneity issues interfering with a causal inference of the results.

1.4.2.1 Instrumental Variables

my main identification strategy is to use instrumental variables. Following Dimitrov and Tice (2006), my first instrument, MI, is a dummy variable equal to one if a firm reports nonzero minority interest on its balance sheet and zero otherwise. Nonzero minority interest appears when a firm has less than 100% ownership in a subsidiary and shows that the company may have engaged in acquiring the majority stake in another firm at some point in time. Since diversification and unrelated acquisition are ways of expanding the firm scope and forming conglomerates, this variable is relevant to conglomeration and business complexity. In addition, the historical nature of this variable means that when firms undertake such majority acquisitions, the non-zero minority interest may remain on their balance sheet for years. Thus, minority interest may be correlated with the firm's characteristics in the first year, during which nonzero minority interest appears on the balance sheet. However, as time passes and the firm gets farther from the acquisition event, the presence of minority interests on the balance sheet is less likely to correlate with contemporaneous firm fundamentals and other time-varying unobservables associated with voluntary disclosure. my second instrument, $PNDIV$, borrowed from Campa and Kedia (2002), is the proportion of conglomerates in a given industry year, where industries are identified based on the Fama-French 48 industry classification. This variable shows the overall attractiveness of each sector to conglomerates.

I incorporate the two above instruments in the following 2-Stage Least Squares (2SLS) setup,

$$Business\ Complexity_{i,j,t} = \alpha + \beta_1 MI_{i,t} + \beta_2 PNDIV_{j,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,j,t},$$

$$VolDisc_{i,j,t} = \alpha + \beta \widehat{Business\ Complexity}_{i,j,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,j,t}, \quad (2)$$

where I estimate the measures of business complexity in the first stage using MI and $PNDIV$ and then employ the estimated complexity measures in the second stage to investigate the effect on voluntary disclosure. All other variables are as defined before, with the notable mention that $PNDIV$ is defined at the industry-year level. The results from running Model (2) are provided in Table **1.3**, with the odd columns corresponding to the first stage and the even columns showing the results of the second stage regressions.

The Kleibergen-Paap Wald F-statistics reported in the first stage columns reject the null hypothesis that the instruments are weak. Comparing the coefficients in the second stage and baseline regressions suggests that the original results are downward biased. In terms of the economic magnitude, the findings indicate that a conglomerate, on average, increases its voluntary disclosure by about 1.7 times (=0.712/0.43) that of standalone firms. Furthermore, adding one segment increases its voluntary disclosure by 82% (=0.352/0.43) compared to the average standalone firm, while a one-standard-deviation increase in *Comp* produces a onefold increase in disclosure. Overall, the instrumental variable analysis corroborates my main inference that business complexity has a sizable and causal positive effect on firms' voluntary disclosure, consistent with hypothesis H1.

1.4.2.2 Mergers & Acquisitions

Merger and acquisition (M&A) activities often involve integrating two or more companies, which require significant changes to the organizational structure. For example, M&As can create new business units and consolidate existing divisions. These changes can increase the complexity of the business structure, as the newly formed organization must ensure that all systems and processes work together seamlessly. As a robustness test, therefore, I employ M&As as a source of quasi-exogenous shocks to business complexity and explore the effect on voluntary disclosure.

I acquire the data on business M&A activities from SDC for my sample of firms from 1995 to 2020. I require the acquirer to have owned less than 50% of the target firm's shares six months before the transaction and more than 50% afterward and exclude those with missing transaction values, following Houston and Shan (2022). I then identify firm years in which an M&A activity has occurred, defining *M&A* as an indicator variable equal to one for three years after the transaction.[6] To ensure that I are investigating the effect of business complexity on voluntary disclosure, I employ Model 2 in the first-stage estimation of business complexity using the M&A measure and the second stage using the predictive business complexity as the main independent variable, and all other variables as defined earlier. The results are provided in Table **1.4**, with the odd columns corresponding to the first stage and the even columns showing the results of the second stage regressions. I find results consistent with the main identification strategy, in that not only do M&A activities produce a significant increase in business complexity, but also that such an increase is synonymous with increased voluntary disclosure. The economic magnitude of the estimated coefficients again suggests that the baseline results are downward biased. M&A activities resulting in a conglomeration leads to at least a twofold (=0.97/0.43) voluntary disclosure increase compared to a standalone firm, while

[6] The results are unchanged if I keep the indicator variable equal to one for a different number of years.

those that expand businesses by an additional segment generate a 109% (=0.467/0.43) increase. Alternatively, a one-standard-deviation increase in *Comp* generates a 133% (=2.375×0.24/0.43) rise in disclosure. Thus, using M&As as a quasi-exogenous shock reinforces the baseline evidence on the causal and positive relationship between business complexity and voluntary disclosure, in line with hypothesis H1.

1.4.3. Additional Tests

1.4.3.1 Changes in Business Complexity

Thus far, I have found evidence of an economically meaningful relationship between business complexity and voluntary disclosure. In this subsection, I conduct additional robustness tests. My findings are based on the premise that if the number of disclosures increases due to complexity, I expect the relationship to become stronger as the number of business segments increases. To assess this plausibility, I study the marginal effect of increasing the number of business segments on voluntary disclosure in different subsamples. I employ $Seg(I)$ and $Comp(I)$ as the main explanatory variables in Model (1), where $Seg(I)$ is a binary indicator that equals one if the firm has I segments and zero for standalone firms, and $Comp(I)$ denotes *Comp* for a firm with I segments and zero for standalones, with I ranging from 2 to 6. Table **1.5** presents the subsample results.

The magnitude of the $Seg(I)$ coefficient gets larger as the number of segments increases, suggesting that a conglomerate is more incentivized to disclose more information relative to an average standalone firm as its business gets more complex. A visual representation of the coefficient estimates and their 95% confidence intervals is presented in Figure **1.2**. For example, the estimate of the $Seg(I)$ coefficient is between 0.040 (t-statistic=2.88) when comparing standalone firms to those with two segments and 0.277 (t-statistc=3.05) when comparing standalones to those with six segments. I find a similar pattern in the $Comp(I)$ coefficient, with its estimates ranging from 0.139 (t-statistic=3.57) when comparing standalone firms to those with two segments to 0.435 (t-statistic=3.34) when comparing standalones to those with six segments. These findings are aligned with the hypothesis that the growing business complexity drives frequent voluntary disclosures.

I next aim to investigate the changes in voluntary disclosure for firms that switch from standalone to conglomerates and vice versa. Since a status change in conglomeration posits a drastic change in the level of firm complexity, I expect that voluntary disclosure will experience a sudden shift. Specifically, I define *Switch to Conglo* as an indicator variable equal to one for standalone firms that switch to conglomerates and compare them to those that never experience a status change in an 11-year window around the year of change, considering only the first status change and only firms that undergo such a change. I also define $Switch\ to\ Standalone$ in a similar manner. I use these measures of status change as the main explanatory variables in Model (1), with the results provided in Table **1.6**. Columns (1) and (2) of the table include standalone firms that switch to conglomerates and those that remain a standalone throughout the sample period, whereas columns (3) and (4) include conglomerates that switch to standalone firms and those that stay a conglomerate. Columns (2) and (4) present the regression dynamics, in which the year before the status change is selected as the reference year.

Results indicate a significant increase in voluntary disclosure as standalone firms switch to conglomerates, with the estimate of $Switch\ to\ Conglo$ coefficient equal to 0.063 (t-statistic=4.17), and the regression dynamics demonstrating a significant increase in the year of status change. A similar finding in the opposite direction for voluntary disclosure is observed for conglomerates that switch back to a standalone firm, with the estimate of $Switch\ to\ Standalone$ coefficient equal to -0.078 (t-statistic=-3.34) and the regression dynamics showing a significant reduction of voluntary disclosure in the year of status change. The coefficient estimates and their 95% confidence intervals are visually depicted in Figure **1.3**. Similar to the previous results, these findings document a significant increase in voluntary disclosure as standalone firms evolve to conglomerates, and a significant reduction in the opposite case.

1.4.3.2 Good vs. Bad News

Prior studies suggest that managers may react differently when disclosing unfavorable news versus good news. For example, they may be incentivized to withhold bad news to delay the incorporation of information into share prices (Kothari, Shu, and Wysocki, 2009). Conversely, managers may also adjust the disclosure to minimize the cost of shareholder litigation and are more likely to issue negative news when exposed to the risk of litigation (although no such relationship is found for favorable news) (Cao and Narayanamoorthy, 2011). We, therefore, investigate whether the effect of complexity on disclosure established above is limited to the cases where disclosures convey bad news or a similar effect also exists for those communicating positive news.

I categorize forecasts beating the analysts' consensus as good news and those with shortfalls relative to analysts' consensus as bad news. I then estimate Model (1) by replacing the dependent variable with the two disclosure measures defined based on the news they convey and report the results in Table **1.7** with positive news as the dependent variable in Columns (1) to (3) and negative news in Columns (4) to (6). The results suggest that while the business complexity effect of disclosing bad news is more pronounced, complicated firms still disclose more than their standalone counterparts, regardless of the news sentiment.

1.5. Mechanisms

This section further explores the business complexity-voluntary disclosure relationship and provides insights into the underlying mechanisms that could explain this finding. Specifically, I investigate the demand for information by other stakeholders, managerial intention, and operating performance as potential mechanisms.

1.5.1. Demand for Information

As firms become more complex and information asymmetry increases, the demand for information would also increase. Disclosure of information benefits shareholders by reducing information asymmetry, increasing liquidity, decreasing transaction costs, and improving the efficiency of their investments. Prior research documents that institutional investors have a causal impact on various firm policies, including disclosure (Bird and Karolyi, 2016). For example, the presence of institutional investors, their monitoring, and their attention materially impact firms' voluntary disclosure (Boone and White, 2015; Guay, Samuels, and Taylor, 2016; Lin, Mao, and Wang, 2018; Abramova, Core, and Sutherland, 2020).

Analysts are another group of market participants who demand more disclosure from complex firms. Although they have no direct means of monitoring, like shareholders, they can impact a firm's disclosure policy by deciding to follow the firm. Managers, therefore, are incentivized to increase analysts' coverage since analysts directly influence investors' beliefs. Also, higher analyst coverage increases investors following the firm and reduces the cost of capital by decreasing information asymmetry among market participants (Lang and Lundholm, 1996). In a survey by Graham, Harvey, and Rajgopal (2005), 50.8% of managers agreed or strongly agreed that they use voluntary disclosure to increase their analyst coverage. Furthermore, Chapman and Green (2018) provide evidence that analysts influence managers' guidance choices. Managers are more likely to disclose the information analysts ask for in a conference call in subsequent calls or earnings announcements. Higher voluntary disclosure in more complex firms would reduce analysts' information acquisition costs.

We, therefore, test hypothesis **H2**, predicting that voluntary disclosure in more complex firms increases as institutional investors and analysts demand more information. I measure institutional investor ownership (*Institutional Ownership*) based on the proportion of a firm's number of outstanding shares owned by 13f institutions and analyst coverage using the number of analysts covering the firm (*Number of Analysts*). To test these mechanisms, I employ the following cross-sectional model.

$$VoldDisc_{i,t} = \alpha + \beta Business\ Complexity_{i,t} \times Measure_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t}, \quad (3)$$

where $Measure_{i,t}$ denotes the proxy for each channel. Results are presented in Table **1.8**. I find the association between business complexity and voluntary disclosure stronger when firms have more institutional ownership and greater analyst following. Specifically, the coefficient on the interaction between *Institutional Ownership* and each of the proxies for multi-segment firms is consistently positive and statistically significant at the 5% level. Similar results are found when *Number of Analysts* is employed instead of *Institutional Ownership*. Taken together, the results are consistent with hypothesis **H2** that the increase in voluntary disclosure in more complex firms is more pronounced when institutional ownership and analyst coverage are higher.

1.5.2. Managerial Intention and Operating Performance

Managerial intention to improve the information environment can be another channel through which business complexity leads to higher voluntary disclosure. For example, previous studies show that senior executives' compensation is strongly associated with disclosure quality when their board of directors emphasizes the importance of effective communication with investors (Hui and Matsunaga, 2015). Therefore, I expect firms to issue more disclosure when their CEO has higher pay-performance sensitivity. Following Coles, Daniel, and Naveen (2006) and Core and Guay (2002), I measure pay-performance sensitivity using a CEO's portfolio Delta, equivalent to the CEO's wealth change for a 1% change in stock price. This measure is available for firms in the Execucomp database, which covers S&P 1500 firms, and hence the tests on managerial intention as a potential channel are limited to these firms.

I also examine how firms' operating performance affects the relationship between business complexity and voluntary disclosure. Firms can signal higher operating performance through voluntary disclosures (Lang and Lundholm, 1993; Schrand and Walther, 2000). I use *ROA* and *Loss* as proxies for operating performance.

This analysis focuses on how firms with different levels of CEO Delta and operating performance behave in a cross-sectional setting. The results from estimating Model (3), where *Measure* denotes either CEO Delta or operating performance, are provided in Table **1.9**. The effect of business complexity on voluntary disclosure is stronger when the pay-performance sensitivity of CEO is higher (columns (1)-(3)), for firms with higher *ROA* values (columns (4)-(6)), but weaker when firms experience a negative *Loss* during a fiscal year (columns (7)-(9)), consistent with hypothesis **H3**.

1.6. Financial Consequences

This section explores the potential financial consequences of multi-segment firms' increased voluntary disclosure. I investigate whether such actions affect their information environment, firm value, and cost of capital.

1.6.1. Information Environment

I investigate whether complex firms' issuance of more voluntary disclosure helps improve their information environment using the following regression model,

$$Outcome_{i,t} = \alpha + \beta Business\ Complexity_{i,t} \times VoldDisc_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t}, \quad (4)$$

where $Outcome_{i,t}$ denotes a measure of the information environment, and all the other variables are defined earlier. Drawn from the extant literature, I employ three proxies for a firm's information environment: (1) *Turnover*, defined as the sum of share trading volume over the fiscal year, normalized by the number of shares outstanding at the beginning of the year; (2) *Analyst Forecast Error*, defined as the difference between the analyst consensus forecast and actual earnings per share divided by the stock price; and (3) *Price Nonsynchronicity*, a measure of firm-specific information impounded in stock prices. Firms with higher *Turnover* and smaller *Analyst Forecast Error* are often viewed as having lower information asymmetry. Following Chen, Goldstein, and Jiang (2007), *Price Nonsynchronicity* is measured by 1-R^2, where R^2 is obtained from regressing a firm's daily stock returns on the daily returns on the CRSP value-weighted market index and daily returns on the 3-digit SIC industry portfolio in which the firm belongs to. Roll (1988) is the first to argue that *Price Nonsynchronicity* captures the private information revealed through the trading activity of speculators. Chen, Goldstein, and Jiang (2007) find *Price Nonsynchronicity* to measure the private information in price that is not otherwise available to firm managers. Given their business complexity, I argue that complicated firms would have a larger *Price Nonsynchronicity* than single-segment firms.

Regression estimates of Model (4) are presented in Table **1.10**. Several interesting findings emerge from the table. First, the coefficients on the interaction between *VolDisc* and a proxy for business complexity mainly bear the expected signs. But they are only statistically significant when *Price Nonsynchronicity* is used as a proxy for a firm's information environment (columns (6)-(9)). When complicated firms strategically disclose more information, such actions help to reduce the amount of firm-specific (or private) information reflected in the stock price, lowering the level of information asymmetry of these firms. However, the results are weaker when I use *Analyst Forecast Error* (columns (4)-(6)), especially *Turnover* (columns (1)-(3)). In contrast to those in columns (7)-(9), the coefficients of the interaction between the business complexity measure and *VolDisc* are all statistically insignificant, suggesting no statistical difference in the information environment between multi- and single-segment firms when the former issue more disclosure. In other words, complicated firms improve their information environment but not beyond single-segment firms. Second, the results suggest that conglomerate firms have a weaker information environment than their standalone peers. For example, the coefficients of *Conglo*, *#Seg*, and *Comp* are all negative and statistically significant in columns (1)-(3), indicating that the more complex the business is, the lower the information environment. Finally, as expected, the coefficient of *VolDisc* produces mostly the correct sign and is statistically significant in a majority of cases, suggesting that firms benefit from issuing more voluntary disclosures; their informaion environment enhances.

1.6.2. Firm Value and Cost of Capital

I test whether complicated firms benefit from their strategic disclosure behavior. Specifically, I ask whether these firms enjoy improved firm value and lower cost of capital when they increase voluntary disclosure through their management forecasts. Again, I employ Model (4) to test these predictions, where *Outcome* is represented by firm value and cost of capital. I use Tobin's Q as a proxy for firm value and the implied cost of equity capital and interest expenses deflated by total assets as proxies for the cost of equity and debt capital, respectively. A recent study by Lee, So, and Wang (2021) evaluates different expected-return proxies by comparing their measurement error variances in the cross-section and time series frameworks. Based on the performance of firm-level expected-return proxies, the mechanical-based implied cost of capital performs best in the time series, whereas the characteristic-based implied cost of capital performs best in the cross-section. Motivated by these findings, I employ the characteristic-based implied cost of capital as a proxy for the cost of equity capital.[7]

Table **1.11** reports results on the financial consequences of firms' disclosure behavior. Columns (1)-(3) show negative and statistically significant estimates of the coefficients on *Conglo*, *#Seg*, and *Comp* but positive and statistically insignificant estimates of the coefficient on *VolDisc*. As business complexity increases, firm value decreases, but as *VolDisc* increases, firm value increases, albeit insignificant. Importantly, the coefficient estimates of the interaction between *VolDisc* and business complexity proxies are consistently positive and statistically significant at the 5% level. For example, in column (1), the estimated coefficient on *Conglo* is -0.130 (t-statistic=-4.98), whereas the coefficient on its interaction with *VolDisc* is 0.041 (t-statistic=2.20). Thus, increasing disclosure helps complex firms partly offset their business complexity's adverse valuation effect.

Conversely, as business complexity increases, the cost of capital rises. Expectedly, as firms increase their issuance of voluntary disclosure, such actions help reduce information asymmetry and lower their cost of capital. For instance, columns (4)-(9) show the estimates of the coefficient on *VolDisc* to be consistently negative and statistically significant, and those of the coefficient on *Conglo*, *#Seg*, and *Comp* positive and statistically significant. For example, in column (4), the estimated coefficient on *Conglo* is 0.002 (t-statistic=3.58), but the coefficient on its interaction with *VolDisc* is -0.001 (t-statistic=-2.06).

In summary, the enhanced firm value and reduced cost of capital are strong motivations for conglomerates to disclose more, even at the expense of possible high proprietary costs.

1.7. Conclusion

As corporations grow and expand the scope of their businesses, they face increased complexity due to operating in multiple segments. The higher cost of information processing coupled with investors' limited attention increases the importance of voluntary disclosure, even though the revelation of information may impose additional proprietary and agency costs on firms. I explore how conglomerates mitigate the consequences of business complexity and find that as the scope of operations increases, firms tend to increase their voluntary disclosure in terms of management earnings forecast frequency. Using instrumental variables, I show that this relationship is causal. Moreover, the increase in voluntary disclosure occurs regardless of the

[7] For robustness, I replicate my analysis using the mechanical-based implied cost of capital and report the results in the Internet Appendix Table **??**. The baseline findings remain materially unaffected.

tone of the news conveyed by management earnings forecasts.

I show that the demand for information by institutional shareholders and analysts, managerial intention, and operating performance are potential channels affecting the relationship between business complexity and voluntary disclosure. The baseline finding is more pronounced in firms with higher institutional ownership and analyst coverage. Furthermore, operating performance is a deciding factor, as complex firms with a higher return on assets disclose more, whereas complex firms with realized loss reported in the fiscal year resort to disclosing less. Finally, The results indicate that voluntary disclosure helps complex firms improve the information environment, resulting in an improved firm valuation and lower cost of capital for multi-segment firms compared to their standalone counterparts.

This study highlights the potential managerial and policy implications of voluntary disclosure in complex businesses, providing insights into the effectiveness of such disclosure practices in promoting transparency, accountability, and investor confidence in increasingly complex financial markets. The results can provide managers with valuable insights into the effectiveness of voluntary disclosure practices, motivating them to make informed decisions about what information to disclose and when to maximize the benefits of transparency and accountability, as well as providing the incentive to improve their relationships with investors, by tailoring their disclosure practices to meet investor expectations and building trust. Furthermore, policymakers can employ these findings to design better regulatory frameworks that incentivize firms to engage in more effective voluntary disclosure practices, while also balancing the need for transparency with the potential costs of disclosing sensitive information.

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Figure 1.1.
Business Segments of General Electric Co. in 2017

This figure shows different business segments reported for General Electric Co. in the 2017 fiscal year and their corresponding share in the firm's total sales. The largest segments in terms of sales are power and aviation, followed by healthcare and oil & gas.

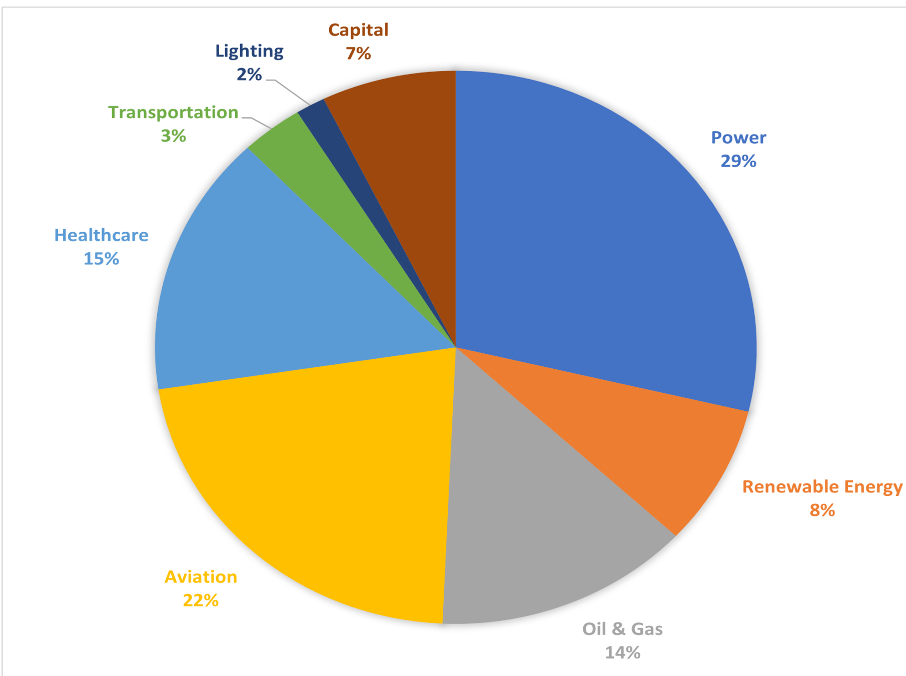

Figure 1.2.
The Marginal Effect of the Number of Segments on Voluntary Disclosure

This figure shows the magnitude of voluntary disclosure for subsamples of firms based on the different numbers of business segments. The coefficients and the 95% intervals presented in the figure are obtained from estimating the regression of the measure of voluntary disclosure on a dummy variable indicating the number of business segments in subsamples where the number of segments is equal to one or I, with I between 2 and 6. Specifically, I estimate the following model:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Seg(I)_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where $Seg(I)$ is an indicator variable that equals one if the firm has I segments, and zero if it has one segment. The trend shows a monotonic increase in voluntary disclosures as the number of segments in which a firm operates increases, compared to standalone firms.

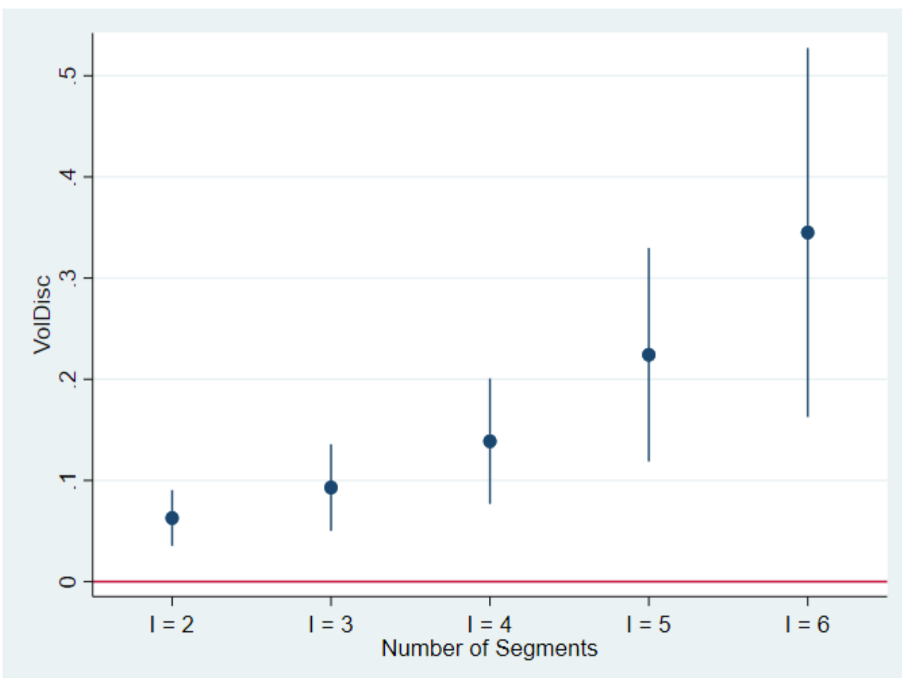

Figure 1.3.
The Effect of Changes in Conglomeration Status on Voluntary Disclosure

Figure 3 shows the magnitude of voluntary disclosure for firms that switch from a standalone to a conglomerate and vice versa. The coefficients and the 95% intervals presented in the figures are obtained from estimating the regression of the measure of voluntary disclosure on indicators of status change in an 11-year window. Specifically, I estimate the following model:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Switch\ to\ Conglo/Standalone_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where $Switch\ to\ Conglo$ corresponds to firms switching from standalones to conglomerates in the left graph and $Switch\ to\ Standalone$ corresponds to firms switching from a conglomerate to a standalone in the right graph. The trend shows an increase in voluntary disclosures as standalone firms switch to conglomerates and a reduction in the opposite case.

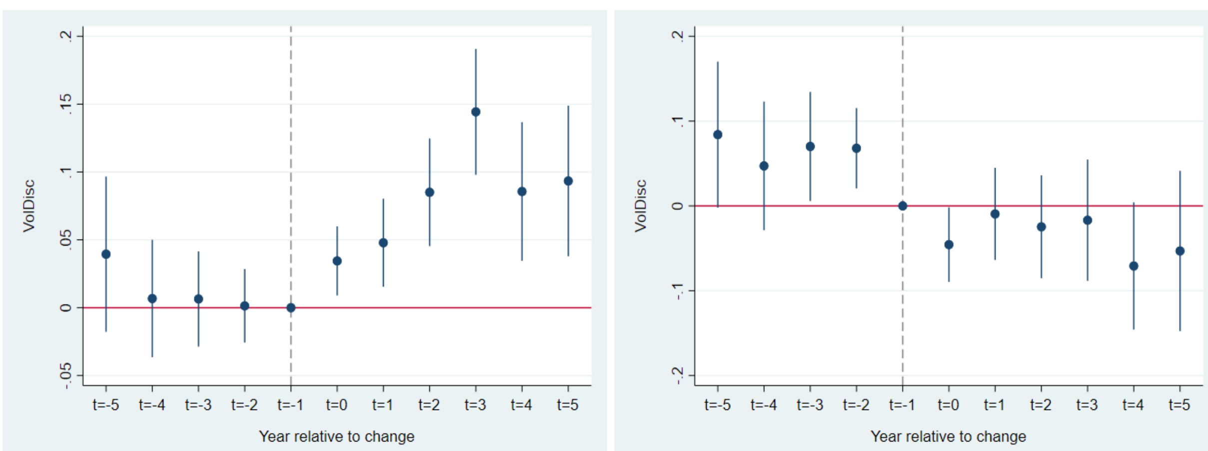

Table 1.1.
Summary Statistics

This table reports the summary statistics of the main variables for the full sample, conglomerates, and standalone firms during the 1995-2020 period. Summary statistics include the mean (Mean), standard deviation (SD), the 25th percentile (P25), median (P50), and the 75th percentile (P75), with the number of observations (Observations) reported in the last row of the table. It also presents the mean difference (column (16)) of each variable between conglomerates and standalone firms and its t-statistic (column (17)). *VolDisc* is the natural logarithm of one plus the number of management forecasts related to earnings per share (EPS) issued over the year. *Conglo* is a dummy variable equal to 1 if a firm is a conglomerate and zero otherwise. *#Seg* is the number of segments, and *Comp* is equal to 1-HHI, where HHI is the Herfindahl-Hirschman index computed as the sum of squares of segments' sales as a fraction of aggregate firm sales. *#Seg* and *Comp* are proxies for conglomerates. Control variables are defined as follows. *ReadIndex* is the first principal component based on six readability measures, namely, Flesch Kincaid, Fog Index, LIX index, RIX index, ARI, and SMOG. *Size* is the natural logarithm of one plus the book value of assets. *MB* is the market value over book value of equity. *Loss* is a dummy variable equal to one for firms having a negative net income. *Leverage* is the total debt over assets. *ROA* is the ratio of income before extraordinary items over assets. *SpecialItems* is special items as present in balance sheet divided by firm assets. *Volatility* is the standard deviation of monthly return over the fiscal year. *Return* is the average monthly return during the fiscal year. All variables are winsorized at 1% and 99% levels to mitigate the effect of outliers and are defined in Appendix A.

	Full sample					Conglomerates					Standalone Firms					Difference	
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	(6)−(11)	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Main Variables																	
VolDisc	0.53	0.82	0.00	0.00	1.10	0.68	0.88	0.00	0.00	1.61	0.43	0.75	0.00	0.00	0.69	0.25***	40.50
Conglo	0.40	0.49	0.00	0.00	1.00												
#Seg	1.78	1.17	1.00	1.00	2.00	2.94	1.08	2.00	3.00	3.00	1.00	0.00	1.00	1.00	1.00	1.94***	308.59
Comp	0.17	0.24	0.00	0.00	0.39	0.42	0.20	0.29	0.46	0.58	0.00	0.00	0.00	0.00	0.00	0.42***	368.01
Control Variables																	
ReadIndex	0.01	2.35	-1.05	0.46	1.59	0.06	2.19	-0.83	0.46	1.50	-0.03	2.45	-1.22	0.46	1.65	0.09***	5.24
Size	5.80	1.97	4.32	5.71	7.15	6.52	1.96	5.12	6.55	7.89	5.31	1.82	3.96	5.18	6.50	1.21***	84.66
MB	3.16	5.35	1.18	2.09	3.77	2.73	4.50	1.17	1.96	3.26	3.46	5.83	1.18	2.22	4.18	-0.73***	-19.12
Loss	0.38	0.49	0.00	0.00	1.00	0.29	0.45	0.00	0.00	1.00	0.45	0.50	0.00	0.00	1.00	-0.16***	-44.58
Leverage	0.22	0.23	0.01	0.17	0.35	0.25	0.21	0.07	0.23	0.37	0.20	0.23	0.00	0.12	0.33	0.05***	28.26
ROA	-0.05	0.28	-0.08	0.03	0.08	0.01	0.18	-0.01	0.04	0.08	-0.09	0.32	-0.16	0.02	0.08	0.10***	54.41
SpecialItems	-0.02	0.06	-0.02	-0.00	0.00	-0.02	0.06	-0.02	-0.00	0.00	-0.02	0.06	-0.01	0.00	0.00	0.00***	4.55
Volatility	0.16	0.10	0.09	0.13	0.19	0.14	0.09	0.08	0.11	0.17	0.17	0.10	0.10	0.14	0.21	-0.03***	-44.58
Return	0.15	0.71	-0.28	0.03	0.37	0.15	0.63	-0.22	0.06	0.35	0.15	0.76	-0.32	0.01	0.39	-0.00	-0.45
Observations			73,331					29,569					43,762				

Table 1.2.
Voluntary Disclosure and Business Complexity

This table reports the results from regressing a firm's voluntary disclosure on its business complexity measure, as follows:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Business\ Complexity_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t; $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Conglo$, $\#Seg$, and $Comp$, in year t. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Conglo	0.063***	0.026**				
	(4.86)	(2.08)				
#Seg			0.036***	0.015**		
			(5.63)	(2.48)		
Comp					0.181***	0.094***
					(6.28)	(3.37)
ReadIndex		0.004		0.004		0.004
		(1.57)		(1.56)		(1.56)
Size		0.172***		0.171***		0.171***
		(20.95)		(20.77)		(20.72)
MB		0.001*		0.001*		0.001*
		(1.70)		(1.72)		(1.73)
Loss		-0.089***		-0.089***		-0.089***
		(-11.45)		(-11.49)		(-11.52)
Leverage		-0.053**		-0.053**		-0.054**
		(-2.08)		(-2.08)		(-2.14)
ROA		-0.006		-0.006		-0.005
		(-0.39)		(-0.35)		(-0.31)
SpecialItems		-0.111***		-0.112***		-0.113***
		(-2.62)		(-2.64)		(-2.65)
Volatility		-0.118***		-0.118***		-0.118***
		(-3.46)		(-3.46)		(-3.47)
Return		-0.047***		-0.047***		-0.047***
		(-16.03)		(-16.03)		(-16.03)
Observations	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2	0.586	0.603	0.587	0.604	0.587	0.604
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.3.
Identification Strategy - Instrumental Variables

This table reports the results of the identification strategy using two instrumental variables to establish causality in the relationship between business complexity and voluntary disclosure in the following two-stage least squares approach:

$$\text{1st Stage:} \quad Business\ Complexity_{i,j,t} = \alpha + \beta_1 MI_{i,t} + \beta_2 PNDIV_{j,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,j,t},$$

$$\text{2nd Stage:} \quad VolDisc_{i,j,t} = \alpha + \beta \widehat{Business\ Complexity}_{i,j,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,j,t}.$$

In the first stage of the regression, I run $Business\ Complexity_{i,j,t}$ against two instrumental variables, $MI_{i,t}$ and $PNDIV_{j,t}$, $Controls_{i,t}$, and fixed effects. $Business\ Complexity_{i,j,t}$ denotes the business complexity of firm i in industry j, as measured by *Conglo*, *#Seg*, and *Comp* in year t. $MI_{i,t}$ is defined as a dummy variable that equals one if firm i has non-zero minority interest in year t and zero otherwise, and $PNDIV_{j,t}$ is defined as the proportion of conglomerate/diversified firms in industry j (using Kenneth French's 48 industry classifications) in year t. I also report the Kleibergen-Paap Wald F-statistics. In the second stage, I run $VolDisc_{i,j,t}$, the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in industry j and year t, on the predicted $Business\ Complexity_{i,j,t}$ from the first stage regression, $Controls_{i,t}$, and fixed effects. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, *ReadIndex*, *Size*, *MB*, *Loss*, *Leverage*, *ROA*, *SpecialItems*, *Volatility*, and *Return*. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
	Dependent Variable					
	Conglo	*VolDisc*	*#Seg*	*VolDisc*	*Comp*	*VolDisc*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Conglo}$		0.712***				
		(3.84)				
$\widehat{\#Seg}$				0.352***		
				(3.86)		
$\widehat{Comp}$						1.910***
						(4.09)
MI	0.066***		0.130***		0.022***	
	(6.81)		(5.13)		(4.56)	
PNDIV	0.392***		0.864***		0.181***	
	(6.98)		(6.23)		(6.63)	
Observations	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2		-0.093		-0.131		-0.169
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	45.1		31.78		31.82	

Table 1.4.
Mergers and Acquisitions as Shocks to Business Complexity

This table reports the results using mergers and acquisitions as quasi-exogenous shocks to business complexity and the ensuing changes in voluntary disclosure in the following two-stage least squares approach:

$$\begin{aligned} \text{1st Stage:} \quad & \textit{Business Complexity}_{i,t} &=& \alpha + \beta M\&A_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t}, \\ \text{2nd Stage:} \quad & \textit{VolDisc}_{i,t} &=& \alpha + \beta \widehat{\textit{Business Complexity}}_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t}. \end{aligned}$$

In the first stage of the regression, I run $Business\ Complexity_{i,t}$ against $M\&A_{i,t}$, $Controls_{i,t}$, and fixed effects. $Business\ Complexity_{i,j,t}$ denotes the business complexity of firm i, as measured by $Conglo$, $\#Seg$, and $Comp$ in year t. $M\&A_{i,t}$ is defined as a dummy variable that equals one if firm i has experienced an M&A activity in year t, for three years, and zero otherwise. I also report the Kleibergen-Paap Wald F-statistics. In the second stage, I run $VolDisc_{i,t}$, the natural logarithm of one plus the number of management earnings forecasts issued by firm i in year t, on the predicted $Business\ Complexity_{i,t}$ from the first stage regression, $Controls_{i,t}$, and fixed effects. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
	Dependent Variable					
	Conglo	*VolDisc*	*#Seg*	*VolDisc*	*Comp*	*VolDisc*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Conglo}$		0.970***				
		(3.36)				
$\widehat{\#Seg}$				0.467***		
				(3.30)		
$\widehat{Comp}$						2.375***
						(3.26)
M&A	0.034***		0.070***		0.014***	
	(6.66)		(6.03)		(5.71)	
Observations	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2		-0.214		-0.270		-0.291
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	44.37		36.35		32.58	

Table 1.5.
The Marginal Effect of Increasing the Number of Segments

This table reports the marginal effect of increasing the number of business segments on a firm's voluntary disclosure in the following model:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Business\ Complexity_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the model is estimated using subsamples of firms with different numbers of segments. The dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts issued by firm i in year t; $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Seg(I)$ and $Comp(I)$ in year t. $Seg(I)$ is an indicator variable that equals one if the firm has I segments, and zero if it has one segment. $Comp(I)$ is the $Comp$ computed for a firm with I segments, and is zero if it has one segment. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	$I = 2$		$I = 3$		$I = 4$		$I = 5$		$I = 6$	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Seg(I)$	0.040***		0.051**		0.078**		0.165***		0.277***	
	(2.88)		(2.39)		(2.56)		(3.11)		(3.05)	
$Comp(I)$		0.139***		0.123***		0.161***		0.259***		0.435***
		(3.57)		(2.80)		(3.10)		(3.14)		(3.34)
Observations	56,641	56,641	52,612	52,612	47,665	47,665	45,118	45,118	44,439	44,439
Adjusted R^2	0.607	0.607	0.605	0.605	0.611	0.611	0.610	0.610	0.614	0.614
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.6.
Voluntary Disclosure and Changes in Conglomeration Status

This table reports the results from regressing a firm's voluntary disclosure on a measure denoting a change in the conglomeration status, as follows:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Switch\ to\ Conglo/Standalone_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t; and $Switch\ to\ Conglo/Standalone_{i,t}$ denoting firms that undergo a status change in conglomeration, in year t. $Switch\ to\ Conglo$ is a dummy variable equal to one for five years if a standalone firm evolves into a conglomerate, and zero for five years before. $Switch\ to\ Standalone$ is similarly defined for conglomerates that devolve back into standalone firms. $Controls_{i,t}$ is a vector of firm-specific control variables used in the baseline model. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. Columns (1) and (2) include standalone firms that switch to conglomerates and those that remain a standalone throughout the sample period, whereas columns (3) and (4) include conglomerates that switch to standalone firms and those that remain a conglomerate. Columns (2) and (4) present the regression dynamics, in which the year before the status change is the reference year. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020 and limited to five years before and after a status change for each firm. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Variable	(1)	(2)	(3)	(4)
Switch to Conglo	0.063***			
	(4.17)			
Switch to Standalone			-0.078***	
			(-3.34)	
Change[t=-5]		0.039		0.084*
		(1.35)		(1.92)
Change[t=-4]		0.007		0.047
		(0.31)		(1.22)
Change[t=-3]		0.006		0.070**
		(0.36)		(2.14)
Change[t=-2]		0.001		0.068***
		(0.10)		(2.81)
Change[t=0]		0.034***		-0.046**
		(2.65)		(-2.04)
Change[t=1]		0.048***		-0.009
		(2.89)		(-0.34)
Change[t=2]		0.085***		-0.025
		(4.20)		(-0.80)
Change[t=3]		0.144***		-0.017
		(6.10)		(-0.46)
Change[t=4]		0.086***		-0.071*
		(3.29)		(-1.85)
Change[t=5]		0.093***		-0.053
		(3.30)		(-1.10)
Observations	43,688	43,688	16,254	16,254
Adjusted R^2	0.611	0.611	0.634	0.634
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 1.7.
Disclosure of Good vs. Bad News and Business Complexity

This table reports the results of regressing a firm's positive and negative disclosure on business complexity in the following model:

$$Good/Bad\ News_{i,t} = \alpha + \beta Business\ Complexity_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $Good/Bad\ News_{i,t}$ is a dummy variable equal to 1 if the EPS forecast is above/below the analysts' consensus and zero otherwise; $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Conglo$, $\#Seg$, and $Comp$, in year t. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Dependent Variable					
	Good News			*Bad News*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Conglo	0.009*			0.018***		
	(1.87)			(2.71)		
#Seg		0.006**			0.006*	
		(2.51)			(1.93)	
Comp			0.019*			0.046***
			(1.69)			(3.13)
Observations	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2	0.305	0.305	0.305	0.391	0.391	0.391
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.8.
Institutional Ownership, Analyst Coverage, and Business Complexity

This table reports the results of regressing a firm's voluntary disclosure on business complexity, while controlling for different levels of institutional ownership and analyst coverage in the following model:

$$VolDisc_{i,t} \quad = \quad \alpha + \beta Business\ Complexity \times Measure_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t; $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Conglo$, $\#Seg$, and $Comp$, in year t. $Measure$ denotes proxies for institutional ownership and analyst coverage; $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Definition of *Measure*					
	Institutional Ownership			*Number of Analysts*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Conglo × Measure	0.140***			0.007***		
	(4.25)			(3.65)		
Conglo	-0.032*			-0.009		
	(-1.89)			(-0.62)		
#Seg × Measure		0.034**			0.002***	
		(2.32)			(3.24)	
#Seg		-0.001			0.001	
		(-0.06)			(0.10)	
Comp × Measure			0.299***			0.015***
			(4.22)			(3.78)
Comp			-0.037			0.016
			(-0.96)			(0.52)
Measure	0.025	0.024	0.033	0.011***	0.009***	0.011***
	(0.84)	(0.64)	(1.13)	(6.09)	(4.46)	(6.37)
Observations	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2	0.604	0.604	0.604	0.606	0.606	0.606
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.9.
Managerial Intention, Operating Performance, and Business Complexity

This table reports the results of the effects of a firm's voluntary disclosure on business complexity controlling for managerial intention in the following setup:

$$VolDisc_{i,t} = \alpha + \beta Business\ Complexity_{i,t} \times Measure_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t. $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Conglo$, $\#Seg$, and $Comp$, in year t. $Measure$ denotes measures of CEO pay-performance sensitivity and operating performance (measured by the return on assets, ROA, and $Loss$). $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Definition of *Measure*								
	Managerial Intention			*Return on Assets*			*Loss*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Conglo × Measure	0.031***			0.129***			-0.057***		
	(3.26)			(4.56)			(-4.10)		
Conglo	0.006			0.029**			0.046***		
	(0.26)			(2.29)			(3.18)		
#Seg × Measure		0.009***			0.079***			-0.025***	
		(3.29)			(4.80)			(-3.84)	
#Seg		0.007			0.015**			0.023***	
		(0.69)			(2.47)			(3.30)	
Comp × Measure			0.048***			0.400***			-0.127***
			(3.21)			(5.61)			(-4.30)
Comp			0.061			0.100***			0.138***
			(1.22)			(3.55)			(4.33)
Measure	-0.024***	-0.028***	-0.019**	-0.027	-0.103***	-0.025	-0.064***	-0.043***	-0.065***
	(-2.79)	(-3.01)	(-2.49)	(-1.56)	(-3.90)	(-1.46)	(-6.55)	(-3.08)	(-7.04)
Observations	28,391	28,391	28,391	73,331	73,331	73,331	73,331	73,331	73,331
Adjusted R^2	0.622	0.622	0.622	0.604	0.604	0.604	0.604	0.604	0.604
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.10.
Information Environment and Business Complexity

This table reports the results from regressing a firm's information environment proxy on measures of business complexity, measures of voluntary disclosure, and their interactions, as follows:

$$Information_{i,t} \quad = \quad \alpha + \beta Business\ Complexity_{i,t} \times VolDisc_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $Information_{i,t}$ is a measure of firm i's information environment in year t as proxied by (1) $Turnover$, defined as the sum of trade volumes in the fiscal year divided by the lagged number of shares outstanding; (2) the *Analyst Forecast Error*, defined as analysts consensus minus actual EPS divided by the stock price; and (3) *Price Nonsynchronicity*, defined as firm-specific variation obtained from regressing a firm's daily stock returns on daily CRSP value-weighted index return and daily 3-SIC industry index returns. $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by *Conglo*, *#Seg*, and *Comp*, in year t. $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, *ReadIndex*, *Size*, *MB*, *Loss*, *Leverage*, *ROA*, *SpecialItems*, *Volatility*, and *Return*. θ_i and μ_t denote firm and year fixed effects, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Definition of *Information*								
	Turnover			*Analyst Forecast Error*			*Price Nonsynchronicity*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Conglo × VolDisc	-0.009			-0.014			-0.009***		
	(-0.31)			(-0.87)			(-3.61)		
Conglo	-0.183***			0.040			0.004		
	(-5.05)			(1.20)			(1.07)		
#Seg × VolDisc		0.006			-0.006			-0.003***	
		(0.57)			(-0.97)			(-3.08)	
#Seg		-0.098***			0.017			0.002	
		(-6.24)			(1.35)			(1.14)	
Comp × VolDisc			-0.041			-0.008			-0.016***
			(-0.76)			(-0.31)			(-3.53)
Comp			-0.526***			0.049			0.010
			(-6.97)			(0.80)			(1.36)
VolDisc	0.076***	0.059**	0.083***	-0.029**	-0.025	-0.034***	-0.001	0.001	-0.001
	(3.10)	(1.97)	(3.60)	(-2.26)	(-1.58)	(-2.88)	(-0.46)	(0.27)	(-0.87)
Observations	73,311	73,311	73,311	62067	62067	62067	73,312	73,312	73,312
Adjusted R^2	0.535	0.535	0.536	0.628	0.628	0.628	0.695	0.695	0.695
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.11.
Financial Consequences of Voluntary Disclosure in Complicated Firms

This table reports the results from regressing a firm's financial outcome measure against its business complexity measure, voluntary disclosure, and the interaction of the two latter variables in the following model:

$$Financial\ Outcome_{i,t} \quad = \quad \alpha + \beta Business\ Complexity_{i,t} \times VolDisc_{i,t} + \Gamma Controls_{i,t} + \theta_i + \mu_t + \epsilon_{i,t},$$

where the dependent variable $Financial\ Outcome_{i,t}$, alternately, represents firm i's firm value, measured by Tobin's Q, and its equity cost of capital (CC), proxied by Lee, So, and Wang's (2021) measure of a composite characteristic-based cost of capital, and the cost of debt, as computed by the interest expense divided by the total debt. $Business\ Complexity_{i,t}$ denotes the extent of firm i's business complexity, as measured by $Conglo$, $\#Seg$, and $Comp$, in year t. $VolDisc_{i,t}$ is defined as the natural logarithm of one plus the number of management earnings forecasts, issued for firm i in year t. $Controls_{i,t}$ is a vector of firm-specific control variables, namely, $ReadIndex$, $Size$, MB, $Loss$, $Leverage$, ROA, $SpecialItems$, $Volatility$, and $Return$. θ_i and μ_t denote firm and year fixed effects to account for time-invariant differences across firms and time trends, respectively. All specifications include firm and year fixed effects and are estimated at the firm-year level. The sample period is from 1995 to 2020. All variables are winsorized at the 1st and 99th percentiles and defined in Appendix A. t-statistics reflected in parentheses are computed based on standard errors adjusted for clustering at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Proxy for *Financial Outcome*								
	Firm Value			*Implied Cost of Equity Capital*			*Cost of Debt Capital*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Conglo × VolDisc	0.041**			-0.001**			-0.038**		
	(2.20)			(-2.06)			(-2.23)		
Conglo	-0.130***			0.002***			0.019		
	(-4.98)			(3.58)			(0.67)		
#Seg × VolDisc		0.014**			-0.001***			-0.009	
		(2.10)			(-4.28)			(-1.37)	
#Seg		-0.039***			0.001**			0.024**	
		(-3.89)			(2.45)			(2.09)	
Comp × VolDisc			0.079**			-0.002**			-0.058*
			(2.34)			(-2.13)			(-1.85)
Comp			-0.333***			0.005***			0.133**
			(-6.78)			(3.91)			(2.34)
VolDisc	0.016	0.010	0.020	-0.003***	-0.001***	-0.003***	-0.035**	-0.037**	-0.041***
	(0.99)	(0.49)	(1.27)	(-7.69)	(-3.43)	(-8.44)	(-2.45)	(-2.15)	(-3.16)
Observations	73,279	73,279	73,279	66,496	66,496	66,496	69,670	69,670	69,670
Adjusted R^2	0.664	0.664	0.664	0.785	0.785	0.785	0.765	0.765	0.765
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 2

2. Powering Down Pollution: How Corporations Navigate EPA Enforcement in the Electricity Sector

2.1. Introduction

Climate change and its interconnection with air pollution have garnered increasing attention throughout the 21st century. This attention intensifies in industries with significant pollution footprints, especially the electricity sector.[8] The Biden Administration aims to ambitiously cut emissions in this sector by 50% by 2030 and eradicate fossil fuel emissions by 2035. Meeting these targets necessitates the implementation of stringent regulations and their rigorous enforcement to effectively curb the activities of major polluters.[9] As a result, abundant resources have been allocated to fortify the US Environmental Protection Agency (EPA), the key government body responsible for setting environmental standards, monitoring pollution, and enforcing regulations. The 2021 report highlights this commitment, showing that the EPA directed over $2.5 billion toward Environmental Programs and Management (EPA, 2022b), while its enforcement actions prompted non-compliant facilities to invest over $8.5 billion to ensure compliance (EPA, 2022c). However, despite these substantial investments, ongoing concerns about the effectiveness of EPA's enforcement efforts remain. For example, evidence suggests that assigning specific environmental monitoring responsibilities to state-level agencies results in weak deterrence against non-compliance.[10] Furthermore, limited enforcement power and the tendency to impose insufficient penalties may further undermine the efficacy of EPA initiatives.[11] Although EPA enforcement plays a crucial role in ensuring adherence to environmental regulations,

[8] Electricity producers are responsible for about 65%, 35%, and 30% of total SO2, NOx, and CO2 emissions in the US, and with the increasing electrification such as adoption of electric vehicles, this percentage could potentially increase at least in short-run.

[9] "E.P.A. describes how it will regulate power plants after Supreme Court setback," https://www.nytimes.com/2022/07/07/climate/epa-greenhouse-gas-power-plant-regulations.html.

[10] A report by the EPA's Office of Inspector General raises concerns about inefficacy of the states' oversight mentioning that *"state enforcement programs frequently do not meet national goals and states do not always take necessary enforcement actions. State enforcement programs are underperforming: EPA data indicate that noncompliance is high and the level of enforcement is low"*.
https://www.epaoig.gov/sites/default/files/2015-10/documents/20111209-12-p-0113.pdf

[11] EPA's National Strategy for Improving Oversight of State Enforcement Performance in 2013 highlights the *"failure of states to take appropriate penalty actions which results in ineffective deterrence for noncompliance"* as an unresolved and recurring issue which needs a focused national effort to address.
https://www.epa.gov/sites/default/files/2014-06/documents/state-oversight-strategy.pdf

there remains a notable gap in available information on the efficacy and outcomes of these initiatives within the electricity sector. Thus, this study aims to address these challenges by leveraging publicly available emissions data at the plant level. Specifically, it examines how corporations strategically react to EPA enforcement actions and the financial consequences of these responses. Additionally, it evaluates the impact of these regulatory effects on the environment and society.

EPA enforcement actions typically result from violations of environmental regulations. Depending on the severity of these violations, the affected plant(s) may be required to pay federal or state/local financial penalties, implement specific measures to return to compliance, and (or) undertake Supplemental Environmental Projects (SEPs). My analysis starts with exploring how EPA enforcement actions influence the operations of specifically targeted power plants from 2001 to 2020. I delve into the effects of such actions on the emissions of carbon dioxide (CO2), sulfur dioxide (SO2), and nitrogen oxides (NOx) from these plants, along with their electricity production levels. By employing power plants in close geographical proximity as a control group in a stacked difference-in-differences (DiD) regression analysis, I find that plants targeted by the EPA significantly decrease their electricity output and CO2, SO2, and NOx emissions.

One might argue that the endogenous relationship between certain time-variant plant characteristics and the exposure of power plants to EPA enforcement actions could influence the baseline evidence. I employ an instrumental variable (IV) analysis to address this potential endogeneity issue. To be valid, instruments must exhibit a positive correlation with a power plant's exposure to environmental enforcement while not impacting plant-level decisions and outcomes other than through enforcement actions. To proxy for the exposure to environmental enforcement, I utilize each county's total number of air enforcement actions from emission sources, such as power plants and manufacturing plants. To account for the size and concentration of power plants within each county, I adjust the county-level number of enforcement actions by the number of power plants or the share of plants in the county's total generation capacity. The analysis reveals that these two instruments are positively associated with the likelihood of experiencing an enforcement action. In addition, the first stage of the 2-Stage Least Square (2SLS) regressions suggests that these instruments successfully satisfy the relevance condition. Moreover, it is highly improbable that the occurrence of enforcement actions in other proximate emission sources would significantly influence operational decisions and production levels in nearby power plants, except through the increase in these plants' exposure to environmental regulations. Employing these instruments, I find that the baseline results remain robust, further supporting the notion of a causal impact of environmental monitoring on plant-level outcomes.

I then explore the strategies that power plants implement to reduce emissions in response to EPA enforcement actions. These plants adopt various approaches to lower their emissions, including installing scrubbers, investing in advanced pollution control technologies, transitioning to alternative types of generators, adjusting their fuel mix and quality, or improving their overall generation efficiency. This analysis yields several significant findings: (1) Facilities targeted by the EPA undertake a range of measures to curtail emissions. They enhance scrubber deployment, invest in pollution abatement technologies, expand the use of combined cycle generators and gas turbines, and reduce reliance on steam generators. Scrubbers and abatement technologies significantly lower emissions, and introducing new generator types allows plants to improve environmental performance through changes in their fuel mix. (2) Targeted plants reduce their reliance on coal and opt for cleaner fuel sources, primarily favoring gas. This shift reflects a broader trend toward environmentally friendlier energy sources. (3) I observe a substantial reduction in the total sulfur used in power generation, stemming from reduced coal usage and overall production. Fuel sulfur content, a crucial indicator of fuel quality and environmental impact, directly influences SO2 emissions. (4) There is an improvement in the efficiency of coal-fired electricity generation following enforcement actions. These findings provide valuable insights into how EPA enforcement actions drive strategic changes in power plant operations, fuel utilization, and emission reduction technologies.

Subsequently, I analyze the potential factors that influence the effectiveness of EPA enforcement efforts. I evaluate the role of utility firms' organizational structure and the presence of affiliated sibling plants in shaping their compliance behaviors. I discover that the impact of EPA enforcement is mainly driven by multi-plant utility entities. Subsequently, I explore how operational flexibility and possible economies of scale in fuel procurement within multi-plant utility firms contribute to their responsiveness to environmental regulations. Remarkably, I observe that EPA enforcement effects are more pronounced in plants with geographically proximate sibling facilities and those with a higher reliance on coal in their siblings. These observations highlight the importance of understanding the power plant structure at the firm level to grasp how utility plants vary in their responses to EPA enforcement and adherence to environmental regulations. Furthermore, this study explores whether the disciplinary effect of enforcement actions extends beyond the directly targeted plants and contributes to the improved environmental performance of non-targeted plants owned by the same firm. Employing a stacked DiD analysis, I find that non-targeted plants, which are part of the same corporate entity as plants penalized by the EPA, also show reductions in CO2, SO2, and NOx emissions, along with decreased electricity generation, mirroring trends seen in directly targeted plants. These non-targeted plants implement emission mitigation strategies closely aligned with those adopted by the targeted ones, especially when they use the same fuel types and operate similar generators.

I also explore how a firm's financial resources impact its ability to implement emission reduction strategies and transition to cleaner production methods. Utility firms may adopt approaches to enhance their environmental performance, including updating generator types, installing scrubbers, and altering fuel mix, which require significant capital investment. Therefore, the availability of financial resources is a critical factor enabling utility firms to respond to environmental enforcement. Using cash holdings as a proxy for the availability of internal financial resources, my analysis shows that utility firms with higher cash reserves tend to reduce pollution emissions more successfully.

Furthermore, I investigate whether there are differences in enforcement outcomes between cases directly managed by the EPA and those delegated to state-level agencies. Previous research underscores variations in the stringency of environmental enforcement between state agencies and the EPA, as well as shortcomings in states' monitoring efforts (Woods, 2008; Blundell, 2020). Motivated by these findings, I examine whether the enforcing regulatory body influences enforcement outcomes. The results reveal that the impact of EPA enforcement is more pronounced in power plants targeted by the federal agency.

The regulatory status of utility firms also plays a crucial role in shaping their responses to EPA enforcement. Following the restructuring of the electricity market in parts of the US during the 1990s, many traditional, vertically-integrated utilities separated their transmission and generation operations and became deregulated entities, competing in open markets. In contrast, utilities unaffected by restructuring remained regulated, requiring regulatory approval for capital investments and setting electricity prices. The electricity prices are determined such that these utilities gain a fair rate of return on their investments. This distinction in regulatory status can directly affect a utility firm's ability to transition towards more environmentally friendly electricity production. These findings show that reduction in emissions are more pronounced among regulated utilities.

Collectively, EPA enforcement actions on impacted targeted plants are not uniform, with factors such as the organizational structure of parent firms, financial resource availability, the enforcing agency, and the regulatory status of utility firms playing critical roles in the heterogeneous responses of power plants to EPA enforcement. Consequently, the effectiveness and outcomes of these actions can vary widely, underscoring the importance of considering these multifaceted factors when assessing the impact of EPA enforcement on environmental compliance and performance across the power industry.

Finally, I investigate the cost implications of adhering to EPA enforcement for cleaner and more sustainable electricity generation. Results reveal that compliance with enforcement actions results in higher fuel costs, a major operational expense for fossil-fuel-powered utilities, and significant investments in pollution control technologies and new generators. I then assess the impact of these enforcement actions and strategic responses on the financial performance of utility firms by examining key financial metrics at the parent company level. My analysis shows significant post-enforcement increases in total assets, long-term debt, operating revenue, and operating expenses. The rise in total assets aligns with the heightened capital expenditure at targeted plants, while increased long-term debt suggests reliance on this form of financing for capital investments. Additionally, the operating expense escalation is attributed to higher fuel costs and the additional operating and maintenance costs linked to new capital investments. Despite these higher costs, I note an increase in operating revenue after enforcement actions. However, this concurrent rise in revenues and costs leaves the overall operating income of the utility firms largely unaffected.

Given the noted decline in production levels, the resulting increase in operating revenue implies a corresponding rise in electricity sales prices. The ultimate burden of environmental costs and their transfer to end users remains a question of interest to the public, policymakers, and researchers. Prior studies (e.g., Fabra and Reguant (2014) and Woo et al. (2017)) have quantified the extent to which increased carbon emission costs are passed through to electricity prices. However, I specifically investigate whether utility firms transfer additional costs from EPA enforcement onto their customers through increased electricity sales prices. Analysis of electricity sales price data at the parent company level indicates that, on average, prices rise by 6.1%-7.9% in the aftermath of EPA enforcement actions. This increase in prices is predominantly observed in regulated utilities. Consequently, the results highlight a critical implication: the transfer of enforcement-related costs to consumers could counteract the intended goal of deregulation policies aimed at decreasing electricity costs for consumers.

This research contributes to three strands of the literature. First, it contributes to studies examining the influence of environmental regulations on firms' environmental performance. Prior research shows that passage of Gasoline Content Regulations (Auffhammer and Kellogg, 2011), greenhouse gas reporting program (Tomar, 2021), California cap-and-trade program (Bartram, Hou, and Kim, 2022), New Source Review Standards (Chan and Zhou, 2021), and a text-based measure of regulatory exposure (Fan and Wu, 2022) impact emissions and environmental outcomes. Yet there remains a gap in understanding the specific effects of environmental enforcement in ensuring regulatory compliance. To the best of my knowledge, only two papers closely relate to this area. First, Dasgupta, Huynh, and Xia (2021) focus on the geographical spillover effect of environmental enforcement and identify socially-responsible institutional investors as the main driver underlying this effect. Second, Lim (2016) strictly examines the impact of EPA enforcement on NOx emissions in Californian firms. This study, however, provides a more comprehensive examination of EPA enforcement impact across the U.S. electricity sector. I conduct a detailed analysis of plant-level operational responses, explore factors that amplify the effects of EPA actions, and investigate how these enforcement efforts permeate through the organizational structures of utility firms. This approach yields valuable new insights into how the operational, financial, and organizational characteristics of targeted plants, as well as the jurisdiction of the agency and environmental regulatory frameworks, influence the effectiveness of EPA enforcement actions.

This study further contributes to the body of research exploring how environmental costs are passed on to customers. Previous studies have explored the degree to which increases in fuel costs (Marion and Muehlegger, 2011; Ganapati, Shapiro, and Walker, 2020; Kim, 2022) and emissions costs (Sijm, Neuhoff, and Chen, 2006; Fabra and Reguant, 2014; Woo et al., 2017; Miller, Osborne, and Sheu, 2017) are reflected in consumer prices. Building on this evidence, this work demonstrates that the heightened costs resulting from EPA enforcement actions are indeed transferred to consumers through increased electricity rates. This finding aligns with prior research, indicating a high cost pass-through level in the electricity market. This phenomenon can be attributed to the inelastic nature of electricity demand and the relatively low costs associated with price adjustments (Sijm, Neuhoff, and Chen, 2006; Fabra and Reguant, 2014).

Finally, this work extends the existing body of knowledge on the spatial network dynamics within multi-establishment firms. Prior research has documented how local economic shocks can propagate through a firm's organizational structure (Cravino and Levchenko, 2017; Duchin, Goldberg, and Sosyura, 2017; Giroud and Mueller, 2019; Bena, Dinc, and Erel, 2021; De Vito, Jacob, and Xu, 2021; Giroud et al., 2021). Additionally, other studies indicate that multi-establishment firms might leverage their organizational structure to manage the effects of environmental regulations (Cui and Moschini, 2020; Bartram, Hou, and Kim, 2022). Building on these insights, this research not only confirms that the impact of EPA monitoring and enforcement also permeates the internal network of establishments within firms, but also uniquely identifies that utility firms do not appear to shift pollution emissions to non-targeted establishments. This finding contributes a new dimension to our understanding of how firms respond to environmental regulation within their organizational networks.

The structure of the remainder of this paper is as follows: Section **2.2** provides a brief overview of the US electricity sector, covering the deregulation process, market structure dynamics, and different facets of electricity generation. Section **3.2** details the data, sample construction, and summary statistics. Section **3.3** analyzes the effectiveness of EPA enforcement actions and examines corporate strategic responses to such actions, Section **2.5** explores the factors Influencing corporate responses to EPA enforcement, Section **2.6** evaluates the financial impact of EPA enforcement on utility firms. Finally, Section **3.4** provides the conclusion.

2.2. The Electricity Sector

The U.S. electricity sector is a complex and diverse landscape, shaped by its historical evolution, the availability of resources, technological advancements, and shifts in regulatory frameworks. To navigate the complexities of this ever-evolving energy landscape, I provide a brief overview encompassing the deregulation process, market structure dynamics, and the facets of electricity generation.

2.2.1. Deregulation in U.S. Electricity Markets

Traditionally, electric utilities in the U.S. functioned as regulated, vertically integrated monopolies, exerting control over the entire energy delivery process, including generation, transmission, distribution, metering, and billing. State regulators closely monitored these utilities to ensure that electricity prices covered operational and investment costs, along with a fair return. In the 1990s, numerous U.S. states began deregulating their electricity sectors to foster competition and reduce costs.[12] This restructuring compelled electric utilities to divest their generating assets, paving the way for independent energy suppliers owning generators. Since building new power line infrastructure was not cost-effective for each supplier, electric utilities retained these assets, evolving into transmission and distribution utilities, which remain regulated. These regulatory frameworks are pivotal in determining retail and wholesale electricity prices establishing electricity markets.

One critical consequence of this wave of deregulation is the creation of Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs). These entities maintain considerable over-

[12] As of 2023, 29 U.S. states have deregulated their electricity sectors. https://quickelectricity.com/deregulated-energy-states/#:~:text=US%20States%20with%20Deregulated%20Energy, natural%20gas%2C%20or%20both%20services.

sight over the transmission systems of the participating utilities and are responsible for ensuring non-discriminatory access to all participants in the market. Presently, approximately two-thirds of the U.S. electricity demand is met within regions governed by ISOs and RTOs, while the remaining third of the load is supplied by vertically integrated utilities.[13] Although their rates and investments remain regulated, many utilities in non-restructured areas still have the option to engage in organized wholesale markets. In states with deregulated markets, both utility firms and independent producers participate in a competitive environment facilitated by market mechanisms. Competition and production costs influence the strategies utilities employ to enhance performance. These strategies may include modifying their fuel mix, retrofitting generators, or incorporating technologies to reduce pollution.

2.2.2. *Market Structure Dynamics*

Utilities are the crucial link in electricity delivery, connecting electricity generation with consumption. There are three distinct types of utilities, each characterized by its unique operational framework and governance structure: (1) Investor-owned utilities, such as Duke Energy and Pacific Gas & Electric, are private, profit-oriented companies that typically cater to expansive geographic regions and provide most end-use electricity. Their activities are subject to oversight by federal (Federal Energy Regulatory Commission, FERC) and state-level public utility commissions (PUCs). In states with vertically integrated electric utilities, PUCs regulate generation, transmission, and distribution to customers. In restructured states, PUCs only regulate distribution, while the ISO/RTO oversees the generation markets and transmission system. The FERC regulates wholesale transactions and the interstate transmission system. (2) Public utilities, owned by local governments, function as non-profit entities, typically focusing on community needs and maintaining affordable electricity rates. They serve areas with less financial incentive for private investment (Borenstein and Bushnell, 2015). A prime example is the Los Angeles Department of Water and Power, the largest municipal utility in the U.S., with a generating capacity of approximately 8,100 megawatts in 2021-2022 and serving the needs of over four million residents and local businesses.[14] (3) Cooperative utilities are customer-owned and operated, primarily in rural or underserved regions, to address local electricity demands. Their governance model ensures that the priorities and interests of their consumer members guide their operational decisions.

[13] https://www.rabobank.com/knowledge/d011403204-powering-the-future-navigating-the-complexities-of-the-evolving-us-electricity-landscape.

[14] https://en.wikipedia.org/wiki/Los_Angeles_Department_of_Water_and_Power.

2.2.3. *Facets of Electricity Generation*

In the U.S., the primary energy sources for electricity generation are fossil fuels (including natural gas, coal, and petroleum), nuclear energy, and renewable resources.[15] As depicted in Figure 1, there has been a notable shift in the electricity supply's composition: coal's share decreases from 50.9% in 2001 to 19.3% by 2020, while natural gas rises from 17.1% to 40.5%, and renewables increase from 7.7% to 19.5%. Predominant fossil fuel-based generators include natural gas combined cycle (CC) generators, gas turbines (GT), internal combustion engines (IC), and steam turbines (ST). The usage of steam turbines, which mostly depend on coal for electricity generation, has declined due to environmental concerns and the competitive edge of natural gas and renewables; yet they continue to be a significant part of the energy mix.

The burning of fossil fuels for electricity generation releases several pollutants, including sulfur dioxide (SO2), nitrogen oxides (NOx), and carbon dioxide (CO2), which contribute to a range of environmental and health issues like respiratory problems, ground-level ozone formation, acid rain, and global warming. Emissions such as carbon monoxide (CO) and particulate matter (PM) also pose health threats. In 2019, the U.S. power sector is responsible for 65% (1.27 million tons) of the nation's total SO2 emissions, 35% (1.34 million tons) of NOx emissions, and nearly 30% (1.72 billion tons) of CO2 emissions.[16] The Clean Air Act (CAA) and subsequent amendments, including measures like the National Ambient Air Quality Standards (NAAQS) and New Source Performance Standards (NSPS), have been implemented to mitigate these emissions. Notably, the 1990 Acid Rain Program specifically targeted SO2 and NOx emissions from power plants. Compliance is monitored through the installation of Continuous Emission Monitoring Systems (CEMS) in power plants, with enforcement actions taken to ensure future compliance and environmental remediation in cases of non-compliance.

Thus, the electricity sector offers a distinctive setting for examining how market structures influence utility responses to EPA enforcement actions, applicable to both deregulated and non-deregulated areas. Furthermore, the vast geographical dispersion of utilities across numerous regions creates an ideal context for analyzing the effects of EPA enforcement on companies operating in varied locations. For instance, Figure **2.2** illustrates the diverse distribution of power plants across U.S. counties in 2020, highlighting that certain densely populated areas contain over 200 plants. This study primarily focuses on CO2, SO2, and

[15] https://www.eia.gov/energyexplained/electricity/electricity-in-the-us.php#: :text=Fossil%20fuels%20are%20the%20largest,U.S.%20electricity%20generation%20in%202022.

[16] https://www.epa.gov/newsreleases/epas-2019-power-plant-emissions-data-demonstrate-significant-progress.

NOx emissions, primarily due to the readily available data on these pollutants.

2.3. Data and Summary Statistics

This study utilizes data from multiple sources. Emissions and enforcement actions data are sourced from the EPA. The EPA's Clean Air Markets Division (CAMD) continuously monitors and reports emissions of CO2, SO2, and NOx from power plants with over 25MW nameplate capacity. For enforcement actions, I employ all formal administrative and judicial cases in the ICIS-Air and Clean Air Act (CAA) related cases in the ICIS-FE&C dataset. I only include activities with a total penalty greater than $5,000 but the findings are robust to the choice of this threshold. For a subset of cases in ICIS-Air resulting from high-priority violations (HPVs), the 'Day Zero' date is recorded by state agencies and reported to EPA subsequently. Hence, I obtained that information through a Freedom of Information Act request. For other non-HPV activities in ICIS-Air, the settlement date is used as the violation or initiation date of enforcement action is unavailable. Lastly, the EPA-EIA crosswalk(Huetteman et al., 2021) is used to match EPA data with the corresponding plants in the EIA.

The data relating to the operations of power plants is gathered from various datasets provided by the US EIA: 1) Electricity disposition, revenue, and sales to ultimate customers from EIA-861, 2) Characteristics of utility firms, power plants, and generators along with generator-level ownership from EIA-860, 3) Quantity of fuel, heat content, and net generation for each fuel type from EIA-923, 4) Fuel sulfur content from EIA-767 during 2001-2005 and from EIA-923 during 2008-2020 (data is unavailable in 2006 and 2007), 5) Fuel costs from EIA-423 and FERC-423 during 2001-2008 and from EIA-923 during 2009-2020, 6) Electricity sales by non-utilities from EIA-923 during 2004-2020 (data is unavailable during 2001-2003), and 7) FERC Form 1 for the annual financial information of investor-owned utilities.

I begin constructing the sample using plants listed in EIA-860 from 2001-2020. I only include plants located in the contiguous US that operate primarily on fossil fuels for at least 50% of their capacity. Plants with missing emissions data are excluded, and the analysis is focused on investor-owned utilities and independent power producers.[17] Since my analyses are centered on an 11-year window surrounding enforcement actions, I focus on actions occurring between 2006 and 2015 to allow sufficient years before and after each enforcement action.

[17]Publicly-owned utilities and industrial or commercial power producers are not included in the sample, although the findings remain robust when they are included.

Missing sulfur contents in 2006 and 2007 are extrapolated using the average sulfur percentage in 2005 and 2008. The rest of the missing values are estimated using the average sulfur percentage of that particular fuel in plants located within a 100 KM distance. Moreover, fuel cost data is available only for larger coal-fired plants with greater than 50 MW nameplate capacity or other plants with greater than 200 MW nameplate capacity. For smaller plants, the median fuel cost of nearby plants is used as an estimate, which is a plausible strategy given the small geographical variation in fuel prices and quality. For non-utilities, wholesale and retail sales and prices are collected from EIA-923 and EIA-861, and missing values are estimated using median prices from nearby plants. For utilities, sales and prices are obtained from EIA-861. When there are both retail and wholesale sales, I define electricity sales price as the weighted average wholesale and retail prices.

Table **3.1** provides summary statistics for key variables in the study. The average plant in the sample annually emits over 1.171 million tons of CO2, 3.061 thousand tons of SO2, and 1.136 thousand tons of NOx, generating over 1.603 TWh. Coal-fired plants typically have 0.348 scrubbers and invest $4.828 million annually in pollution abatement technologies. On average, power plants add 0.14 generators annually, including 0.016 new steam generators, 0.07 new gas turbines, and 0.054 new combined cycle generators. On average, a plant uses over 7.889 TBTUs of coal, 268 BBTUs of petroleum, and 6.98 TBTUs of gas, and sources 70.5% of its electricity from gas, 21.3% from coal, and 8.2% from petroleum. The average cost is $6.047 per MMBTU of heat from fossil fuels, with an average sulfur content of 0.268 pounds per MMBTU. The average heat rates for coal, petroleum, and gas are 0.087, 0.087, and 0.098, respectively. Finally, within the subsample of investor-owned parent utility firms, the average total asset is $5.4 billion dollars. Long-term debt consists 27% of total assets. Operating revenue, operating expenses, and operating income are on average 39%, 20.7%, and 4.1% of total assets, respectively. Moreover, the average price of electricity is $67.39 per MWh throughout the sample period.

2.4. Management Navigating EPA Enforcement

In this section, I focus on evaluating the impact of EPA enforcement actions on curbing pollution emissions in the electricity sector and explore the diverse strategies utility firms use to navigate and respond to these regulatory measures.

2.4.1. Pollution Emissions and Electricity Generation

I begin by assessing the effects of EPA enforcement actions on plants directly targeted, utilizing a stacked DiD approach. In this analysis, the treatment group consists of plants subject to enforcement actions, with the initial enforcement incident establishing the event time in cases of multiple enforcement actions. The control group includes plants within a 100-kilometer radius of the treated plants, which have not been directly targeted, nor have any of their affiliate plants received enforcement actions during the study period.

Given the localized nature of the electricity market, variables such as the stringency of environmental regulations, fuel procurement options and costs (Cicala, 2015), the structure of the electricity market, and electricity prices are relatively stable within a small geographical area. This similarity suggests that the treatment and control groups are comparably matched in terms of characteristics that are not plant-specific. To examine the impact of environmental enforcement, I run the following regression:

$$y_{i,t,c} = \beta_0 + \beta_1 Post_{t,c} * Treated_i + \lambda_{i,c} + \omega_{t,c} + \epsilon_{i,t,c}, \tag{5}$$

where $y_{i,t,c}$ shows the outcome variable of plant i at time t in cohort c. Focusing on an 11-year window around each event, each cohort includes one treated plant and the control plants surrounding it. I include cohort-by-plant ($\lambda_{i,c}$) and cohort-by-year ($\omega_{t,c}$) fixed effects to control for time and time-invariant plant characteristics within each cohort. $Treated_i$ is equal to one for treated plants and zero otherwise. $Post_{t,c}$ is equal to one after the enforcement actions and zero otherwise. I cluster standard errors at the cohort-plant level.

Table **2.2** reports the results for key plant-level outcomes. Columns 1-3 indicate reductions in CO2, SO2, and NOx emissions by 38%, 45%, and 28%, respectively. Furthermore, Column 4 reveals a 24% decrease in electricity generation post-enforcement actions. These findings underscore the significant effectiveness of EPA enforcement in diminishing pollution emissions. While a portion of the emissions reduction can be attributed to decreased electricity generation, supplementary results in Table A2 of the Appendix demonstrate significant declines in SO2 and NOx intensities (pollution emitted per unit of electricity generated) following enforcement actions. This result suggests that reductions in pollution emissions is not merely a consequence of lower electricity production.

The reduction in emissions and electricity generation observed may stem from strategic organizational restructuring, wherein electricity generation and emissions are reallocated from targeted plants to other non-targeted sibling plants within the same parent utility company. This strategy, known as emission leakage, is documented by Bartram, Hou, and Kim (2022) in the aftermath of the 2013 California cap-and-trade program. To ascertain the occurrence of such strategic behavior, I analyze the effect of enforcement actions on *Plant Share*, defined as the ratio of a plant's electricity generation to the total output of the parent utility firm. The findings, detailed in Table A3 of the Appendix, reveal no significant shifts in *Plant Share* post-enforcement, indicating a lack of evidence for emission-shifting practices. Moreover, Table A3 highlights a significant decrease in the capacity factor of plants, defined as the actual electricity generation as a proportion of the maximum possible generation within a year, pointing to a production reduction aimed at enhancing environmental performance.

To further understand the dynamics of the effect before and after events, I replace the *Post* dummy with indicator variables that represent each event year before and after enforcement actions. In particular, I use the regression specification presented in Eq. 6.

$$y_{i,t,c} = \beta_0 + \sum_{\tau=-5}^{-2} \beta_\tau Treated_i * \mathbb{1}[t - t_{0,c} = \tau] + \sum_{\tau=0}^{5} \beta_\tau Treated_i * \mathbb{1}[t - t_{0,c} = \tau] + \lambda_{i,c} + \omega_{t,c} + \epsilon_{i,t,c} \tag{6}$$

In Eq. 6, $\tau \in [-5, +5]$ shows the time relative to the event year. The $t_{0,c}$ denotes the event year for each cohort. Figure **2.3** depicts the dynamics of β_τ coefficients for focal plant's operations. Sub-figures (a)-(d) indicate that prior to enforcement action, there are no consistent discrepancies between the treatment and control groups in terms of pollution emissions and electricity generation. However, a gradual decline in both emissions and electricity generation is observed following the enforcement.

2.4.2. Identification Strategy

The above analysis has employed plants within a 100-kilometer radius to mitigate the impact of spatial factors on operational decisions of power plants. Moreover, I have accounted for all time-invariant characteristics of each plant through cohort-by-plant fixed effects. Nevertheless, concerns remain regarding the influence of time-variant characteristics or omitted variables that could affect plants' susceptibility to EPA enforcement as well as their emissions and operational strategies. To reinforce the results and tackle potential endogeneity concerns, I have opted for an instrumental variable analysis. For the instrument to be considered valid, it must be correlated with the likelihood of a plant facing environmental enforcement (demonstrating relevance) without directly impacting the plant-specific outcomes (satisfying the exclusion restriction criterion).

To measure the exposure of plants to environmental regulations, my analysis centers on the frequency of air-related enforcement actions within each county. In constructing instruments, I consider enforcement actions targeting a broad range of emission sources, including manufacturing plants, oil and gas extraction sites, refineries, and facilities producing chemicals, metals, and minerals, rather than focusing solely on those targeting power plants. My metric for gauging exposure to environmental regulations is determined at the county level. Consequently, this approach restricts the inclusion of control plants to counties distinct from those of the targeted plants, yet still within a 100-kilometer radius.

The frequency of enforcement actions within each county is a proxy for the probability of any given power plant potentially being targeted by the EPA.Therefore, for plant i in county j at time t, I first count the number of enforcement actions that target *other* emission sources in the same county-year ($\#Enforcement_{-i,j,t}$). Furthermore, the number of plants within each county and their relative sizes may influence their likelihood of facing environmental enforcement. We, therefore, adjust the county-level enforcement action count with two weighting factors to account for this to devise the instruments. First, I employ the proportion of a plant's nameplate capacity relative to the total nameplate capacity of its county as one weighting factor. This instrument for power plant i at time t in county j is computed as follows:

$$EnforceExposure_{1,i,j,t} = \frac{NamePlate_{i,j,t}}{Nameplate_{j,t}} * \#Enforcement_{-i,j,t}.$$

For the second instrument, I assign equal weight to all plants operating within each county and compute it in the following manner.

$$EnforceExposure_{2,i,j,t} = \frac{1}{\#Plants_{j,t}} * \#Enforcement_{-i,j,t}.$$

The identifying assumption is that an increased frequency of enforcement actions within a specific geographical area elevates the probability of plants being targeted by the EPA. Nonetheless, it is reasonably improbable that enforcement activities directed at other emission sources within a county (even when the majority operate in different industries and sectors) would influence emissions and operational choices at power plants due to EPA enforcement exposure.

Before conducting the 2SLS regressions, I first assess the relevance of the instruments to the probability of a plant receiving enforcement actions. In columns 1 and 2 of Panel A, Table **2.3**, I analyze the relationship between receiving an enforcement action ($Enforcement$, represented by a dummy variable that equals 1 if a plant is targeted within a year) and the instruments across all power plants in the US with available emission data. The findings indicate that a one-standard-deviation increase in $EnforceExposure_1$ and $EnforceExposure_2$ raises the likelihood of enforcement by 2.9% and 1.2%, respectively. In columns 3 and 4, I analyze the relationship between $Enforcement$ and the two instrumental variables in my primary sample, where targeted plants are carefully matched with control plants within a 100-kilometer radius. The analysis reveals that a one-standard-deviation rise in the values of the instruments boosts the probability of a plant receiving enforcement actions by 1.6% and 0.9%, respectively. These outcomes robustly confirm the significant correlation between the instruments and the likelihood of enforcement.

Next, using the two instruments, I formally run the following 2SLS regressions:

$$Post_{t,c} * Treated_{i,j} = \beta_0 + \beta_1 Post_{t,c} * EnforceExposure_{i,j,t_0} + \lambda_{i,c} + \omega_{t,c} + \epsilon \tag{7}$$

$$y_{i,j,c,t} = \beta_0 + \beta_1 \widehat{Post_{t,c} * Treated_{i,j}} + \lambda_{i,c} + \omega_{t,c} + \epsilon \tag{8}$$

Eq. 7 shows the first stage regression, where $EnforceExposure_{i,j,t_0}$ is used as an instrument for the endogenous treatment variable of plant i in county j at the time of enforcement action t_0. Eq. 8 shows the second stage regression in which I regress the outcome variables for plant i in cohort c and county j at time t on fitted values of the first stage regression. Panels B1 and B2 of Table **2.3** report the results of the 2SLS regressions. Column 1 in both panels presents the first-stage estimation outcomes, where the untabulated Cragg-Donald F-statistics of 62.208 and 131.459 robustly refute the null hypothesis of weak instruments in the first stages. Employing instrumental variables in columns 2-4 across Panels B1 and B2 demonstrates that the observed reductions in electricity generation and CO2, SO2, and NOx emissions identified in the baseline analysis do not result from endogeneity bias. Notably, the instrumental variable analysis reveals that the extent of emission reductions is even more pronounced than initially observed. These results lend robust support to the causal interpretation of the preliminary findings.

2.4.3. Corporate Response Strategies

Utility firms employ diverse strategies to comply with EPA enforcement actions. Options include scaling back production, adopting emission-reducing technologies, altering the quality and type of fuel used, and improving the efficiency of electricity generation. This section delves into the operational adjustments and measures utility firms undertake to decrease emissions and improve their environmental footprint.

A viable approach to reducing emissions involves investing in pollution abatement technologies or adopting new, more eco-friendly electricity generators. Panel A of Table **2.4** explores shifts in such investments. Among these, scrubbers are a strategic choice for power plants aiming to enhance environmental performance. Often integrated into coal-fired generators, these devices capture SO2 emissions from exhaust gases. The results presented in Column 1 of Panel A reveal a notable 5.1% increase in the adoption of scrubbers after enforcement actions.

Next, I examine the impact of enforcement actions on plants' capital investment in pollution abatement technologies. The capital investments encompass the acquisition of structures and/or equipment purchased to reduce, monitor, or eliminate airborne pollutants. Examples of air pollution abatement technologies include flue gas particulate collectors, scrubbers, continuous emissions monitoring equipment (CEMs), and nitrogen oxide control devices. Column 2 shows that targeted plants increase their investment in abatement technologies by 19.8% in response to EPA enforcement. Furthermore, I investigate plants' decisions to modify or augment their generator types to boost environmental performance. This approach could improve thermal efficiency since newer generators typically exhibit higher heat rates. Additionally, plants may need to switch generator types to facilitate fuel changes. For instance, given that steam generators predominantly utilize coal as their primary fuel, plants aiming to enhance their environmental footprint by shifting towards gas would necessitate building new gas turbines or combined cycle generators. In columns 3-7 of Panel A, I use the number of new generators becoming operational as the dependent variable. The findings indicate that targeted plants augment the total count of all generators by 3.1%. This overall increase is primarily attributed to a rise in gas turbines and combined cycle generators, which see increments of 2.5% and 1.6%, respectively. Conversely, the introduction of new steam turbines falls by 1% following EPA enforcement, with the effect on internal combustion generators proving negligible.

As highlighted in section **2.2**, coal and petroleum emit significantly more pollutants than natural gas. Given that the type of fuel used is a key factor in a plant's emissions profile, transitioning to cleaner fuels represents an effective strategy for emission reduction. Panel B of Table **2.4** details the impact of enforcement actions on power plants' fuel selection and usage patterns. Columns 1-3 show a marked 45% reduction in coal usage, with no notable change in the consumption of petroleum or gas. Further analysis in columns 4-6 examines the dependency on each fuel type, using each share in the total fuel mix as a dependent variable. The findings indicate a 2.7% decrease in coal dependency (12.7% relative to the average *Coal Share*) and a 3.4% increase in gas reliance (4.8% relative to the average *Gas Share*). Considering the higher costs of natural gas compared to coal, this shift in the fuel mix not only alters emissions but also affects the operational costs of utility firms. Specifically, the last column of Panel B reveals a 16% increase in fuel expenses for plants targeted by EPA enforcement.

Changing the fuel mix, especially the transition from coal to gas, necessitates a change in generator types, representing a significant capital investment that may not be a feasible option for all targeted plants. Alternatively, improving the quality of fuels might be a potentially more accessible way to achieve emission reduction. Therefore, in Panel C of Table **2.4**, I explore the effect on the quantity of sulfur entering the production process. Column 1 indicates that total sulfur input in targeted plants decreases by 30% following enforcement actions, a result significant at the 1% level. Column 2 delves into the sulfur intensity of the fossil fuels utilized in the generation process. Results suggest a reduction in sulfur intensity by approximately 1.8%. A closer look at columns 1 and 2 indicates that most of the decline in total sulfur content is attributable to decreased production levels. Nonetheless, there is a significant improvement in the sulfur intensity (and thus, quality) of fuel inputs following enforcement actions. This reduction in sulfur intensities could be due to either a shift in the fuel mix, such as substituting coal with natural gas (which has negligible sulfur content), or enhancing the quality of coal used, for instance, opting for Subbituminous coal over Bituminous coal. Further investigation into the specific changes in sulfur intensities for coal and gas reveals that, conditional on the use of coal, targeted plants select coal varieties with approximately 4.9% lower sulfur intensity. Conversely, the sulfur intensity of the petroleum used increases by about 3.6%, likely reflecting a strategic decision by power plants to manage costs by opting for cheaper, lower-ranked fuel oils. Given the minimal reliance on petroleum for electricity generation and its primary use during peak hours, the increased sulfur intensity of petroleum has a negligible effect on the overall environmental performance of power plants, as corroborated by the findings in columns 1 and 2.

Finally, enhancing the efficiency of the electricity generation process emerges as another pivotal measure targeted power plants undertake to lower their emissions. Efficiency is quantified as the electricity generated per unit of heat input. Panel D of Table **2.4** indicates that, although there is no discernible evidence of improvements in overall efficiency, there is a notable 0.3% increase in coal generation efficiency post-EPA enforcement. This modest enhancement in efficiency translates into significant savings for an average plant, amounting to 4,809 MWh or approximately $324,078 in savings, calculated at a rate of $67.39 per MWh.

2.5. Factors Influencing Corporate Responses to EPA Enforcement

The emission mitigation strategies employed by utility firms are diverse and shaped by several key factors, such as their organizational structure, availability of financial resources, the enforcing agency, and the broader regulatory environment. Additionally, the rigor of environmental enforcement can vary based on the regulatory agency overseeing compliance. This section delves into the determinants that amplify the impact of enforcement actions, shedding light on the diverse responses of power plants to these regulatory measures.

2.5.1. The Organizational Structure of Utility Firms

2.5.1.1 Sibling Plants' Characteristics

The organizational structure of utility firms plays a crucial role in shaping their responses to environmental enforcement and their ability to reduce emissions. Specifically, utility firms that operate multiple plants across various locations may exhibit enhanced operational flexibility when navigating environmental regulations. The presence of multiple plants within a single utility firm can leverage economies of scale in fuel procurement, facilitating a more efficient response to environmental challenges. For instance, transitioning to cleaner fuels across several plants could be more cost-effective than implementing such changes in isolation. To assess the influence of organizational structure, I revisit the analyses in Table **2.5**, incorporating an interaction term with a dummy variable indicating whether the targeted plant is part of a multi-plant utility firm. The findings suggest that previously observed responses predominantly originate from plants within multi-plant utilities, while emissions and electricity production remain unchanged in single-plant utilities.

In the subsample of multi-plant utilities, I explore how organizational structure attributes influence the response of targeted plants to enforcement actions. My analysis begins with exploring the impact of geographical proximity between targeted plants and their sibling facilities, assessing whether having siblings nearby intensifies a plant's responsiveness to environmental enforcement. Geographical distance can affect enforcement effectiveness through various mechanisms. For instance, the potential for economies of scale in fuel procurement increases as the proximity between power plants grows closer. Moreover, given that state or local agencies typically regulate air quality programs, regulatory scrutiny will likely be more rigorous for sibling plants closer to the targeted facility. Panel A of Tables **2.6** demonstrates that enforcement actions have a heightened impact when the distance between sibling plants decreases.

In Panels B and C of Table **2.6**, I delve into the differential impacts of enforcement actions on emissions, electricity generation, and fuel inputs, considering the fuel mix used by sibling plants. For this purpose, I construct indicators such as *Siblings Coal Share*, *Siblings Petro Share*, and *Siblings Gas Share* to represent the aggregate ratio of coal, petroleum, and gas utilized as fuel inputs by a targeted plant's siblings. Panel B shows that plants with siblings relying more on coal exhibit more substantial reductions in electricity generation and SO2 and NOx emissions. Following this, Panel C investigates the influence of siblings' fuel mix on post-enforcement fuel mix decisions. The analysis shows that changes observed in targeted plants, such as decreased coal usage, increased reliance on gas, and elevated fuel costs, are significantly linked to the coal consumption patterns of their siblings. These results highlight the role of fuel procurement economies of scale in enhancing the efficacy of enforcement actions.

Overall, the insights gleaned from this section underscore the significant influence of sibling plant characteristics on the outcomes of targeted plants. Specifically, the proximity of targeted plants to their siblings and the capacity to capitalize on economies of scale in fuel mix adjustments are critical factors that substantially improve the effectiveness of EPA's monitoring and enforcement actions.

2.5.1.2 Impact Propagation Through Organizational Structure

This section builds on the established role of sibling utility plants in shaping firms' responses to EPA enforcement by exploring the internal spillover and propagation effects of environmental enforcement across the network of affiliated establishments. Specifically, I investigate whether the impact of environmental enforcement extends beyond the targeted plants, enhancing the environmental footprint of non-targeted utility plants within the same organizational network.

Prior research has employed the spatial distribution and internal networks of establishments to demonstrate the transmission of shocks within internal networks and local economic shocks across regions (e.g., Duchin, Goldberg, and Sosyura, 2017; Giroud and Mueller, 2019; Bena, Dinc, and Erel, 2021; Giroud et al., 2021). This analysis adopts a methodology similar to previous studies, utilizing stacked DiD tests over an 11-year timeframe, spanning five years before and after each enforcement event (from $t-5$ to $t+5$). I exclude plants that are the direct targets of enforcement actions within the sample period. Instead, the treatment group consists of plants indirectly impacted by enforcement actions through their sibling plants. In contrast, the control group comprises plants within a 100-kilometer radius of the treated plants that neither directly experience enforcement actions nor have siblings that do during the study window. The identifying assumption is that treated and control plants are plausibly similar in terms of exposure to environmental regulations, fuel procurement options, and costs, and electricity market structure among others, but differ only in terms of their indirect exposure to EPA enforcement through the network of establishments.

Panel A of Table **2.7** reports the impact of enforcement actions on on the operations of indirectly affected plants, focusing on emissions (columns 1-3) and electricity generation (column 4), as determined using Eq. 5. The findings reveal significant CO2, SO2, and NOx emissions reductions by 27.9%, 52.7%, and 29.5%, respectively, as well as a 22.7% decrease in electricity generation of treated plants post-enforcement actions. To better understand the dynamics of changes in operational outcomes, I run Eq. 6 regressions in an event-study framework. Figure **2.4** plots the estimated β_τs and their 95% confidence interval. The sub-figure graphs (a)-(d) indicate no significant emissions or electricity generation disparities between the treatment and control groups before enforcement actions. However, I observe notable declines in both pollution emissions and electricity generation following these events, with effects lasting several years. This pattern reinforces the view that the observed impacts are not attributable to pre-existing trends but are direct consequences of enforcement actions on one of the siblings.

Next, I explore the adaptive strategies employed by sibling facilities of the targeted plants in response to mitigating their emissions. Columns 1 and 2 of Panel B offer insights into how the enforcement actions influence the adoption of scrubbers and the investment in other pollution abatement technologies. This analysis indicates that while EPA enforcement actions do not markedly affect the installation of scrubbers, they do lead to a noticeable shift in capital investment strategies. Sibling facilities of targeted plants are more inclined to integrate new generators into their operations, with a pronounced preference for combined cycle technology or gas turbines. The shift highlights a strategic move by plants towards regulatory compliance and a competitive stance in the evolving energy market. This trend exemplifies how environmental regulations drive innovation and sustainable practices in the energy sector.

2.5.2. *Availability of Financial Resources*

Existing literature has significantly highlighted how financial constraints and access to capital influence firms' environmental performance (e.g., Bartram, Hou, and Kim, 2022; Xu and Kim, 2022). The strategies that utility companies may deploy to enhance their environmental footprint and adhere to environmental laws, such as updating generator types, fitting scrubbers, or altering their fuel mix, demand substantial financial outlays. Therefore, the ability of these firms to obtain financing for such investments critically influences their capacity to execute strategies that yield environmental benefits.

In this part, I assess the financial readiness of utility firms to undertake these investments by evaluating their cash holdings, defined as the ratio of cash to total assets, as a measure of their available financial resources. This test focuses exclusively on targeted plants for which financial statement data (i.e., FERC Form 1) is accessible. Panel A of Table Table **2.8** presents the results of interacting $Post \times Treated$ variable with the cash holdings. The findings show a significant relationship: the effects of EPA enforcement actions are markedly more substantial among targeted plants with stronger financial positions, suggesting that financial health not only enables utility firms to comply with environmental regulations but also amplifies the positive impact of enforcement actions on environmental performance. This evidence underscores the critical role of financial stability in facilitating the adoption of capital-intensive environmental improvements within the utility sector.

2.5.3. *Agency of Enforcement*

The EPA oversees numerous national environmental policies, yet it relies heavily on state governments to carry out the bulk of environmental enforcement duties. Within the EPA, the Office of Enforcement and Compliance Assurance (OECA) is instrumental in shaping national enforcement strategies and supervising the execution of these initiatives at the state level. This structure allows for a blend of centralized policy formulation and decentralized enforcement, ensuring that environmental standards are uniformly applied nationwide while accommodating regional specificities. Despite states holding the authority to oversee various environmental initiatives, the EPA assumes a pivotal oversight role in verifying that these state-operated programs conform to and achieve federal environmental targets, thus promoting a cohesive national framework for environmental protection and compliance. Furthermore, the EFA retains the right to perform independent inspections and intervene in non-compliance when it deems that a state has not taken adequate action against a facility for a violation. The EPA's dual capacity to both delegate enforcement responsibilities and retain the right to direct intervention underscores a dynamic regulatory framework. This framework is designed to foster state initiative and responsiveness to local environmental challenges while preserving the integrity of national environmental goals in safeguarding public health and the environment against non-compliance risks.

However, concerns have been raised regarding the effectiveness of state agencies in monitoring environmental standards and, at times, their lenient enforcement of environmental regulations (Woods, 2008; Blundell, 2020). Furthermore, research by Glicksman and Earnhart (2007) has indicated that federal oversight and enforcement efforts offer greater deterrence against violations. In light of these findings, this analysis seeks to determine whether a similar disparity exists between state-level and federal enforcement actions within the electricity sector. To explore this, I introduce an interaction between my primary variable of interest and a binary indicator representing the enforcing agency's jurisdiction: state or federal. The findings in Panel B of Table **2.8** reveal a more significant reduction in emissions and power generation following federal enforcement actions compared to those initiated at the state level. This suggests that federal enforcement actions carry a heavier impact, reinforcing the notion that federal oversight may lead to more stringent adherence to environmental standards and regulations. This comparison not only highlights the variance in enforcement efficacy between state and national levels but also underscores the critical role of federal intervention in driving environmental compliance and improving overall sectoral performance.

2.5.4. Regulatory Dynamics in the Electricity Sector

The deregulation initiatives within the U.S. electricity sector during the late 1990s were designed to introduce competition and reduce consumer costs. This transformative period marked a departure from the traditional model of vertically integrated utilities towards a more dynamic system where electricity trading occurred in open markets. This transition aimed to replace the regulated, cost-of-service generation model with market-based pricing mechanisms to enhance efficiency and lower prices. Despite these deregulation efforts, certain regions, primarily those that have not undergone restructuring, continue to have utility firms wielding considerable market power. In these areas, both the investments made by utilities and the prices charged for electricity remain under the scrutiny and regulation of public agencies. This regulatory framework ensures these utilities receive a fair investment return, creating a financial environment conducive to stability and predictable earnings.

Prior research suggests the benefits of deregulating the electricity sector, including efficiency improvements and cost reductions. Fabrizio, Rose, and Wolfram (2007) identifies cost savings at deregulated plants resulting from more efficient operations, notably in labor and non-fuel expenses. Cicala (2015) documents a decline in procurement costs for gas and coal plants after deregulation, while Cicala (2022) reports additional cost reductions attributed to more efficient dispatching by Independent System Operators (ISOs), which improve transmission coordination and facilitate inter-utility trade.

I hypothesize that utilities operating within regulated markets, assured of a reasonable return on investment, may exhibit a greater propensity to invest in and adopt modifications mandated by EPA enforcement actions. This willingness can be attributed to the financial security that regulation affords, enabling these utilities to undertake necessary investments to comply with environmental standards without the immediate pressure of market forces. This hypothesis underscores the nuanced impact of regulatory environments on utility firms' investment behaviors, especially in response to environmental compliance demands. Thus, I explore how the competitive dynamics of the electricity market and the regulatory status of utility firms influence their capacity or inclination to enhance performance. Specifically, I investigate the interaction between the $Post \times Treated$ with a dummy variable that is equal to 1 if the targeted plant belongs to a regulated utility firm, and zero otherwise. The results in Panel C suggest that the impact of EPA enforcement actions is predominantly evident in plants associated with regulated utilities. The evidence suggests that regulatory frameworks and market competition jointly influence utility firms' environmental performance, with regulated entities likely facing less market pressure and, therefore, possessing greater flexibility to invest in emissions reduction after regulatory enforcement.

2.6. Economic Consequences of Corporate Strategic Responses to EPA Actions

I have, thus far, provided a comprehensive and detailed examination of utility firms' strategic responses to enforcement actions. Specifically, such actions have led utilities to implement significant changes such as installing pollution control equipment, upgrading facilities for lower emissions, scaling back production, and altering their fuel mix. In this section, I explore how corporate strategic responses to EPA actions affect financial performance and energy prices.

2.6.1. *EPA Enforcement and Financial Performance*

The earlier sections have provided a comprehensive and detailed examination of utility firms' strategic responses to enforcement actions. Specifically, EPA enforcement actions have led utilities to implement significant changes such as installing pollution control equipment, upgrading facilities for lower emissions, scaling back production, and altering their fuel mix. These modifications may necessitate considerable increases in both capital expenditures and operational costs for utilities and ultimately impact their financial performance. Investor-owned utilities are required to disclose their thorough financial information in FERC Form 1. Hence, To examine this issue, I focus on these utilities and conduct the following regression at the parent utility firm level:

$$\text{Financial Indicator}_{p,t,c} = \beta_0 + \beta_1 Post_{t,c} * Treated_p + \lambda_{p,c} + \omega_{t,c} + \epsilon_{p,t,c} \tag{9}$$

where Financial Indicator$_{p,t,c}$ represents a financial outcome variable of a parent firm p at time t in cohort c. I analyze six key financial indicators: a firm's total assets (measured in billions of dollars), long-term debt, operating revenue, production expenses, operating income, and electricity price per megawatt-hmy (MWh). For each of these metrics, I apply the natural logarithm to one plus their respective values to facilitate my analysis. The control group comprises firms in proximity to treated parent utility firms but not directly subjected to enforcement actions at their establishments during the sample period. I select the three control utility firms nearest to each treated utility firm. This analysis spans an 11-year window surrounding each enforcement event, and each cohort is composed of one treated utility firm alongside the nearest control utility firms. To account for both temporal dynamics and static firm characteristics within each cohort, I incorporate cohort-specific fixed effects for parent utility firms ($\lambda_{p,c}$) and year ($\omega_{t,c}$). The variable $Treated_p$ is assigned a value of one for treated firms and zero for otherwise. Similarly, $Post_{t,c}$ is set to one following the enforcement actions and zero otherwise. I cluster standard errors at the cohort-firm level. Table **2.10** reports the results.

Several noteworthy findings emerge from the table, aligning with the prior findings. Firms with targeted establishments exhibit statistically significant rises in key financial metrics: total assets, long-term debt, operating revenue, and production expenses, as detailed in Columns (1)-(4). For example, the observed increase in total assets (Column (1)) corresponds with the findings reported in Table **2.4**, indicating that targeted firms have escalated their investment in new generators and the acquisition of additional scrubbers. Similarly, consistent with the results of Table **2.8**, the enhanced access to financing aids targeted firms in responding to EPA enforcement actions, and such lending facility is reflected in the significant increase in their long-term debt (Column (2)). However, while EPA actions lead to increases in both operating revenue and production expenses for firms, these concurrent rises offset one another, thereby not materially affecting the firms' operating income. For instance, the coefficient of *Post×Treated* in Column (5) is 0.001, yet it is statistically insignificant at conventional significance levels.

Overall, these results suggest that EPA enforcement actions have effectively compelled utility firms to decrease pollution levels without detrimentally affecting their financial performance.

2.6.2. EPA Enforcement and Electricity Prices

Thus far, my analysis indicates that EPA actions targeting specific establishments minimally affect the financial performance of their parent firms. These firms appear to offset increased compliance costs with a corresponding rise in operating revenue. This evidence might indicate that utilities transfer additional costs of environmental compliance to consumers through increased electricity prices. This section offers insights into these findings. Using the natural logarithm of the electricity price as the dependent variable, the result in column (6) of Table **2.10** suggests that the average price of electricity increases by 8.2% post-EPA enforcement. This pass-through of costs to end users undermines policymakers' objective of deregulating electricity markets to reduce costs for consumers.

The degree to which utility firms are able to pass through costs to ultimate customers highly depends on their regulatory status and market competition. Electricity sales price for non-regulated utilities is not available in FERC Form 1 data. Hence, in order to compare the differential impact between regulated and non-regulated utilities, I need to obtain electricity prices from another source. Schedules 6 and 7 of EIA-923 and EIA-861 report sales amounts and sales prices of electricity for non-regulated and regulated utilities, respectively. Missing electricity prices are extrapolated using the median price of electricity sold by plants within a 100 KM distance. The average price of electricity would be the weighted average wholesale and retail prices. Using the electricity price data obtained from EIA, I repeat the previous test for electricity prices with regulated and non-regulated utilities in column (1) of Table **2.11**. Results show that the impact on price is qualitatively the same as the prior findings in Table **2.10**. In column (2), I interact the main variables with a dummy variable equal to 1 if the utility is regulated and zero otherwise. The findings reveal that in regulated utilities, electricity sales prices experience a significant increase of 20.5%. Conversely, in the case of non-regulated utilities, the impact on prices is found to be negligible.

In summary, the findings suggest that the greater market power of regulated utilities enables them to transfer the costs of adopting cleaner production methods onto their customers. This observation aligns with existing literature, which has consistently documented the ability of electricity market participants to pass a wide range of costs through to consumers (e.g., Sijm, Neuhoff, and Chen, 2006; Fabra and Reguant, 2014; Kim, 2022).

2.7. Conclusion

The electricity sector in the United States has significantly contributed to environmental pollution, primarily through its dependence on fossil fuels such as coal and natural gas for power generation. However, the extent of pollution and the environmental impact have changed over the years, mainly due to a gradual transition towards cleaner energy sources and the implementation of more stringent environmental regulations. While EPA's regulatory measures and enforcement actions are crucial in addressing environmental challenges, there remains a gap in understanding how utilities navigate these EPA mandates, the financial implications of their compliance, and the consequent impact on consumer welfare.

This research reveals that when power plants are subject to EPA enforcement, there is a notable decrease in both pollution emissions and electricity production. These reductions in emissions are accomplished by implementing various measures, including installing advanced pollution control technologies such as scrubbers, improving pollution abatement processes, investing in energy-efficient generators, and shifting away from coal-based electricity generation. The ability to achieve these outcomes is often facilitated by economies of scale in fuel procurement, the availability of substantial financial resources, and the regulatory status of utility firms. Moreover, the influence of EPA enforcement is not confined to the directly targeted plants but extends across the entire corporate group, enhancing environmental performance throughout the targeted and non-targeted facilities.

Looking at targeted utility firms' financial outcomes, I find that companies experience increases in assets, long-term debt, operating revenue, and production costs, although operating income remains unaffected. My analysis suggests that while firms' financial performance is largely resilient to the increased compliance costs, these expenses are ultimately transferred to consumers, resulting in higher electricity prices. This shift of environmental costs to consumers could negatively impact social welfare by placing the financial burden of cleaner electricity production on the public. The necessity for policy interventions becomes evident as EPA compliance costs are passed onto consumers, underscoring the importance of aligning environmental protection with the broader economic and social well-being of the community. Such policies must prioritize fairness, ensure transparency in their implementation, and advocate for sustainable practices that do not disproportionately burden consumers. This approach requires a delicate balance, ensuring that environmental goals are met without compromising the affordability and accessibility of essential services for all segments of society.

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Figure 2.1.
U.S. Electricity Generation by Energy Source

This figure shows electricity generation in megawatt hours (MWh) using different types of energy sources during the 2001-2020 sample period.

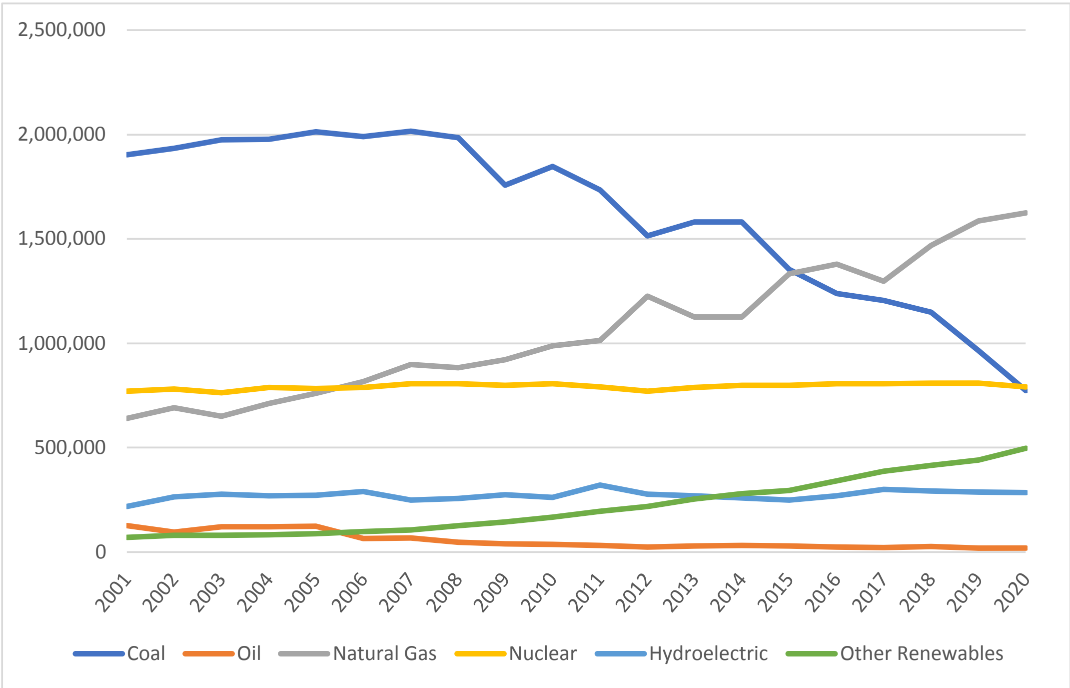


Figure 2.2.
The Geographical Dispersion of U.S. Power Plants in 2020

This figure shows the geographical dispersion of all power plants across different US counties in 2020.

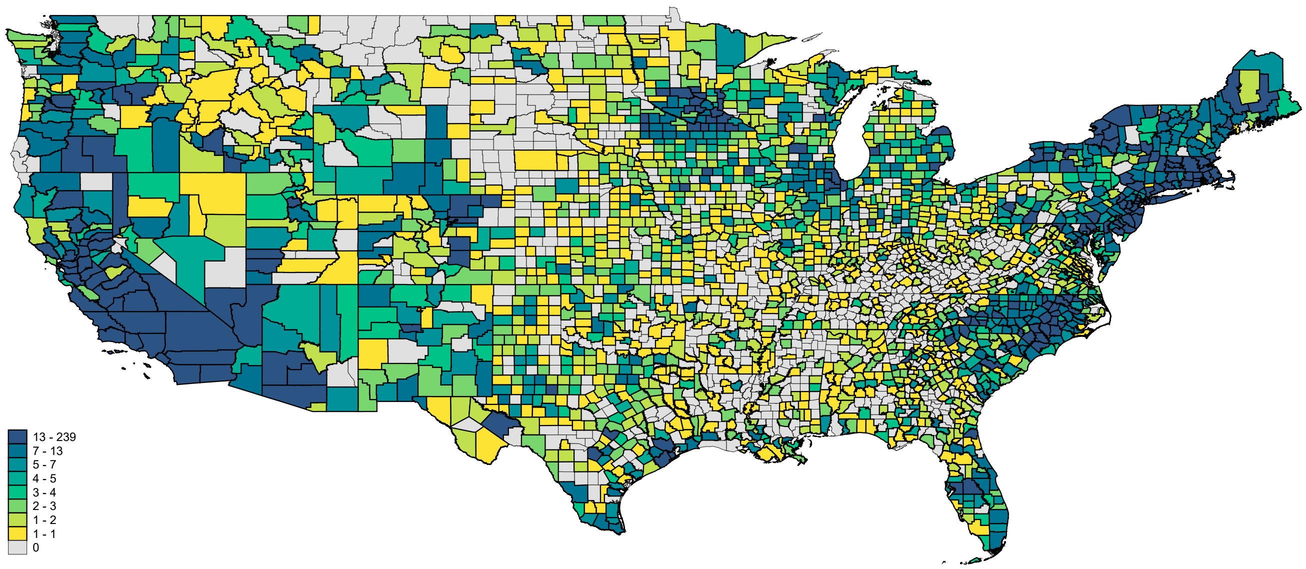
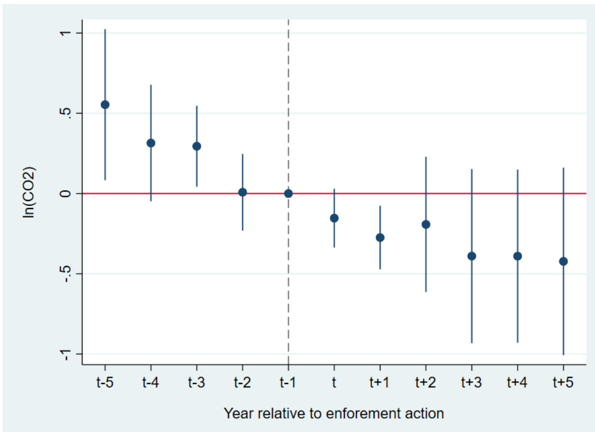
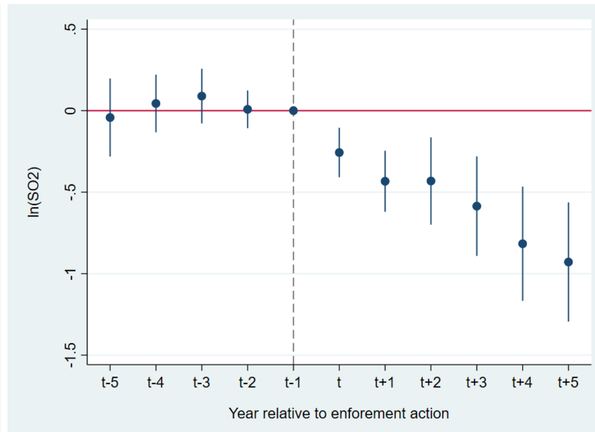


Figure 2.3.
Dynamic Effects of EPA Enforcement on Environmental Outcomes

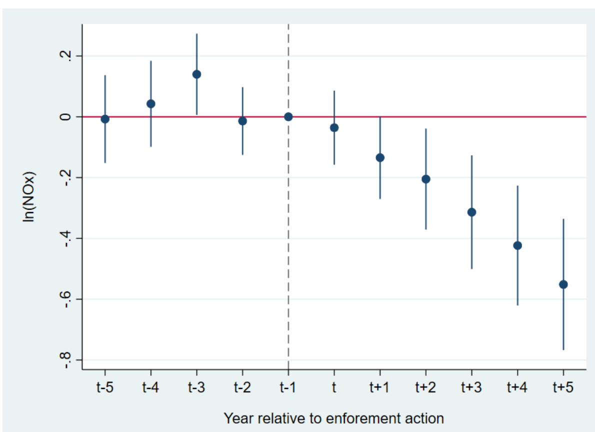
The figure shows the dynamics of EPA enforcement impact on targeted power plants' releases of CO2, SO2, and NOx emissions, and electricity generation in Figures (a)-(d), respectively. Each subfigure plots estimated coefficients and their 95% confidence intervals obtained from regressing outcome variables on dummy variables indicating the distance (in years) relative to the event following Eq. 6.



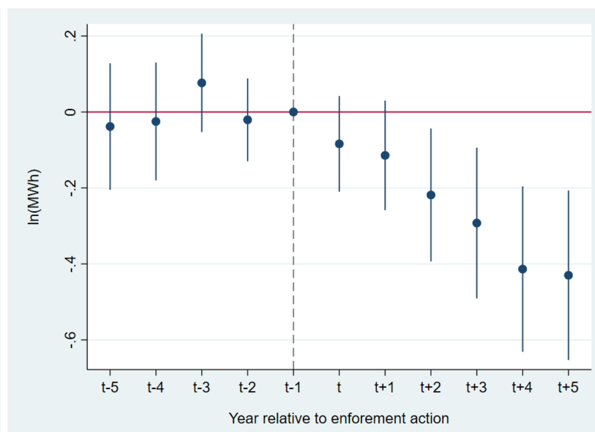
(a) CO2 emissions



(b) SO2 emissions



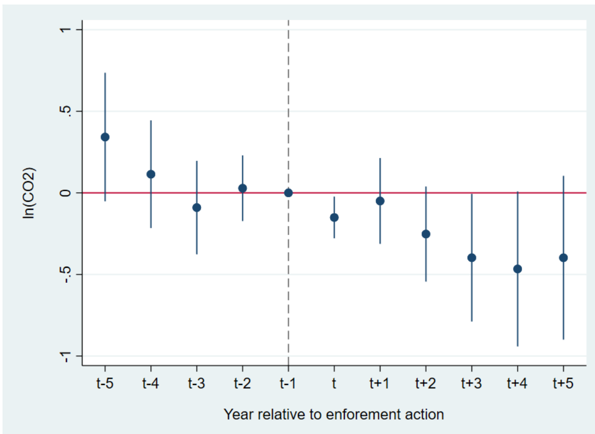
(c) NOx emissions



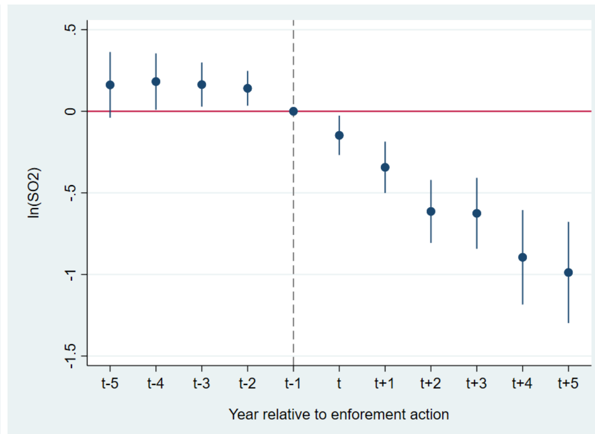
(d) Electricity Generation

Figure 2.4.
Dynamic Propagation of EPA Enforcement within Utility Firms

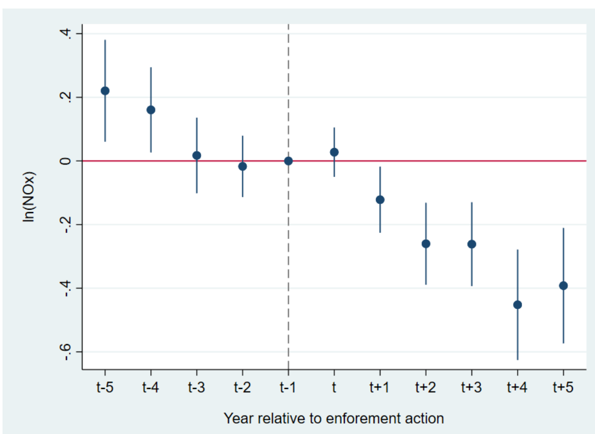
This figure shows the dynamic spillover effect of EPA enforcement actions on non-targeted siblings' emission releases of CO_2, SO_2, NO_x, and electricity generation, respectively, in Figures (a)-(d). Each subfigure plots estimated coefficients and their 95% confidence intervals obtained from regressing outcome variables on dummy variables indicating the distance (in years) relative to the event following Eq. 6.



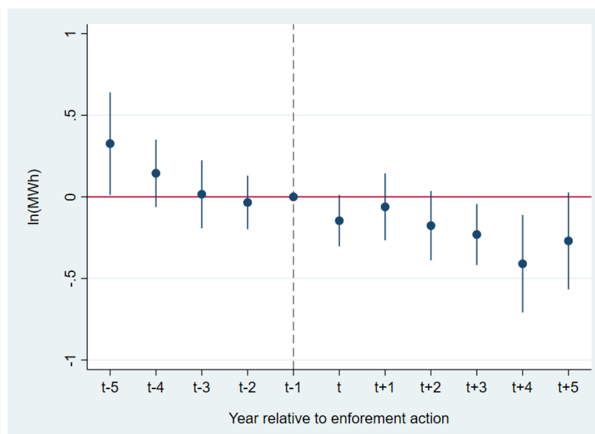
(a) CO2 emissions



(b) SO2 emissions



(c) NOx emissions



(d) Electricity Generation

Table 2.1.
Summary Statistics

This table reports descriptive statistics of the main variables employed in the empirical analysis, including the number of observations (NObs), mean (Mean), standard deviation (Stdev), 25th percentile (25th), median (Median), and 75th percentile (75th) in the 2001-2020 period. The appendix details the definition of all the variables. All continuous variables are winsorized at the 1st and 99th percentiles.

	NObs	Mean	Stdev	25th	Median	75th
	(1)	(2)	(3)	(4)	(5)	(6)
Pollution Emissions and Electricity Generation						
CO2 $\times 10^{-6}$	12820	1.171	2.37	0.015	0.221	1.128
SO2 $\times 10^{-3}$	12820	3.061	11.44	0.000	0.002	0.020
NOx $\times 10^{-3}$	12820	1.136	3.16	0.029	0.107	0.438
MWh $\times 10^{-6}$	12820	1.603	2.51	0.111	0.442	2.032
Instrumental Variables						
$EnforceExposure_1$	12820	0.704	1.17	0.000	0.142	0.923
$EnforceExposure_2$	12820	0.336	0.43	0.000	0.182	0.500
Capital Investments						
Scrubbers	8060	0.348	0.97	0.000	0.000	0.000
$ Abatement	5322	4.828	21.90	0.000	0.000	0.000
Generators	12820	0.140	1.01	0.000	0.000	0.000
Steam	12820	0.016	0.22	0.000	0.000	0.000
Gas Turbine	12820	0.070	0.88	0.000	0.000	0.000
Internal Combust.	12820	0.000	0.02	0.000	0.000	0.000
Combined Cycle	12820	0.054	0.46	0.000	0.000	0.000
Fuel Choice and Quality						
Coal MMBTU $\times 10^{-6}$	12820	7.889	23.11	0.000	0.000	0.000
Petro MMBTU $\times 10^{-6}$	12820	0.268	1.08	0.000	0.000	0.076
Gas MMBTU $\times 10^{-6}$	12820	6.980	11.36	0.105	1.745	8.170
Coal Share	12793	0.213	0.40	0.000	0.000	0.000
Petro Share	12793	0.082	0.24	0.000	0.000	0.011
Gas Share	12793	0.705	0.43	0.037	0.999	1.000
Fuel $/MMBTU	12820	6.047	3.70	3.666	5.238	7.810
Sulfur $\times 10^{-3}$	12820	5.012	17.60	0.000	0.000	0.106
Sulfur/MMBTU	12820	0.268	0.63	0.000	0.000	0.157
Coal Sulfur/MMBTU	2815	1.179	0.86	0.561	0.914	1.662
Petro Sulfur/MMBTU	6280	0.141	0.28	0.021	0.085	0.192
Efficiency						
MWh/MMBTU	12820	0.096	0.03	0.084	0.094	0.109
Coal MWh/MMBTU	2815	0.087	0.02	0.075	0.091	0.098
Petro MWh/MMBTU	6280	0.087	0.09	0.073	0.089	0.098
Gas MWh/MMBTU	10496	0.098	0.03	0.085	0.096	0.115
Utility-Level Variables						
Assets ($ B)	1787	5.413	5.88	1.362	3.379	7.163
Longterm Debt	1787	0.271	0.10	0.233	0.287	0.322
Operating Revenue	1787	0.395	0.18	0.284	0.361	0.450
Production Expenses	1787	0.207	0.15	0.114	0.169	0.246
Operating Income	1787	0.042	0.02	0.033	0.042	0.049
$/MWh	1807	67.393	25.72	48.975	64.416	83.373

Table 2.2.
Power Plant Environmental Outcomes and EPA Enforcement Actions

This table reports the effect of EPA enforcement on targeted power plants using stacked DiD regressions. The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.481**	-0.595***	-0.335***	-0.269***
	(-2.39)	(-4.30)	(-4.29)	(-3.20)
Observations	12820	12820	12820	12820
Adjusted R^2	0.854	0.902	0.917	0.900
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.3.
Instrumental Variable Analysis

This table reports results using instrumental variables regressions. Panel A tests the validity of two instruments (i.e., $EnforceExposure_1$ and $EnforceExposure_2$) employed in the 2-stage least square (2SLS) regressions shown in Panel B. For each power plant, $EnforceExposure_1$ is the number of air enforcement actions that other emission sources receive in the same county-year multiplied the share of the plant's from total county capacity. For each power plant, $EnforceExposure_2$ is the number of air enforcement actions that other emission sources receive divided by the total number of operating power plants in each county-year. In Panel A, I regress a binary indicator, *Enforcement*, which equals one if the plant receives an enforcement action in that year and zero otherwise, on each of the instruments. Columns (1) and (2) include the enitre sample of power plants with available emissions data, whereas Columns (3) and (4) contains a sample of targeted plants that receive an enforcement action and plants in the control group located in a different county but within 100KM radius around targeted ones. Panels B1 and B2 report the 2SLS regression results separately for the two instrumental variables. Column (1) shows the results of the first-stage regressions, while the remaining columns indicate the second-stage results. The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants outside of the county but within 100 kilometers radius around the treated ones, but the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Enforcement			
	(1)	(2)	(3)	(4)
$EnforceExposure_1$	0.025***		0.014**	
	(4.85)		(2.15)	
$EnforceExposure_2$		0.027***		0.020**
		(4.01)		(2.22)
Observations	18955	18955	11715	11715
Adjusted R^2	0.125	0.125	0.284	0.284
Year FE	Yes	Yes		
Plant FE	Yes	Yes		
Cohort × Year FE			Yes	Yes
Cohort × Plant FE			Yes	Yes

Table 2.3 - Continued
Instrumental Variable Analysis

	Panel B1: $EnforceExposure_1$				
	1st Stage	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)	(5)
$\widehat{Post \times Treated}$		-16.884**	-4.319**	-2.220**	1.009
		(-2.39)	(-2.07)	(-1.96)	(1.09)
$Post \times EnforceExposure_1$	0.055***				
	(2.62)				
Observations	11715	11715	11715	11715	11715
Adjusted R^2		-3.104	-0.732	-0.573	-0.336
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes

	Panel B2: $EnforceExposure_2$				
	1st Stage	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)	(5)
$\widehat{Post \times Treated}$		-8.547***	-3.044**	-1.256**	0.316
		(-2.72)	(-2.32)	(-2.20)	(0.60)
$Post \times EnforceExposure_2$	0.155***				
	(3.56)				
Observations	11715	11715	11715	11715	11715
Adjusted R^2		-0.896	-0.417	-0.269	-0.210
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes

Table 2.4.
Managerial Decisions Following EPA Enforcement Actions

This table reports the results from stacked DiD regressions that examine the impact of EPA enforcement on power plants' operational decisions. Panel A reports the impact of enforcement on the installation of scrubbers, the dollar amount spent on pollution abatement, and new generators. Panel B shows the enforcement impact on the usage and share of different types of fuels. Panel C presents the effect on the sulfur content of fuels in the extensive (columns 1-2) and intensive margins (columns 3-4). Panel D shows the change in operational efficiency (i.e., heat rate) of targeted plants following enforcement actions. Finally, The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Scrubbers, Abatement, and New Generators						
				Type of New Generators			
	ln(Scrubbers)	ln($Abatement)	ln(New Generators)	ln(Steam)	ln(Gas Turbine)	ln(Internal Combust.)	ln(Combined Cycle)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treated	0.051**	0.181*	0.031***	-0.010**	0.025***	0.000	0.016*
	(2.26)	(1.81)	(2.70)	(-2.13)	(4.45)	(0.69)	(1.66)
Observations	7905	5037	12820	12820	12820	12820	12820
Adjusted R^2	0.867	0.540	0.076	0.102	-0.018	-0.141	0.010
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: Fuel Mix						
	Fuel Input			Fuel Share			Fuel Cost
	ln(Coal MMBTU)	ln(Petro MMBTU)	ln(Gas MMBTU)	Coal Share	Petro Share	Gas Share	ln(Fuel $/MMBTU)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treated	-0.596***	-0.065	0.077	-0.027**	-0.007	0.034***	0.152***
	(-3.18)	(-0.31)	(0.51)	(-2.55)	(-0.65)	(2.93)	(6.50)
Observations	12820	12820	12820	12791	12791	12791	12820
Adjusted R^2	0.983	0.828	0.949	0.983	0.927	0.968	0.845
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4 - Continued
Managerial Decisions Following EPA Enforcement Actions

	Panel C: Sulfur Content			
	ln(Sulfur)	ln(Sulfur/MMBTU)	ln(Coal Sulfur/MMBTU)	ln(Petro Sulfur/MMBTU)
	(1)	(2)	(3)	(4)
Post × Treated	-0.356***	-0.018*	-0.050*	0.035***
	(-3.54)	(-1.80)	(-1.92)	(3.09)
Observations	12820	12820	2234	5757
Adjusted R^2	0.959	0.959	0.900	0.528
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel D: Efficiency			
	ln(MWh/MMBTU)	ln(Coal MWh/MMBTU)	ln(Petro MWh/MMBTU)	ln(Gas MWh/MMBTU)
	(1)	(2)	(3)	(4)
Post × Treated	-0.001	0.003***	0.001	-0.000
	(-0.88)	(3.30)	(0.30)	(-0.21)
Observations	12820	2234	5757	10286
Adjusted R^2	0.788	0.882	0.100	0.764
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.5.
The Organizational Structure of Firms and EPA Enforcement Actions

This table reports how the effectiveness of EPA enforcement various with regards to utility firms organizational structure. *Multi − Plant* dummy is equal to 1 if the treated plant belongs to a utility firm that has more than one operating plant and zero otherwise. The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Multi-Plant	-0.359	-1.117***	-0.755***	-0.554***
	(-0.87)	(-4.28)	(-5.40)	(-3.56)
Post × Treated	-0.268	0.065	0.111	0.058
	(-0.82)	(0.35)	(1.23)	(0.58)
Observations	12820	12820	12820	12820
Adjusted R^2	0.854	0.903	0.918	0.901
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.6.
Characteristics of Sibling Power Plants and EPA Enforcement Actions

This table reports how the effectiveness of EPA enforcement actions varies with the characteristics of sibling power plants (i.e., power plants owned by the same parent utility firm) from multi-plant utility firms. The characteristics include the average distance between targeted plants and their siblings (Panel A) and the share of different fuel types in siblings (Panels B and C). The dependent variables are plant level pollution emissions and electricity generation in Panels A and B, and fuel choice and fuel costs in Panel C. The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Distance			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Distance	-0.008	0.245***	0.281**	0.076
	(-0.08)	(3.41)	(2.34)	(1.09)
Post × Treated	-0.324	-1.158***	-0.849***	-0.406*
	(-0.82)	(-4.04)	(-3.78)	(-1.83)
Observations	3315	3315	3315	3315
Adjusted R^2	0.967	0.962	0.930	0.909
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes
	Panel B: Siblings Fuel Composition and Plant Outcomes			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Siblings Coal Share	-0.769**	-1.297***	-0.812***	-0.712***
	(-2.29)	(-4.00)	(-3.97)	(-2.95)
Post × Treated × Siblings Petro Share	-0.434	-1.391	0.293	0.215
	(-0.95)	(-0.90)	(0.76)	(1.22)
Post × Treated × Siblings Gas Share	0.496	0.298	0.280	0.458**
	(1.18)	(1.20)	(0.84)	(2.06)
Observations	3315	3315	3315	3315
Adjusted R^2	0.967	0.962	0.930	0.911
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.6 - Continued
Characteristics of Sibling Power Plants and EPA Enforcement Actions

	Panel C: Siblings Fuel Composition and Plant Fuel Choice						
	Fuel Input			Fuel Share			Fuel Cost
	ln(Coal MMBTU)	ln(Petro MMBTU)	ln(Gas MMBTU)	Coal Share	Petro Share	Gas Share	ln(Fuel $/MMBTU)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treated × Siblings Coal Share	-1.314**	-0.734	-0.537	-0.079**	-0.002	0.081**	0.244***
	(-2.08)	(-1.40)	(-1.21)	(-2.16)	(-0.09)	(2.20)	(3.59)
Post × Treated × Siblings Petro Share	-8.278**	-0.426	1.415	-0.209*	-0.039	0.248	0.247***
	(-2.23)	(-0.93)	(1.47)	(-1.87)	(-0.23)	(0.89)	(4.55)
Post × Treated × Siblings Gas Share	0.248	-1.165*	1.275*	-0.004	0.041*	-0.037	0.032
	(1.42)	(-1.74)	(1.82)	(-0.25)	(1.67)	(-1.32)	(0.53)
Observations	3315	3315	3315	3309	3309	3309	3315
Adjusted R^2	0.981	0.912	0.960	0.979	0.827	0.954	0.865
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7.
Effects of EPA Enforcement Actions on Siblings of Targeted Plants

This table reports the results of EPA enforcement actions on non-targeted power plants that belong to the same parent as the targeted ones. It excludes plants that have received an enforcement action. Panel A shows the impact on emissions and electricity generation. Panel B depicts a plant's decision to use scrubbers, invest in pollution abatement technologies, and add new generators. The Treated dummy equals one if the plant receives an enforcement action in one of its siblings and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after a sibling receives its first EPA enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. The t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Emissions and Electricity Generation			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.327**	-0.749***	-0.350***	-0.257***
	(-2.20)	(-7.27)	(-5.71)	(-2.97)
Observations	14036	14036	14036	14036
Adjusted R^2	0.886	0.914	0.917	0.832
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel B: Scrubbers, Abatement, and New Generators						
				Type of New Generators			
	ln(Srubbers)	ln($Abatement)	ln(Generators)	ln(Steam)	ln(Gas Turbine)	ln(Internal Combust.)	ln(Combined Cycle)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × Treated	-0.013	-0.046	0.055***	0.002	0.022***	0.000	0.033***
	(-0.56)	(-0.63)	(5.16)	(0.86)	(3.33)	(0.66)	(3.98)
Observations	7832	5412	14036	14036	14036	14036	14036
Adjusted R^2	0.840	0.548	0.055	-0.034	0.007	-0.223	0.027
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.8.
Heterogeneity in Effectiveness of EPA Enforcement Actions

This table reports how different factors impact the effectiveness of EPA enforcement actions. In Panel A, I study the variation in efficacy of EPA enforcement across utility firms with different levels of financial resources availability measured by their cash holdings. *Cashholding* equals to treated firms' cash and cash equivalents as a percentage of their total asset in the year of enforcement actions. In this test, I only include treated firms for which I have cash holding information. In Panel B, I examine how the effectiveness of EPA enforcement actions differs among federal versus state-level enforcement actions. *Federal* is a dummy that equal 1 if an enforcement action is handle by EPA and reported in ICIS-FE&C and zero if the case in undertaken by state-level agencies and reported in ICIS-Air. In Panel C, I study the impact of utility firms regulatory status on their responsiveness to enforcement actions. In this Panel, *Regulated* is equal to 1 if the utility firms is regulated and zero otherwise. The Treated dummy equals one if the plant receives an enforcement action and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Financial Resource Availability			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Cash Holding	-0.344***	-0.112***	-0.091***	-0.093**
	(-4.09)	(-2.91)	(-2.73)	(-2.03)
Post × Treated	-0.276	-1.046***	-0.640***	-0.421***
	(-1.22)	(-5.74)	(-5.75)	(-3.26)
Observations	3298	3298	3298	3298
Adjusted R^2	0.872	0.947	0.929	0.895
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.8 - Continued
Heterogeneity in Effectiveness of EPA Enforcement Actions

	Panel B: Federal vs State Enforcement Actions			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Federal	-0.705	-1.319***	-0.903***	-1.019***
	(-1.25)	(-3.29)	(-4.07)	(-3.61)
Post × Treated	-0.355	-0.359**	-0.173**	-0.087
	(-1.63)	(-2.54)	(-2.22)	(-1.16)
Observations	12820	12820	12820	12820
Adjusted R^2	0.854	0.903	0.918	0.901
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel C: Regulatory Status			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Regulated	-0.704**	-0.980***	-0.704***	-0.463***
	(-2.07)	(-3.75)	(-4.76)	(-2.86)
Post × Treated	-0.249	-0.272	-0.103	-0.117
	(-0.88)	(-1.50)	(-1.05)	(-1.07)
Observations	12820	12820	12820	12820
Adjusted R^2	0.854	0.903	0.918	0.900
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 2.9.
Electricity Prices and EPA Enforcement Actions

This table shows the association between EPA enforcement actions and utility-level electricity prices for multi-plant utility firms. The $Post \times Treated$ is interacted with a dummy variable, Restructured, denoting the restructuring status of the electricity market. The Treated dummy equals one if the utility firm receives an enforcement action in one of its plants and zero otherwise. The control group consists of plants within 100 kilometers radius around the treated ones; the plants have neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals one after the first enforcement action in any plant. Each cohort consists of one treated utility and the control utilities operating surrounding its plants. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. The t-statistics are reported in parentheses. Standard errors are clustered at the firm-cohort level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(Retail \$/MWh)	ln(Wholesale \$/MWh)	ln(Avg \$/MWh)
	(1)	(2)	(3)
Post × Treated × Restructured	0.084	-0.280**	-0.167*
	(1.14)	(-2.51)	(-1.96)
Post × Treated	0.012	0.242***	0.194***
	(0.22)	(3.03)	(3.81)
Observations	321	2814	2830
Adjusted R^2	0.750	0.553	0.585
Cohort × Year FE	Yes	Yes	Yes
Cohort × Utility FE	Yes	Yes	Yes

Table 2.10.
Financial Consequences of EPA Enforcement Actions

This table focuses on the impact of EPA enforcement actions on financial outcomes of parent utility firms for which I have financial data. The Treated dummy equals one if the utility firm receives an enforcement action in one of its plants and zero otherwise. The control group consists of three utility firms located closest to targeted plants but have received no enforcement action in any of their plants. The Post dummy equals one after the first enforcement action received by each utility firm. Each cohort consists of one treated utility and the control utilities operating surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. The t-statistics are reported in parentheses. Standard errors are clustered at the firm-cohort level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(Assets $ B)	ln(Longterm Debt)	ln(Operating Revenue)	ln(Production Expenses)	ln(Operating Income)	ln($/MWh)
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treated	0.060**	0.020***	0.025**	0.028**	0.002	0.046**
	(2.00)	(3.66)	(2.03)	(2.29)	(1.09)	(2.19)
Observations	1850	1850	1850	1850	1850	1849
Adjusted R^2	0.977	0.800	0.751	0.760	0.671	0.905
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Utility FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.11.
Electricity Prices and EPA Enforcement Actions

This table shows the association between EPA enforcement actions and utility-level electricity prices. The $Post \times Treated$ is interacted with a dummy variable, Regulated, that is equal to 1 if the utility firm is regulated and zero otherwise. The Treated dummy equals one if the utility firm receives an enforcement action in one of its plants and zero otherwise. The control group consists of three utility firms located closest to targeted plants but have received no enforcement action in any of their plants. The Post dummy equals one after the first enforcement action received by each utility firm. Each cohort consists of one treated utility and the control utilities operating surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. The t-statistics are reported in parentheses. Standard errors are clustered at the firm-cohort level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Post × Treated	0.061*	-0.016
	(1.93)	(-0.39)
Post × Treated × Regulated		0.205***
		(3.49)
Observations	5126	5126
Adjusted R^2	0.563	0.566
Cohort × Year FE	Yes	Yes
Cohort × Utility FE	Yes	Yes

Chapter 3

3. Unveiling the Nexus: Tracing the Footprints of Lobbyists in Mutual Fund Voting

3.1. Introduction

Lobbying, a process of exerting political influence by corporations and interest groups on politicians, has experienced significant growth over the past 24 years. Lobbying expenses increased more than twofold, from $1.45 billion in 1998 to $4.1 billion in 2022.[18] This growth, which is partly due to the influx of first-time lobbying clients,[19] has heightened public concerns about the adverse consequences of lobbying practices.[20] In addition to lobbying, lobbying firms provide a range of legal, consulting, and public relations services and are deeply involved in their clients' business operations. Some of these services are especially relevant to the relationship between institutional investors and their portfolio firms.[21] Despite the extent of lobbying firms' engagement with institutional investors and their portfolio firms, there is limited research on the role of lobbying firms in the adoption of corporate governance practices. Hence, I investigate whether and how the interaction of lobbying firms with mutual funds and their portfolio firms impacts mutual funds' voting behavior.

Voting is one of the main mechanisms that shareholders employ to influence key corporate decisions. Yet, casting votes in a manner consistent with the best interest of investors is not a trivial task, especially for large mutual funds holding shares in many companies. The interactions between mutual funds and portfolio firms and their connections through various channels can shape mutual funds' voting decisions. In this

[18] OpenSecrets: Federal Lobbying.https://www.opensecrets.org/federal-lobbying

[19] The Hill (2022). Top lobbying firms report record-breaking 2021 earnings. Retrieved August 20, 2023, from https://thehill.com/business-a-lobbying/business-a-lobbying/590709-top-lobbying-firms-report-record-breaking-2021.

[20] In a survey conducted by Pew Research Center, 53% of participants expressed the role of lobbyists and special interest groups in Washington as a very serious problem. Retrieved August 20, 2023, from https://www.pewresearch.org/politics/2019/07/22/how-americans-see-problems-of-trust.

[21] For example, certain lobbying firms advise shareholders on launching activism campaigns, unseating recalcitrant directors, removing entrenched management, and designing best practice governance structures. Moreover, they provide portfolio firms with strategies to defend activism campaigns and offer advice on proxy access, say-on-pay, shareholders' ability to call special meetings, responding to shareholder proposals, dealing with Institutional Shareholder Services (ISS), and preparing proxy and annual meeting processes. Retrieved August20, 2023, from https://www.akingump.com/en/services/corporate/shareholder-activism and https://www.akingump.com/en/services/corporate/corporate-governance.

paper, I focus on a specific type of connection, namely, through lobbying activities, and test whether mutual funds exhibit favoritism toward portfolio firms with which they share common lobbyists. If there is such favoritism, mutual funds would be more likely to follow management recommendations when firms are simultaneously served by the same lobbyist. Furthermore, I also investigate whether this favoritism arises from information sharing between the two parties or the sub-optimal bias of mutual funds toward connected managers. The prevalence and growth of lobbying activities and the granularity of mutual fund voting data which discloses shareholders' preferences about optimal firm management and governance provide us with a suitable ground to examine the impact of lobbying activities on mutual funds' voting.

I start by collecting quarterly data regarding lobbying contracts of mutual fund families and public firms. Then, I identify connections that are created by these lobbying activities. I define a mutual fund connected to a firm when both of them are concurrently served by the same lobbying firms. For example, in the second quarter of 2010, Akin, Gump, Strauss, Hauer, & Feld LLP, one of the largest lobbying firms in terms of revenue in the last decades, simultaneously served 8 institutional investors and 58 public firms resulting in 464 lobbying connections.[22] As it was also documented by Kerr, Lincoln, and Mishra (2014), I find that the relationships between lobbying firms and their clients, and the resulting lobbying connections, display a high degree of persistence, with instances of intermittency—where clients cease and subsequently resume their contracts with lobbying firms—occurring very infrequently. Moreover, I use mutual funds' propensity to follow management recommendations in their voting as a proxy for mutual funds' favoritism and pro-management behavior.

In the main analyses, using a rich set of fixed effects to control for various Fund × Year, Firm × Year, and proposal characteristics, I find that connected mutual funds are more likely to vote with management. Depending on the specific choice of fixed effects, being connected increases the likelihood of following management recommendations by 0.6%-2.84%. This increase translates into a 0.7% to 3.3% rise in voting with management relative to the sample mean. I further investigate the impact of lobbying connections across different types of proposals. The results indicate that lobbying connections significantly influence voting behavior in say-on-pay frequency, auditor ratification, compensation, management entrenchment, and information disclosure proposals. However, I did not observe any significant impact on environmental and social

[22] Akin, Gump, Strauss, Hauer, & Feld's lobbying services to public in 2010Q2 included the $520,000 contract with DuPont de Nemours Inc, the $150,000 contract with Boeing Co, and $130,000 contract with PG&E CORP, among others. In the same quarter, it served institutional investors such as Guardian Life Insurance, RS Investment Management, and Allianz Global Investors with $80,000, $80,000, and $50,000 contracts, respectively.

proposals. Furthermore, when I break down information proposals into distinct categories—lobbying, political contribution, executive compensation, and proxy voting disclosures—I find that lobbying connections have a statistically significant impact across all categories except for political contribution disclosure.

Next, I examine whether the degree of mutual funds' pro-management behavior varies based on the scale of lobbying contracts, using two proxies to assess this scale. First, I use the number of common lobbyists as a proxy for scale. I anticipate a more pronounced impact when mutual funds are connected to firms via more common lobbyists. A higher number of common lobbyists can provide mutual funds with access to more information sources, enabling them to make more informed voting decisions. Moreover, it increases the interactions between mutual funds and portfolio firms, thereby boosting the influence of firm management on mutual funds voting behavior. Consistently, the estimation results show that the impact of lobbying connection is more pronounced among fund-firm pairs with a higher number of common lobbyists. Second, I use the dollar value of lobbying contracts as another proxy for the strength of connections. The dollar value of lobbying contracts reflects the depth of engagement and level of effort that lobbying firms put into advocating for their clients. Hence, I anticipate a more pronounced effect as the size of the contract increases. Each lobbying connection consists of two contracts: one between mutual fund families and lobbying firms, and the other between lobbying firms and portfolio companies. Testing them separately, the findings suggest that the impact of lobbying connections becomes stronger as the dollar value of lobbying contracts grows.

The pro-management behavior exhibited by mutual funds can arise from two non-mutually exclusive potential channels: enhanced information sharing and conflict of interest. Firstly, lobbying activities undertaken by firms and the information that is being shared by their interaction with lobbying firms over several years will significantly assist mutual funds in making well-informed voting decisions. This information sharing through lobbyists mitigates the cost of private information production for mutual funds. Prior research has provided evidence supporting the information sharing channel through firm-fund connections (e.g., Cohen, Frazzini, and Malloy, 2008; Duan, Hotchkiss, and Jiao, 2018; Calluzzo and Kedia, 2019). Secondly, the pro-management voting behavior of mutual funds can result from a conflict of interest and the strategic coordination between mutual funds and portfolio firms. In this scenario, managers find it less costly to seek support from their connected institutional shareholders especially when they are indeed under pressure and require such support. In addition, mutual funds might also use voting as a tool to reward managers having more aligned political activities. The presence of a conflict of interest among mutual fund managers has been documented in prior research (e.g., Ferreira, Matos, and Pires, 2018; Sulaeman and Ye, 2023).

To examine the presence of an information acquisition mechanism through lobbying connections, I assess whether the impact of lobbying connections varies based on the level of information asymmetry between corporate management and shareholders. The costs of information production by mutual funds are higher for firms that have higher levels of information asymmetry. The underlying hypothesis is that the influence of lobbying connections should be more pronounced for firms with higher information asymmetry, as information acquired from common lobbyists would be more valuable in such cases. I employ several firm-level proxies of information asymmetry such as volatility, liquidity, intangibility, number of analysts, and analysts' forecast error. Estimation results indicate that the impact of lobbying connections does not depend on the level of information asymmetry which does not support the presence of an information acquisition mechanism through lobbying connections.

Additionally, I examine the conflict of interest in mutual funds voting as a mechanism for pro-management voting behavior. According to this channel, corporate managers leverage their lobbying activities and take advantage of common lobbyists to garner the support of connected mutual funds in proxy voting. This support is especially more valuable when the manager's power is relatively low or the proposal is conflicted. I use several proxies of corporate governance, such as the E-Index, board independence ratio, presence of dual-class shares, and presence of Universal Demand laws, to measure managerial power. This analysis reveals that the impact of lobbying connections is stronger for firms with better corporate governance, indicating that the support of connected mutual funds is more valuable in firms with stronger governance structures. Moreover, I identify conflicted proposals as those in which ISS recommends against management (contentious) or those that pass or fail with a small margin (contested). In these proposals, the benefits of seeking support from connected mutual funds are more likely to outweigh the costs. Consistently, I find that the impact of lobbying connection is stronger for contentious and contested proposals.

While I use an extensive set of fixed effects to control for time-variant fund and firm characteristics, there might still exist some concerns about unobserved characteristics that influence the voting behavior of mutual funds. Furthermore, involvement in lobbying activities, selection of lobbyists, and as a result, formation of lobbying connections are not randomly determined but depend on certain underlying factors that might contaminate the baseline findings. To address such concerns, I employ mergers and acquisitions between mutual funds or lobbying firms to capture exogenous variation in lobbying connections. Mergers and acquisitions have been extensively used in the literature to identify factors such as concentration and common ownership (e.g., He and Huang, 2017; Saidi and Streitz, 2021; Lewellen and Lowry, 2021 among others). While mergers can impact the composition of lobbyists and provide exogenous changes in lobbying connections, it is very unlikely that the subsequent formation or dissolution of lobbying connections would influence mutual funds or lobbying firms' merger decisions. I manually search for mergers and acquisitions that either involve mutual funds or lobbying firms. I come up with a list of 16 mergers among mutual funds and 8 mergers among lobbying firms that impact at least one lobbying connection and repeat the baseline tests. The results indicate that the main findings remain statistically significant, and the economic magnitude of lobbying connections increases by up to 5 times when considering mergers between lobbying firms.

Finally, I study the effectiveness of connected mutual funds support in determining voting outcomes. I find that higher ratios of connected mutual funds increase the likelihood that voting result aligns with management recommendation. This effect is especially more pronounced among contentious and contested proposals. Next, I narrowed down the sample to proposals that have at least one connected mutual fund. Within this subsample, I investigate how the ratio of connected funds that vote with management impacts the voting outcome. The resulting positive association between the ratio of connected funds that vote with management and the realization of management-recommended outcomes suggests that mutual funds have an influential role in determining the voting result. Last, I examine how and whether the market reaction to the proposal outcome depends on connected funds support. Following previous papers (e.g., Cuñat, Gine, and Guadalupe, 2012; Iliev and Lowry, 2015; Calluzzo and Kedia, 2019), I focus on proposals that pass or fail with less than 10% margin. I also require proposals to have at least one connected mutual fund and exclude firms having more than one contested proposal in a meeting. Using market-adjusted cumulative abnormal return in a three-day window around meetings, I find that connected mutual funds' support is associated with positive abnormal return when it is unsuccessful. However, there is no significant market reaction when management's preferred outcome is realized.

This paper contributes to three strands of literature. First, it contributes to the growing literature that studies firms' political and lobbying activities. Previous research has extensively studied the determinants lobbying activities among corporations from both theoretical (e.g., Kerr, Lincoln, and Mishra, 2014; Groll and Ellis, 2014; Hirsch et al., 2023) and empirical (e.g., DellaVigna et al., 2007; Bertrand, Bombardini, and Trebbi, 2014; Kwon, Lowry, and Verardo, 2022) perspectives. Furthermore, there is a substantial body of work that studies the impact of lobbying on firm value (Borisov, Goldman, and Gupta, 2016), productivity

(Huneeus and Kim, 2018), political risk (Cioanta, 2021), and CEO pay (Skaife, Veenman, and Werner, 2013). I contribute to this literature by examining the impact of lobbying on shareholder voting as one of the most important mechanisms of corporate governance.

Second, this study adds to the literature that examines mutual funds voting. In a survey conducted among senior managers of very large institutional investors, McCahery, Sautner, and Starks (2016) documented that 53% of the respondents report that they recently used voting against management as a shareholder engagement practice. Prior research has explored various factors influencing mutual fund voting behavior, including proxy advisors' recommendation (Malenko and Shen, 2016), mutual fund size (Boone, Gillan, and Towner, 2020), net benefits of information production (Iliev and Lowry, 2015), exposure to air pollution (Foroughi, Marcus, and Nguyen, 2021), passive versus active ownership (Brav et al., 2022), and common ownership (He, Huang, and Zhao, 2019). To the best of my knowledge, this study is the first to introduce lobbying activities and the resulting connections to portfolio firms as a determinant of mutual fund voting.

Third, this paper contributes to the literature that focuses on the consequences of the relationship between mutual funds and their portfolio firms. Various types of relationship such as pension-related business ties (Davis and Kim, 2007; Ashraf, Jayaraman, and Ryan, 2012; Cvijanović, Dasgupta, and Zachariadis, 2016; Duan, Hotchkiss, and Jiao, 2018), educational background (Butler and Gurun, 2012), and board of directors affiliations (Cohen, Frazzini, and Malloy, 2008; Calluzzo and Kedia, 2019; Calluzzo, 2023) has been studied as potential factors that can influence mutual funds decisions. The findings of previous research on mutual funds' relationship with firms are mixed. While some research papers document connections as a mechanism to acquire information (e.g., Cohen, Frazzini, and Malloy, 2008; Duan, Hotchkiss, and Jiao, 2018; Calluzzo and Kedia, 2019), there is a list of papers that find evidence supporting the presence of a conflict of interest in mutual funds' decisions. These findings do not support the information acquisition mechanism but support the conflict of interest explanation.

The rest of the paper is organized as follows. Section **3.2** describes the data, sample construction, and summary statistics. Section **3.3** discusses empirical findings and, finally, section **3.4** concludes.

3.2. Data and Summary Statistics

3.2.1. Mutual Fund Voting

Since 2003, the U.S. Securities and Exchange Commission (SEC) has mandated that investment companies disclose their proxy voting records to the public through Form N-PX. To evaluate the voting behavior of mutual funds, I start with the subsample of all mutual fund voting records provided by the ISS Voting Analytics database spanning 2004-2019. This data contains mutual fund votes to each individual proposal (also referred to as item), fund and portfolio company identifiers, meeting type and date, proposal description, portfolio company identifiers, and management and ISS recommendations. In the case of proposals related to the frequency of say-on-pay votes, mutual funds have the option to vote for one year, two years, or three years. For other types of proposals, they can vote for, against, or abstain[23]. Following Iliev and Lowry (2015), I aggregate votes cast as "Against" and "Abstain" into a single category. Also, management and ISS recommendations have the same set of potential values. Additionally, I access information related to each proposal's vote requirement (i.e., the percentage of support needed for passage), the entity sponsoring the proposal (shareholder or management), the level of support garnered, and the final outcome (e.g., Pass, Fail, Withdrawn, etc.) from the ISS Company Vote Results US database. Due to higher support and less conflict, director election items are all excluded in this paper.

I study mutual funds friendliness and voting behavior toward connected firms by focusing on whether they follow management recommendations or not. The main outcome variable, *VoteWithMgmt*, is equal to 1 if mutual funds vote with management and zero otherwise. This variable has been used extensively in the literature to study the voting behavior of shareholders (e.g., Van Nuys, 1993; Davis and Kim, 2007; Ashraf, Jayaraman, and Ryan, 2012; Cvijanović, Dasgupta, and Zachariadis, 2016; Duan and Jiao, 2016; Calluzzo and Kedia, 2019; Heath et al., 2022).

3.2.2. Lobbying Activities

The Lobbying Disclosure Act (LDA) of 1995 was enacted to enhance transparency by mandating the registration of significant lobbying activities. In compliance with this regulation, lobbying entities are obligated to register and disclose their lobbying efforts by regularly submitting LD-1 and LD-2 forms to the

[23] I categorize mutual funds' votes as abstentions if the FundVote variable in ISS Voting Analytics contains any of the following values: Abstain, Do Not Vote, None, or Withhold.

Senate Office of Public Records (SOPR). The LD-1 registration form should be filed by lobbyists for each of their clients at the onset of a lobbying relationship.[24] This form contains essential information such as the name and location of the lobbying firms and their clients, the commencement of the lobbying relationship, and details about the lobbying issues involved, among others. Subsequently, they are required to quarterly file form LD-2 for each client any time their lobbying-related income exceeds $3,000. These quarterly reports provide insights into lobbying expenses, both general and specific issues being lobbied, the Houses of Congress and Federal agencies contacted, bill numbers when applicable, and the names of individuals acting as lobbyists in each issue area. Notably, prior to 2008, lobbyists were only required to submit LD-2 forms semiannually. Hence, I divided semiannual lobbying expenses by two to construct quarterly expenses.

To identify connections between mutual funds and their portfolio firms, it was required to match the firm and fund names in the ISS Voting Analytics with client names listed in LDA data. Utilizing natural language processing, name entity matching algorithms, and manual verification, Kim (2018) has provided the links between lobbying client names to the list of public firm names and their GVKEY identifiers from Compustat at Lobbyview.org. In addition to firms, I also need to identify the lobbying activities of mutual fund families. To do so, I restricted the analysis to largest 200 mutual fund families which collectively account for approximately 93% of ISS Voting Analytics database. I then manually match the name fund families in ISS Voting Analytics to client names in LDA data. This process allowed us to pinpoint lobbying activities associated with mutual fund families. Having compiled data on the lobbying activities and contracts of both mutual funds and their portfolio firms, I were able to identify lobbying connections between each fund-firm pair for each quarter. Among the top 200 mutual fund families, I found that 150 engaged in lobbying at least once during the sample period. Notably, given the specific focus of this study on connections established through lobbyists, I excluded consideration of *in-house* lobbying efforts conducted by mutual funds or portfolio firms, as such efforts do not contribute to the creation of lobbying connections.

3.2.3. Mergers and Acquisitions

Mergers and acquisitions involving financial institutions have been widely employed in the literature to identify the impact of factors such as market concentration and common ownership (e.g., He and Huang, 2017; Saidi and Streitz, 2021; Lewellen and Lowry, 2021 among others). To find the mergers between mutual funds, I use the data provided by the SDC Platinum. The process began with compiling a list of

[24] Organizations engaged in in-house lobbying through their employees are also required to file LD-1 forms themselves.

all completed mergers that occurred during the sample period, where both the target and acquirer operated within the financial sector (i.e., SIC codes falling within the range of 6000-6900). Then, I manually match the names of the target and acquirer with fund family names found in ISS Voting Analytics. My objective was to discern any instances of the creation or dissolution of lobbying connections resulting from these mergers. Through this process, I found 16 mergers during 2006-2018 that impacted lobbying connections in 23 unique fund families. The process of identifying shocks to lobbying connections are further explained in section 3.3.3. Additionally, you can find a detailed list of these mergers in A3.

Similarly, I leveraged information on mergers between lobbying firms to capture plausibly exogenous variations in lobbying connections. Data on mergers and acquisitions involving lobbying firms were sourced from the SDC Platinum database. I started by gathering a comprehensive list of completed mergers where both the target and acquirer firms held a 3-digit NAICS code of 541. Subsequently, I manually matched the names of the target and acquirer entities with the names of lobbying firms listed in the Lobbying Disclosure Act (LDA) database. I focus on deals in which either target or acquirer had previously served mutual funds. In each such deal, I identified any resulting shocks to lobbying connections. Following this procedure, I uncovered a total of eight mergers that had an impact on at least one connection. The list of these mergers and more information regarding the process of identifying shocks to connections are provided in Table A4 and section 3.3.3, respectively.

3.2.4. Firm Characteristics

In addition to the primary sources of data, I have augmented this research with information from several other databases to further analyze the baseline findings. Firstly, I accessed the ISS Governance database to gather data on the presence of various governance provisions. These provisions encompass factors like staggered boards, limitations on shareholder amendments of bylaws, supermajority requirements for charter amendments, supermajority requirements for mergers, poison pills, golden parachutes, and dual-class shares. Six of these provisions are employed to compute the E-Index, a proxy for management entrenchment, as established by Bebchuk, Cohen, and Ferrell (2009). Moreover, I obtained details regarding the composition of the board of directors from Boardex. This data allowed us to calculate board independence, represented as the ratio of independent directors relative to the overall size of the board. Furthermore, I leveraged IBES to access information on analysts' forecast errors and Thomson/Refinitiv to acquire data on institutional ownership. Compustat served as a valuable resource for determining the state of incorporation and deriving firm-level control variables such as size, return on assets (ROA), market-to-book ratio (MB), leverage, tangibility, and age. Finally, I utilized CRSP to access stock trading data, including metrics related to returns, liquidity, and volatility.

3.2.5. Summary Statistics

I start constructing the sample using voting records available in ISS Voting Analytics during 2004-2019. I exclude votes related to director election due to less conflicting nature of these proposals. The main variable of interest, i.e., denoted as *Connected*, would be equal to 1 if a given fund-firm pair have common lobbyists in each quarter and zero otherwise. In the main analyses, I focus on firms and funds that engage in lobbying throughout the sample period. As a result, there will remain 13,405,443 observations in the sample. To showcase the robustness of the main findings, I also provide supplementary analysis in the Appendix that includes all funds and firms. To minimize the effects of outliers on estimates, I winsorize all variables, except for the dummy variables, at the 1 and 99 percent levels.

Table **3.1** reports the composition of the sample. According to Panel A, the sample encompasses a total of 2,465 unique firms and 12,941 unique mutual funds belonging to 150 different fund families. In aggregate, there are 63,576 unique proposal that have been voted upon in my dataset. Although I require that mutual funds and firms engage in lobbying throughout the sample period, it's important to note that not all instances of lobbying result in the creation of connections, where a lobbying firm simultaneously serves a mutual fund and its portfolio firms. Column 2 in Table **3.1** show that 40% of firms experience lobbying connection at least once during the sample period. Similarly, 57.6% of funds and 88% of lobbying fund families experience lobbying connections. Out of the 63,576 proposals in my dataset, 28.2% have at least one connected mutual fund involved in the voting process.

[Table **3.1** Here]

In Panel B, I can see that 52,476 proposals are sponsored by managers whereas only 11,100 of them are shareholder-sponsored. Management and ISS recommend 93.87% and 85.15% of management-sponsored proposal, respectively, and 95.49% of management proposals pass. In contrast, the support of management and ISS is considerably less for shareholder-sponsored proposals. Particularly, management and ISS recommend for 33.93% and 42.2% of shareholder proposals, respectively, which results in a passing rate of only 14.37%. Next, I look at the level of conflict across different proposals. I define contentious proposals as those items for which the management's recommendation is in direct opposition to the recommendation made by ISS. Within this sample, I identify 12,965 such contentious cases. In these contentious proposals, management and ISS provide recommendations for 64.1% and 35.9% of cases, respectively, ultimately resulting in a passing rate of 49.43% for these items. Additionally, I examine another subset of proposals known as Contested (or CloseCall) proposals, which are those that marginally pass or fail by a margin of less than 10%. In this sample, I identify 2,955 such Contested proposals. Among these, management and ISS make recommendations in 60.14% and 68.09% of cases, respectively. Importantly, the statistics reveal that 57.73% of these Contested proposals ultimately pass.

In Panel C of Table **3.1**, I present the mean management and ISS recommendations, as well as the passing rates for various subsamples of proposals categorized by subject matter. These categories of proposals are not mutually exclusive, meaning that a single proposal could belong to more than one category. For detailed insights into the selection criteria used to identify these categories, please refer to Table A1 in the Appendix. Lastly, in Panel D, I furnish various statistics for the primary variables utilized in my analyses. The definition of those variables are provided in Table A2 in Appendix. Statistics show that mutual funds vote with management in 85.7% of cases. Moreover, 6% of votes in the sample are cast by connected mutual funds.

3.3. Empirical Results

3.3.1. Voting by Connected Funds

My analysis starts with examining the impact of lobbying connections on mutual funds voting behavior. Prior research has studied how the quality and type of relationship between mutual funds and their portfolio firms impact mutual funds' decisions such as voting. For instance, previous studies have delved into the consequences of connections stemming from business ties (Davis and Kim, 2007; Ashraf, Jayaraman, and Ryan, 2012; Cvijanović, Dasgupta, and Zachariadis, 2016; Duan, Hotchkiss, and Jiao, 2018), board of directors affiliations (Calluzzo and Kedia, 2019; Calluzzo, 2023), and educational background (Butler and Gurun, 2012). In this paper, I study a distinct type of connection between mutual funds and their portfolio firms. In fact, I test whether mutual funds adopt a more management-friendly approach toward firms with which they have lobbying connections. If such favoritism and pro-management orientation indeed exist toward connected portfolio firms, mutual funds should exhibit a greater likelihood of following management recommendations in their voting. To test this hypothesis, I employ the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} + MgmtSponsored_k + FE + \epsilon_{i,j,f,q,k} \tag{10}$$

The dependent variable, $VoteWithMgmt_{i,j,f,k,q}$, serves as a measure of the pro-management behavior exhibited by mutual funds. It is a dummy variable that equals 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$, as the main variable of interest, is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbyist. Moreover, I control for the sponsor of proposals in all of regressions whenever this variable is not absorbed by fixed effects. $MgmtSponsored_k$ is a dummy variable that is equal to 1 if the proposal is sponsored by management and zero otherwise. Due to the granular nature of the voting data, I incorporate a rich set of fixed effects to control for unobserved heterogeneity. These fixed effects include a combination of Firm × Year, Fund × Year, and Proposal fixed effects which control for all time-variant firm, fund, and proposal characteristics.

First, Firm × Year fixed effects control for all time-varying firm characteristics. Previous research has demonstrated that firm characteristics can significantly impact mutual fund voting behavior (Ng, Wang, and Zaiats , 2009; Bubb and Catan, 2022). Second, Fund × Year fixed effects allow for a comparison of votes of each fund for connected firms versus non-connected firms within a given year. This within Fund × Year comparison rules out the impact of time-varying fund characteristics (such as Matvos and Ostrovsky, 2010; Iliev and Lowry, 2015; Bolton et al., 2020; Heath et al., 2022; Michaely, Ordonez-Calafi, and Rubio, 2021) on voting behavior. Third, I include proposal fixed effects to the regression specification to control for all proposal-specific characteristics and differences between proposals that could influence mutual funds voting. Prior research has documented heterogeneity in mutual fund voting across different proposals (Levit and Malenko, 2011; Bach and Metzger, 2019; Gantchev and Giannetti, 2021; Babenko, Choi, and Sen, 2023). By adding this fixed effect, the result shows the comparison between the voting behavior of connected versus non-connected funds within each proposal. Standard errors are also clustered at the fund level. Positive values of β_1, as the main coefficient of interest, will support my hypothesis regarding the pro-management voting behavior of connected mutual funds.

Columns 1-5 of Table **3.2** report the estimation results of Eq. 10 using various sets of fixed effects. For example, according to column 1, connected funds are 2.76% more likely to vote with management which is equivalent to a 3.2% increase relative to the sample mean. Additionally, column 5 shows the most saturated estimation by including proposal and Fund × Year fixed effects. According to this column, connected firms are 0.6% more likely to vote in favor of management. To demonstrate the robustness of the baseline findings with respect to sample selection processes, I repeat the baseline test for different subsamples of votes in Table A5 in the Appendix. In Panel A, I include the full sample of votes that also contains observations related to mutual funds and firms that have never lobbied throughout the sample period. Panel B presents the same set of tests on the sample of mutual funds and firms that have had at least one connection throughout the sample period. Finally, in Column C, I only include proposals that have received votes from at least one connected mutual fund. Overall, these results support the robustness of the findings to sample selection criteria.

[Table **3.2** Here]

Next, I examine the dynamics of connections between mutual funds and their portfolio firms. Lobbying activities and the relationship between lobbying firms and their clients exhibit considerable persistence. In my sample, the average duration of connections is approximately ten quarters. This analysis begins by pinpointing the time at which each firm-fund pair first established their connection. Then, I study the voting pattern of mutual funds in a 13-meeting period centered around the initiation of this connection. If a connection between a connected pair lasts less than 7 meetings after initiation, I include that firm up to the last connected meeting and exclude it beyond that point. In this test, I employ the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_\tau \sum_{\tau=-6}^{6} \beta_\tau EverConnected_{i,f} * \mathbb{1}[t - t_0 = \tau] + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,k,q} \qquad (11)$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if a fund i belong to fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $EverConnected_{i,f}$ is a dummy variable that equals 1 if the pair of fund i and firm f ever become connected and zero otherwise. $\tau = 0$ shows the first meeting at which a fund-firm pair become connected. The estimated coefficients are presented in Figure **3.1**. While no significant differences are observed between *EverConnected* pairs and the rest of the sample before initiation of connections, the effect gradually emerges following connection creation and becomes statistically significant at 5% level by the third meeting. As illustrated in Figure **3.1**, the pro-management voting behavior among connected funds reaches its peak at the sixth meeting (i.e., $\tau = 5$).

[Figure **3.1** Here]

3.3.1.1 Type of Proposals

The proposals that are included in this sample are from various types. In this section, I investigate whether any differences exist across different proposal types. Particularly, I study the effect across proposals related to say-on-pay frequency, auditor ratification, compensation, environmental and social (E&S) issues, management entrenchment, and information disclosure. A detailed explanation of the classification of proposals is provided in Table A1 in the Appendix. It's important to note that these categories are not mutually exclusive, and it's possible for a single type of proposal to be included in more than one subsample. For instance, proposals pertaining to the disclosure of executive compensation are encompassed within both the compensation-related and disclosure categories.

According to Panel A of Table **3.3**, lobbying connections positively and significantly impact pro-management voting behavior on say-on-pay frequency, auditor ratification, compensation, management entrenchment, and information disclosure proposals. However, there is no significant impact on items related to E&S issues. Furthermore, in Panel B, I decompose the disclosure related into four different groups such as disclosure, political contribution disclosure, executive compensation, and proxy voting disclosure. Column 1 shows that connected mutual funds are 1.53% more likely to follow management on lobbying disclosure proposals on which mostly management recommends against. However, no significant impact is observed for proposals concerning political campaign contribution disclosure. Moreover, columns 3-4 suggest that connected funds are 3.38% and 9.82% more likely to vote with management on executive compensation disclosure and proxy voting disclosure items, respectively.

[Table **3.3** Here]

3.3.1.2 Size of Lobbying Contracts

Next, I examine how and whether the size of lobbying contracts between lobbying firms and their clients impacts the extent of the pro-management behavior exhibited by mutual funds. To do so, I create three different proxies for the strength of the lobbying connection. The first proxy, denoted as *#CommonLobbyists*, indicates the number of different lobbyists that simultaneously serve a fund-firm pair. In my sample, the maximum number of common lobbyists is 5 (11 before winsorization). I anticipate that a more pronounced effect will be observed among funds connected to a portfolio firm by several different lobbyists. Column 1 in Table **3.4** reports the results for interacting *#CommonLobbyists* with the main independent variable. The results suggest a positive association between the impact of lobbying connections and the number of lobbyists involved. In fact, funds connected through a single common lobbyist are 0.53% more likely to vote with management compared to non-connected funds. This effect is fairly comparable to the baseline result that I found in column 5 of Table **3.2**, as more than 77% of connected fund-firm pairs involve just a single common lobbyist. However, fund-firm pairs with 5 common lobbyists exhibit a 2.65% higher likelihood of voting in favor of management.

[Table **3.4** Here]

Moreover, I use the dollar value expended by fund families and firms on lobbying as a proxy for the strength of their relationship with lobbying firms. In columns 2 and 3 of Table **3.4**, I examine the impact of lobbying expenses on mutual fund voting. Results show that the impact is significantly more pronounced when firms/funds pay more to common lobbyists. In terms of economic magnitude, each $100,000 increase in lobbying expenses by fund families (firms) corresponds to a 0.4% (0.2%) increase in the probability of voting in favor of management. The larger coefficient for fund family expenses suggests that the connection between mutual funds and lobbyists has a stronger influence on fund voting behavior than the connection between their portfolio firms and lobbyists.

3.3.2. Mechanisms

The pro-management behavior of connected funds could potentially be attributed to two mechanisms: enhanced information access about connected portfolio firms and/or strategic decisions by managers to cultivate support from connected shareholders. In this section, I conduct analyses to investigate the presence of these two mechanisms.

3.3.2.1 Information Acquisition

Shareholder voting is a fundamental corporate governance mechanism. Casting informed votes (i.e., votes that maximize firm/shareholder value) requires information collection and processing. The costs of doing research and privately collecting and processing information can be substantial for large and diversified mutual funds holding many stocks. This situation led to substantial growth in the proxy advisory industry and more reliance on proxy advisory firms by mutual funds, especially among those with less information production capacities (Iliev and Lowry, 2015; Malenko and Malenko, 2019). The growth in proxy advisory firms has raised some concerns about the shortcomings of their advice like the one-size-fit-all approach and conflict of interest (McCahery, Sautner, and Starks, 2016; Malenko and Malenko, 2019; Malenko, Malenko, and Spatt, 2021). Given these issues with proxy advisory firms' recommendations, other channels of information collection or production can be highly valuable for managers to cast more informed votes.

Lobbying activities undertaken by firms and their lobbying connections with institutional investors can significantly enhance information production and assist mutual funds in making well-informed voting decisions. Lobbying firms acquire abundant information about their clients by providing a variety of services to them. For example, other than lobbying, they provide strategic advice and business consulting, legal services in a wide variety of corporate transactions (e.g., bankruptcy, M&A, IPO, etc.), litigation consulting, government contracts, public relations, shareholder communication, and reputation management, among others. In addition, they provide some services that are directly related to the relationship between institutional investors and their portfolio firms. For example, Akin, Gump, Strauss, Hauer & Feld, one of the largest lobbying firms in the US, help institutional investors in designing best practice governance, board, and committee structures. It also advises activist shareholders in launching campaigns against companies or unseating recalcitrant directors and removing entrenched management (Akin et al., 2023a; Akin et al., 2023b). Simultaneously, it assists companies in safeguarding their interests by establishing robust governance mechanisms and strategies for dealing with potential takeovers and responding to shareholder proposals. These services not only enable mutual funds to access information directly through their common lobbyists but also help them to indirectly use the presence of common lobbyists as a signal that reveals the manager's type.

If such an information acquisition channel exists, I would expect to see a stronger impact for lobbying connections among firms with higher levels of information asymmetry. Information obtained through lobbyists would be more valuable for complicated firms with a worse information environment. Following Maskara and Mullineaux (2011), I use several firm-level proxies of information asymmetry such as volatility, liquidity, intangibility, analysts' coverage, and analysts' forecast error. In Table **3.5**, I report the results of interacting these variables with the *Connected* variable. Results show that firm-level information asymmetry is not associated with the impact of lobbying connections on fund voting.

[Table **3.5** Here]

3.3.2.2 Conflict of Interest

An established connection between a firm and its shareholders can facilitate communications and seeking shareholders' support. In fact, it would be less costly for managers to engage with shareholders that have been already connected to them. Prior research has shown the efficacy of connections such as business ties (Cvijanović, Dasgupta, and Zachariadis, 2016) and educational background (Butler and Gurun, 2012) on mutual funds' pro-management voting behavior. In this section, I examine circumstances in which the value of mutual funds support is higher for managers and hypothesize a more pronounced impact in those situations.

The support of mutual funds becomes more valuable when the manager's power is relatively low. Managerial power can be indicated by the quality of a firm's governance and the level of monitoring pressure from shareholders. In firms with higher levels of governance in which the activities of managers are highly monitored, the support of connected mutual funds is more valuable. Conversely, leveraging lobbying activities to obtain mutual funds' support is less crucial for firms with entrenched management. Therefore, I anticipate a less pronounced impact of lobbying connections in firms with weaker shareholder governance and stronger management entrenchment. Using four different measures of governance and management entrenchment in columns 1-4 of Table **3.6**, I find results that support this hypothesis.

In column 1, I calculate E-Index using the six provisions suggested by Bebchuk, Cohen, and Ferrell (2009). These provisions include the presence of a staggered board, limits to shareholder amendments of the bylaws, supermajority requirements for charter amendments, supermajority requirements for mergers, poison pills, and golden parachute arrangements. The first four provisions impose constitutional limits on shareholder voting power while the last two negate the effect of hostile takeovers. Estimation results show that the impact of lobbying connections diminishes as management entrenchment (E-Index) increases.

Next, I calculate the ratio of independent directors on the board. Higher levels of board independence reflect more intense monitoring of managerial decisions and increase the value of funds support. The impact of board independence has been extensively studied in prior research (Raheja, 2005; Adams and Ferreira, 2007; Boone et al., 2007 Harris and Raviv, 2008; Masulis and Mobbs, 2011; Knyazeva, Knyazeva, and Masulis, 2013). As shown in column 2, I find that the effect of lobbying connections is more pronounced when there is a higher level of board independence. In addition, the presence of multiple classes of common stocks empowers corporate insiders by protecting their control, limits shareholder rights, and provides resistance against a hostile takeover (Masulis, Wang, and Xie, 2009; Gompers, Ishii, and Metrick, 2010; Howell, 2017). Hence, in corporations with dual-class shares, managers possess substantial power, reducing their reliance on shareholder support. Column 3 of the analysis confirms this hypothesis by showing that the impact of lobbying connections is weaker among corporations with dual-class shares. Last, the presence of the Universal Demand (UD) Laws in a state can also shape the value of connected mutual funds' support. Between 1989 and 2005, 23 states introduced UD laws, which raised barriers for derivative lawsuits by requiring board approval before initiating litigation (Appel (2019); Lin, Liu, and Manso (2021)). These laws significantly diminish shareholders' ability to file derivative suits, affecting corporate governance enforcement mechanisms. Hence, I expect to find a weaker impact for lobbying connections in firms incorporated in states with UD laws. Following Appel (2019) and Foroughi et al. (2022), I identify the list of states having UD laws in place. Interacting a dummy variable that shows the status of UD laws in firms' state of incorporation, column 4 supports the fact that lobbying connection is less effective when shareholders' monitoring is restricted.

[Table **3.6** Here]

The level of conflict in voting represents another factor influencing the value of mutual fund support for firm management. In this paper, I consider two categories of proposals as conflicted. The first category includes those proposals that ISS recommends against management. I call these proposals as contentious. These proposals typically receive lower support from shareholders and have been extensively analyzed in the literature to understand mutual fund voting behavior (e.g., Iliev and Lowry, 2015; Cvijanović, Dasgupta, and Zachariadis, 2016; Calluzzo and Kedia, 2019; Lee and Souther, 2020; Ellis, Gerken, and Jame, 2021; Gao and Huang, 2022; Huang, 2023). Given ISS's influence on mutual fund voting, the support of connected mutual funds becomes even more valuable for managers when ISS opposes their recommendations. In column 5 of Table **3.6**, I interact the main independent variable with a dummy variable that equals 1 if the proposal is contentious and zero otherwise. The results illustrate that the impact of lobbying connections is more pronounced for contentious proposals, underscoring the value of these connections in situations of heightened conflict.

The second category of conflicted proposals includes those proposals that narrowly pass or fail during voting. These proposals are particularly sensitive to the individual votes of shareholders and, as such, represent situations where the influence of each vote carries more weight. Managers can fairly anticipate the level of support by shareholders for each proposal before the proxy meetings. As suggested in Cvijanović, Dasgupta, and Zachariadis (2016), items that pass or fail narrowly can be identified in advance by managers, and these are the proposals that it is worthwhile for managers to exert influence and actively seek support from connected mutual funds. In fact, the benefits of seeking connected mutual funds' support are more likely to outweigh its costs in contested proposals. Consistently, Aggarwal, Saffi, and Sturgess (2015) show that mutual funds call back lent securities around the time of contested votes. This implies that these organizations consider the significance of voting to be substantial enough to forgo the income generated from lending those securities. In column 6, I explore the differential impact of lobbying connections among contested versus non-contested proposals. Defining contested proposals as proposals that pass or fail with less than a 10% margin, I find that the impact is stronger in contested items.

3.3.3. Identification Strategies

Although I include a rich set of fixed effects to control for characteristics and omitted variables that could potentially bias my estimation, there might still exist some concerns about the endogeneity problem. Thus, in this section, I use mergers and acquisitions between mutual funds and lobbying firms to obtain exogenous variation in connection status.

3.3.3.1 Mergers and Acquisition of Mutual Funds

In this part, I utilize the merger between mutual funds as a means to identify the impact of lobbying connections. Mergers and acquisitions involving financial institutions have been extensively used in the field to identify factors such as concentration and common ownership (e.g., He and Huang, 2017; Saidi and Streitz, 2021; Lewellen and Lowry, 2021 among others). As previously explained in Section 3.2.3, I match the list of all mergers between financial firms with the names of lobbying clients in LDA. Then, I manually search for the changes in connection status that result from each deal. These changes in lobbying connections are deemed plausibly exogenous since it is very unlikely that the formation or dissolution of lobbying connections with portfolio firms would influence mutual funds' merger decisions. Such merger-induced changes in lobbying connections can be in the form of connection creation or loss. Connection creations that I identified arise in either of the following two cases: 1) when the target firm survives in the ISS Voting Analytics database following the merger and the acquirer is actively engaged in lobbying around the merger. In this scenario, the target becomes connected to lobbyists of the acquirer after the merger, or 2) when the target is actively engaged in lobbying around the merger and the acquirer exists in Voting Analytics around the merger. In this scenario, the acquirer becomes connected to lobbyists of the target following the merger (e.g., mergers of Wells Fargo and Wachovia, or TIAA-CREF and Nuveen Investments deals). Connection losses arise when both the two following conditions are met: 1) the target exists in ISS Voting Analytics both before and after the merger, and 2) the target's parent engages in lobbying activities before the merger. In this scenario, the target loses connection to lobbyists of its former parent. At the end of this process, I identify 16 mergers and acquisitions, listed in Table A3, that result in changes in at least one lobbying connection.

Focusing exclusively on connections that are impacted by mergers and acquisitions between mutual funds, I repeat the main analysis. Utilizing the regression specification in Eq. 10, Table **3.7** reports the result. The impact of lobbying connections remains positive and statistically significant. In terms of economic magnitude, the impact becomes slightly larger using merger-impacted lobbying connections. Particularly, according to the most saturated specification in column 5, connected funds are 0.95% more likely to vote with management.

[Table **3.7** Here]

3.3.3.2 Mergers and Acquisition of Lobbying Firms

Mergers and acquisitions between lobbying firms are another source of plausibly exogenous variation to identify the impact of lobbying connections. While these transactions impact the composition of clients in target and acquirer, it is very unlikely that lobbying firms' engagement in a merger and acquisition would depend on lobbying connections that would be affected. As previously mentioned in section 3.2.3, I start by collecting the list of all completed mergers for which the target and acquirer have a 3-digit NAICS code of 541. Within this list, I manually matched the names of targets and acquirers with the names of the lobbying firms in LDA. Then, I focus on deals in which either the target or acquirer has previously served mutual funds. In each deal, I manually search for those clients (mutual fund or portfolio firms) of the target lobbying firm that are *transferred* to the acquirer following the merger. Transferred clients are defined as clients that meet two criteria: 1) They had a lobbying contract with the target (and not with the acquirer) in the year preceding the merger, and 2) They had a lobbying contract with the acquirer in the first year post-merger. All connections created by transferred clients after the merger are used as an exogenous source of variation in connection creation. Furthermore, there exist connections that are dissolved due to mergers. This happens when mutual funds and their portfolio firms are connected via the target before the merger but become disconnected afterward. These connections are also included in the sample of connections that are impacted by mergers between lobbying firms.

Focusing on the merger-impacted connection, I revisit the baseline findings and report the results in Table **3.8**. While the estimated impact remains consistently positive and statistically significant, the economic magnitude of the impact increases considerably compared to baseline findings. Particularly, column 5 shows that connected firms are 2.92% more likely to vote in line with management recommendations.

[Table **3.8** Here]

3.3.4. Lobbying Connections and Voting Outcome

In this section, I study the efficacy of mutual funds support on voting outcomes. In fact, I want to assess the extent to which mutual fund support contributes to the success of management. As I established earlier, connected mutual funds are more likely to support management recommendations in their voting. Bach and Metzger (2019) show that an abnormal share of shareholder proposals are won by a small margin by management and argue that when managers strongly oppose a shareholder proposal, they take meticulous actions to ensure its failure. Additionally, in a related paper, Listokin (2008) finds that managers are substantially more likely to win proposals by small margins. He concludes that management obtains highly accurate information about the likely voting outcomes and, based on this information, actively intervenes to influence the vote. As a result, I anticipate a higher likelihood of success for firms with a greater number of connected mutual funds. To examine the impact of voting connection on voting outcome, I aggregate the data at the proposal level and run the following regression analysis:

$$Mgmt\ Favorite\ Outcome_{f,k,y} = \beta_0 + \beta_1 Support\ Measure_k + \Gamma Controls + \lambda_y + \omega_f + \epsilon_{f,k,y} \qquad (12)$$

where $Mgmt\ Favorite\ Outcome_{f,k,y}$ is equal to 1 if proposal k's outcome is aligned with management recommendation and zero otherwise. I use two proxies for the support of connected mutual funds. The first proxy, i.e., $Pct\ of\ Funds\ Connected$, is equal to the ratio of funds that are connected to the firm at proposal k's meeting. The second proxy, $Pct\ of\ VoteWithMgmt$, is calculated in the subsample of proposals having at least one connected mutual fund and equals to the ratio of connected mutual funds that vote with pro-management. Moreover, I control for proposal sponsorship and a list of firm-level characteristics such as Size, ROA, MB, Leverage, Stock Return, Tangibility, Age, and IO. The detailed definition of control variables is provided in Table A2 in the Appendix. In these regressions, I include firm and year fixed effects and I cluster standard error at the firm level.

[Table **3.9** Here]

The estimation results are reported in Table **3.9**. According to column 1, higher levels of connected mutual funds increase the likelihood that proposals end up with the outcome that management recommends. Particularly, one standard deviation increase in $Pct\ of\ Funds\ Connected$ increases the probability of management favorite outcome by 0.75%. Furthermore, as I discussed earlier in section 3.3.2.2, conflicted proposals (i.e., either contentious or contested) are the ones in which managers are more likely to exert influence. Hence, connected mutual funds support would play a more important role in these proposals. To examine the heterogeneity in the impact of connected funds, I interact the main independent variable with dummy variables that show conflict in voting. In column 2, I find that while the ratio of connected funds is negatively associated with management's favorite outcome in non-contentious proposals, it positively affects the likelihood of management's favorite outcome in contentious proposals. In fact, one standard deviation increase in $Pct\ of\ Funds\ Connected$ increases the probability of management's favorite outcome by 6.14% if the proposal is contentious. In column 3, I use a dummy that shows whether the proposal voting was contested or not as an interaction variable. I find that higher levels of connected funds have a more pronounced effect on voting outcomes for contested proposals. In terms of the economic magnitude, one standard deviation of increase in $Pct\ of\ Funds\ Connected$ increases the probability of management's favorite outcome by 2.11% if the proposal is contested.

Formerly, I examined how the presence of connected mutual funds impacts voting outcomes. Although the baseline results showed that connected mutual funds are more likely to support management, their support is not guaranteed. Here, by focusing on the subsample of proposals having at least one connected mutual fund, I want to specifically test how and whether the actual support of connected mutual funds impacts the successful of management. $Pct\ of\ VoteWithMgmt$ is defined as the proportion of connected mutual funds that follow management recommendations. Column 4 in Table **3.9** indicates that $Pct\ of\ VoteWithMgmt$ is positively associated with the occurrence of management's favorite outcome. In fact, one standard deviation increase in $Pct\ of\ VoteWithMgmt$ increases the probability of management's favorite outcome by 9.01%.

Furthermore, I examine whether and how the support of mutual funds and the outcome of voting impact the market reaction to voting results. Negative market reactions to successful mutual fund support will suggest that mutual funds' pro-management behavior is value-decreasing. Following previous papers (e.g., Cuñat, Gine, and Guadalupe, 2012; Iliev and Lowry, 2015; Calluzzo and Kedia, 2019), I narrow down my analysis to proposals that pass or fail with a narrow margin. Since the outcome of contested proposals is less likely to be anticipated by the market, the market reaction to those events can be informative about the impact of the proposal on firm value. To do this test, I focus on mutual funds that pass or fail by a 10% margin around the threshold and have at least one connected mutual fund. Moreover, to be able to isolate the impact of contested proposals, I exclude firms having more than one contested proposal in a meeting, resulting in a final sample of 675 proposals for which I run the following regression:

$$\begin{aligned} CAR[-1,+1] = \beta_0 + \beta_1 Pct\ of\ VoteWithMgmt \times Mgmt\ Unsuccessful \\ + \beta_2 Pct\ of\ VoteWithMgmt + \beta_3 Mgmt\ Unsuccessful + \epsilon \end{aligned} \tag{13}$$

$CAR[-1,+1]$ shows market-adjusted cumulative abnormal return over the three-day period around the meeting. As before, $Pct\ of\ VoteWithMgmt$ is the proportion of connected mutual funds that follow management recommendation and $Mgmt\ Unsuccessful$ is equal to 1 if the proposal's outcome is against management recommendation and zero otherwise. The estimation results are reported in Table **3.10**. Results show that a percentage of mutual fund support is associated with positive abnormal returns if management is unsuccessful. Particularly, one standard deviation increase in $Pct\ of\ VoteWithMgmt$ is associated with 0.5% abnormal return when the management recommendation fails. However, there is an insignificant market reaction to connected mutual funds' support upon realization of management's favorite outcome.

[Table **3.10** Here]

3.4. Conclusion

Voting represents a crucial governance mechanism employed by mutual funds to ensure the alignment of managers with their interests. I show that lobbying connections between mutual funds and their portfolio firms impact funds' voting behavior. My findings reveal that mutual funds tend to adopt a more management-friendly stance when they have lobbying ties with the companies they invest in. This pro-management behavior is evident across various types of proposals and becomes more pronounced as the scale of lobbying activities or the number of shared lobbyists increases. While my findings do not support the presence of enhanced information sharing through lobbying connections, they imply that portfolio firms' management can strategically leverage lobbying expenditures and connections developed through lobbying activities to garner support from mutual funds during proxy voting. Support of mutual funds is more pronounced when management faces heightened pressure and shareholder monitoring due to stronger governance, in contentious proposals in which ISS recommends against management, or in contested proposals that narrowly pass or fail. I substantiate the baseline findings by employing exogenous changes in lobbying connections resulting from mergers and acquisitions. Furthermore, this research highlights that the support of connected mutual funds significantly influences voting outcomes and increases the likelihood that management recommendations are realized. However, I document a positive market reaction when connected mutual funds fail to realize managers' preferred outcomes which further supports the conflict of interest channel. Overall, these findings shed light on lobbying as a strategic tool that company management can employ to secure shareholder support during proxy voting, emphasizing the importance of these connections in shaping corporate governance outcomes.

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Figure 3.1.
Voting Behavior Around Lobbying Connection Creation

This figure depicts the differential voting behavior of mutual funds on proposals based on their lobbying connections to portfolio firms. In this test, I run the following regression:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_\tau \sum_{\tau=-6}^{6} \beta_\tau EverConnected_{i,f} * \mathbb{1}[t - t_0 = \tau] + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,k,q}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if a fund i belongs to fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $EverConnected_{i,f}$ is a dummy variable that equals 1 if the pair of fund i and firm f ever becomes connected and zero otherwise. $\tau = 0$ shows the first meeting that a fund-firm pair gets connected. Then, β_τ coefficients display the impact of lobbying connection in $\tau^t h$ meeting after connection initiation.

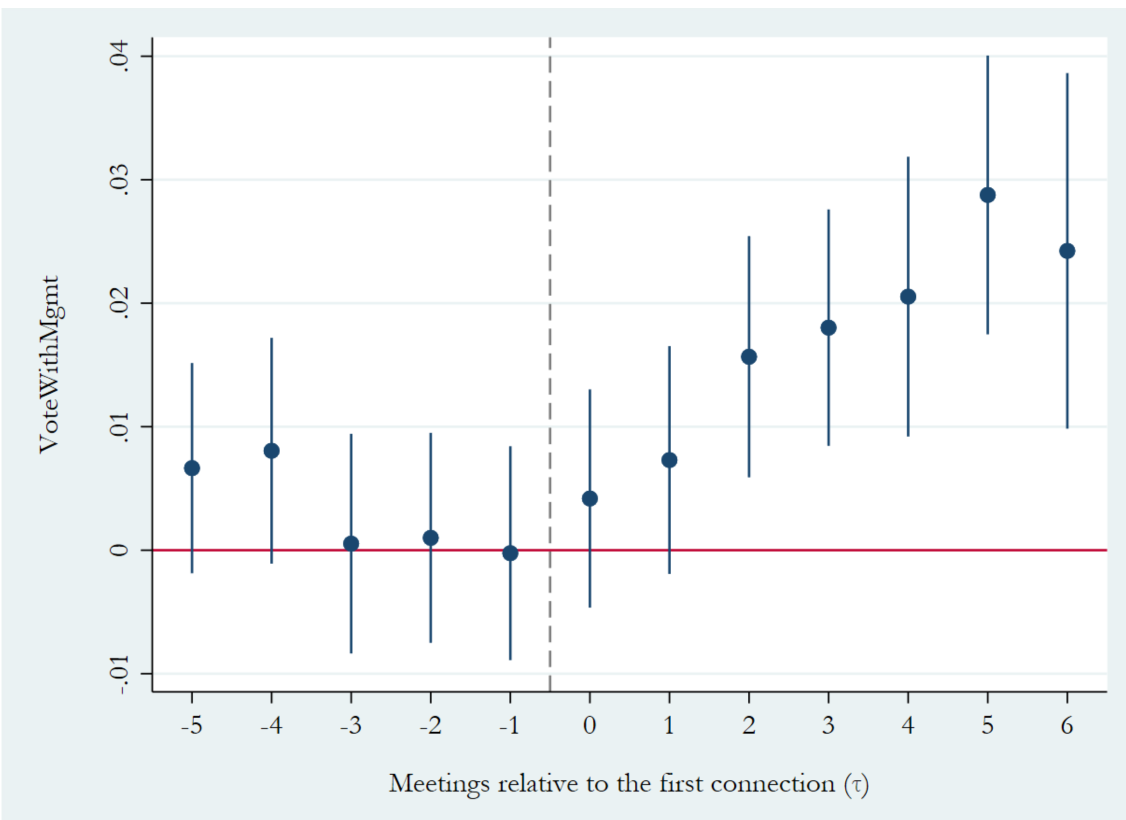


Table 3.1.
Summary Statistics

This table reports descriptive statistics of the main variables employed in the empirical analysis. The sample period is 2004-2019. Panel A depicts the number of firms, funds, unique fund families, and proposals in the sample. Panel B reports statistics for different subsamples of proposals based on proposal sponsorship and voting conflicts, while Panel C shows those by proposal item. These statistics include the percentage of management recommendations, the percentage of ISS recommendations, and the passing likelihood of proposals. Panel D reports descriptive statistics of the main variables employed in the empirical analysis, including the number of observations (NObs), mean (Mean), standard deviation (Stdev), 25th percentile (25th), median (Median), and 75th percentile (75th). The appendix details the definition of all the variables. All continuous variables are winsorized at the 1st and 99th percentiles.

	Panel A: Sample Composition	
	N	% Connected
	(1)	(2)
Firm	2435	40.78
Fund	12839	57.96
Fund Family	150	88.00
Proposal	62853	28.55

	Panel B: Proposal Characteristics			
	N	% Mgmt For	% ISS For	% Passed
	(1)	(2)	(3)	(4)
Management Sponsored	52207	93.88	85.26	95.52
Shareholder Sponsored	10646	31.33	43.99	14.34
Contentious	12456	62.64	37.36	49.16
CloseCall	2942	59.96	68.12	57.55

	Panel C: Proposal Items			
	N	% Mgmt For	% ISS For	% Passed
	(1)	(2)	(3)	(4)
Auditor	21853	99.83	93.70	97.99
Compensation	23427	96.71	81.92	94.41
E&S	2335	0.51	49.42	1.17
Entrenchment	2764	54.56	81.95	62.31
Disclosure	796	0.63	72.99	0.76

Table 3.1 - Continued
Summary Statistics

	Panel D: General Characteristics					
	N	Mean	STDev	25th Percentile	Median	75th Percentile
	(1)	(2)	(3)	(4)	(5)	(6)
VoteWithMgmt	13405443	0.857	0.35	1.000	1.000	1.000
Connected	13405443	0.060	0.24	0.000	0.000	0.000
ISS Voting	13405443	0.876	0.09	0.815	0.886	0.953
#Common Lobbyists	13405443	0.080	0.37	0.000	0.000	0.000
Fund Family Lobby Expense	13405443	0.395	2.16	0.000	0.000	0.000
Firm Lobby Expense	13405443	0.426	2.33	0.000	0.000	0.000
Forecast Error	12801276	0.025	0.10	0.001	0.004	0.011
Forecast Dispersion	12647298	0.010	0.04	0.001	0.002	0.005
Volatility	13326039	0.019	0.01	0.011	0.015	0.022
E-Index	11061976	1.936	1.50	1.000	2.000	3.000
Board Indep.	12465520	0.830	0.10	0.778	0.857	0.900
Dual Class Shares	11061976	0.059	0.24	0.000	0.000	0.000
UD Law	13405443	0.120	0.32	0.000	0.000	0.000

Table 3.2.
Effect of Lobbying Connections on Mutual Fund Voting

This table reports the impact of lobbying connections on mutual funds pro-management voting behavior using the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} + MgmtSponsored_k + FE + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. $MgmtSponsored_k$ is a dummy variable that is equal to 1 if the proposal is sponsored by management and zero otherwise. In columns 1-5, I report results using different sets fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0276***	0.0284***	0.0275***	0.0061***	0.0060***
	(11.09)	(31.63)	(11.05)	(7.00)	(6.90)
MgmtSponsored	0.2785***	0.2679***		0.2785***	
	(65.07)	(62.12)		(65.00)	
Observations	13405443	13405443	13405443	13405443	13405443
Adjusted R^2	0.200	0.155	0.434	0.256	0.490
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes

Table 3.3.
Effect of Lobbying Connection for Different Types of Proposals

This table reports the impact of lobbying connections on mutual funds pro-management voting behavior in different subsamples of voting items. Panel A focuses on broad categories of items while Panel B studies different types of items related to information disclosure. Selection criteria of items used in different subsamples are explained in the appendix. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. Fund-by-Year and Proposal fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Subsamples Based on the Type of Proposals					
	Say-On-Pay Freq.	Auditor	Compensation	E&S	Entrenchment	Disclosure
	(1)	(2)	(3)	(4)	(5)	(6)
Connected	0.0126***	0.0008***	0.0021**	-0.0011	0.0076***	0.0086***
	(8.07)	(2.99)	(2.20)	(-0.83)	(3.61)	(4.16)
Observations	611946	4045103	4915175	1038942	782200	362150
Adjusted R^2	0.634	0.520	0.460	0.538	0.631	0.680
Fund × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: Subsamples for Different Types of Disclosure Proposals			
	Lobby Disclosure	Political Contribution Disclosure	Executive Compensation Disclosure	Proxy Voting Disclosure
	(1)	(2)	(3)	(4)
Connected	0.0154***	0.0009	0.0338**	0.0982*
	(4.87)	(0.37)	(2.15)	(1.69)
Observations	132105	215045	6540	414
Adjusted R^2	0.728	0.686	0.657	0.042
Fund × Year FE	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes

Table 3.4.
Size of Lobbying Contracts and Mutual Fund Voting

This table studies how the number of common lobbyists or the size of lobbying expenses impact the pro-management voting behavior of connected funds. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} \times Inter + \beta_2 Connected_{j,f,q} + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. *Inter* is equal to three different proxies for the strength of lobbying connection for which the detailed definition is provided in the appendix. Fund-by-Year and Proposal fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt		
	(1)	(2)	(3)
Connected × #Common Lobbyists	0.0050***		
	(5.66)		
Connected × Fund Family Lobby Expense		0.0041***	
		(3.96)	
Connected × Firm Lobby Expense			0.0021*
			(1.85)
Connected	-0.0002	0.0036***	0.0047***
	(-0.15)	(3.99)	(5.09)
Observations	13405443	13405443	13405443
Adjusted R^2	0.490	0.490	0.490
Fund × Year FE	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes

Table 3.5.
Information Acquisition

This table examines the differential impact of lobbying connections across funds with higher information processing capacity and firms with worse information environment. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} \times Inter + \beta_2 Connected_{j,f,q} + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. *Inter* shows variables related to information processing and asymmetry for which the detailed definition is provided in the appendix. Fund-by-Year and Proposal fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt					
	(1)	(2)	(3)	(4)	(5)	(6)
Connected × Volatility	-0.0184					
	(-0.32)					
Connected × Amihud Illiquidity		0.0034				
		(0.33)				
Connected × Bid-Ask Spread			-0.0037			
			(-0.45)			
Connected × Intangibility				-0.0032		
				(-1.35)		
Connected × #Analysts					0.0000	
					(0.30)	
Connected × Analysts Forecast Error						-0.0111
						(-1.15)
Connected	0.0062***	0.0059***	0.0061***	0.0064***	0.0054***	0.0059***
	(4.32)	(6.80)	(5.66)	(6.28)	(4.52)	(6.75)
Observations	13360037	13360037	13358656	13047402	13206459	13156392
Adjusted R^2	0.490	0.490	0.490	0.491	0.489	0.489
Fund × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.6.
Conflict of Interest

This table examines the differential impact of lobbying connections across firms with different levels of governance. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} \times Inter_{f,y} + \beta_2 Connected_{j,f,q} + \lambda_{i,y} + \omega_k + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. $Inter_{f,y}$ shows variables that indicate the value of funds' support for managers. Detailed definition of these variables are provided in the appendix. Fund-by-Year and Proposal fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt					
	(1)	(2)	(3)	(4)	(5)	(6)
Connected × E-Index	-0.0023***					
	(-4.41)					
Connected × Board Indep.		0.0338***				
		(5.30)				
Connected × Dual Class Shares			-0.0183***			
			(-8.40)			
Connected × UD Law				-0.0037**		
				(-2.52)		
Connected × Contentious					0.0640***	
					(7.44)	
Connected × Contested						0.0473***
						(7.75)
Connected	0.0072***	-0.0229***	0.0056***	0.0063***	-0.0118***	0.0024***
	(5.19)	(-4.27)	(6.42)	(6.67)	(-6.63)	(3.58)
Observations	11061827	12465388	11061827	13405443	13405443	13405443
Adjusted R^2	0.482	0.486	0.482	0.490	0.491	0.490
Fund × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.7.
Connections Affected by Mergers and Acquisition Between Fund Families

This table reports the impact of lobbying connections that are either arisen or destructed by incidence of mergers and acquisitions among institutional investors. In fact, votes of connected funds are excluded if a connection is neither created nor destructed by a mergers and acquisitions. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} + MgmtSponsored_k + FE + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. $MgmtSponsored_k$ is a dummy variable that is equal to 1 if the proposal is sponsored by management and zero otherwise. In columns 1-5, I report results using different sets fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0386***	0.0285***	0.0384***	0.0093***	0.0095***
	(6.14)	(7.13)	(6.08)	(3.23)	(3.26)
MgmtSponsored	0.2835***	0.2713***		0.2835***	
	(61.52)	(58.17)		(61.44)	
Observations	11414412	11414413	11414412	11414412	11414412
Adjusted R^2	0.204	0.155	0.442	0.259	0.499
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes

Table 3.8.
Connections Affected by Mergers and Acquisitions Between Lobbying Firms

This table reports the impact of lobbying connections that are either arisen or destructed by incidence of mergers and acquisitions among lobbying firms. In fact, votes of connected funds are excluded if a connection is neither created nor destructed by a mergers and acquisitions. I use the following regression specification:

$$VoteWithMgmt_{i,j,f,k,q} = \beta_0 + \beta_1 Connected_{j,f,q} + MgmtSponsored_k + FE + \epsilon_{i,j,f,q,k}$$

where $VoteWithMgmt_{i,j,f,k,q}$ is equal to 1 if fund i of fund family j votes with management to voting item k of firm f in quarter q of year y and zero otherwise. $Connected_{j,f,q}$ is a dummy variable that equals 1 if fund family j is connected to firm f in quarter q by hiring a common lobbying firm. $MgmtSponsored_k$ is a dummy variable that is equal to 1 if the proposal is sponsored by management and zero otherwise. In columns 1-5, I report results using different sets fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: VoteWithMgmt				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0803***	0.0196**	0.0818***	0.0278***	0.0292***
	(7.20)	(2.00)	(7.48)	(3.09)	(3.28)
MgmtSponsored	0.2886***	0.2763***		0.2886***	
	(65.78)	(62.52)		(65.71)	
Observations	12598887	12598887	12598887	12598887	12598887
Adjusted R^2	0.205	0.157	0.440	0.259	0.495
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes

Table 3.9.
Connected Funds' Support and Voting Outcome

This table examines how the presence of connected mutual funds and their support for management impacts the voting outcome. To do so, I collapse the sample with regards to proposals and run the following regression:

$$Mgmt\ Favorite\ Outcome_{f,k,y} = \beta_0 + \beta_1 Support\ Measure_k + \Gamma Controls + \lambda_y + \omega_f + \epsilon_{f,k,y}$$

where $Mgmt\ Favorite\ Outcome_{f,k,y}$ is equal to 1 if proposal k's result is aligned with management recommendation and zero otherwise. In columns 1-3, $Pct\ of\ Funds\ Connected$ is equal to the ratio of funds that are connected to the firm at proposal k's meeting. In column 4, I focus on the subsample proposals that have at least one connected funds. $Pct\ of\ VoteWithMgmt$ shows that ratio connected funds that vote pro-management. In columns 2 and 3, I use *Contentious* and *Contested* interaction variables that show the level of conflict among voters. *Contentious* is a dummy variable that equals 1 if the ISS recommendation is different from the management recommendation and zero otherwise. *Contested* is a dummy variable that equals 1 if the voting result is within 10% of the threshold that passes the item and zero otherwise. I include Firm and Year fixed effects in all regressions. Control variables are defined in the appendix. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the fund level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Mgmt Favorite Outcome			
	(1)	(2)	(3)	(4)
Pct of Funds Connected	0.1051** (2.09)	-0.1751*** (-3.82)	0.0904* (1.75)	
Pct of VoteWithMgmt				0.3200*** (19.00)
Pct of Funds Connected × Contentious		1.0258*** (13.72)		
Pct of Funds Connected × Contested			0.2023* (1.93)	
Contentious		-0.2754*** (-32.83)		
CloseCall			-0.1199*** (-10.18)	
MgmtSponsored	0.3058*** (24.49)	0.1573*** (13.85)	0.2964*** (22.97)	0.0269*** (2.92)
Size	0.0163*** (3.94)	0.0125*** (3.35)	0.0167*** (4.04)	-0.0024 (-0.28)
ROA	0.0249 (1.09)	0.0105 (0.50)	0.0230 (0.99)	0.0249 (0.57)
MB	-0.0005 (-1.38)	-0.0003 (-1.00)	-0.0005 (-1.54)	-0.0002 (-0.35)
Leverage	-0.0661*** (-3.22)	-0.0590*** (-3.12)	-0.0656*** (-3.15)	0.0403 (1.35)
Stock Return	0.0032 (0.88)	0.0005 (0.14)	0.0025 (0.68)	0.0107 (1.48)
Tangibility	-0.0119 (-0.55)	-0.0083 (-0.42)	-0.0134 (-0.61)	-0.0170 (-0.41)
Age	0.0041 (0.37)	0.0054 (0.54)	0.0033 (0.29)	0.0201 (1.48)
IO	0.0222** (2.19)	0.0118 (1.28)	0.0218** (2.14)	0.0144 (0.91)
Observations	58773	58773	58773	17026
Adjusted R^2	0.357	0.421	0.363	0.265
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 3.10.
Lobbying Connections and Market Reaction to Voting Outcome

This table examines the impact of connected mutual funds support on market reaction to the voting outcome. To do so, I focus on the subsample of Contested proposals having at least one connected mutual fund. Moreover, I include only proposals that either pass or fail. Last, firms having more than one eligible proposal in a given day are excluded. I run the following regression:

$$CAR[-1,+1] = \beta_0 + \beta_1 Pct\ of\ VoteWithMgmt \times Mgmt\ Unsuccessful + \beta_2 Pct\ of\ VoteWithMgmt + \beta_3 Mgmt\ Unsuccessful + \epsilon$$

where $CAR[-1,+1]$ is defined as market-adjusted cumulative abnormal return in a three-day period around a meeting. $Pct\ of\ VoteWithMgmt$ shows that ratio connected funds that vote pro-management. $Mgmt\ Unsuccessful$ is equal to 1 if a proposal's result is against management recommendation and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Pct of VoteWithMgmt × Mgmt Unsuccessful	0.0188**
	(2.43)
Mgmt Unsuccessful	-0.0083*
	(-1.77)
Pct of VoteWithMgmt	-0.0050
	(-1.28)
Observations	675
Adjusted R^2	0.004

4. Appendix

4.1. Chapter 1

Table 4.1.
Variable Definition and Data Source

Variable	Definition and Data Source
Main Variables	
VolDisc	Natural logarithm of one plus the number of management earnings forecasts issued over the fiscal year. (I/B/E/S)
Good News	Natural logarithm of one plus the number of management earnings forecasts that beat analysts' consensus over the fiscal year. (I/B/E/S)
Bad News	Natural logarithm of one plus the number of management earnings forecasts that have shortfall relative to analysts' consensus over the fiscal year. (I/B/E/S)
Conglo	Dummy variable which is equal to one if the number of business segments is greater than one and zero otherwise. (Compustat)
#Seg	The number of business segments reported in Compustat Historical Segment database. (Compustat)
Comp	Sales dispersion measure (i.e., 1-HHI) across different business segments where HHI is the Herfindahl-Hirschman index and is computed as the sum of squares of segments' sales as a fraction of aggregate firm sales. (Compustat)
Control Variables	
ReadIndex	The first principal component of six readability indices, namely, Flesch Kincaid, Fog Index, LIX, RIX, ARI, and SMOG. (Bill McDonald's Website)
Size	Natural logarithm of one plus the book value of assets. (Compustat)
MB	Market value of equity over the book value of common equity. (Compustat)
Loss	A dummy variable that is equal to one when firms have negative net income and zero otherwise. (Compustat)
Leverage	Long-term debt plus short-term debt scaled by total assets. (Compustat)
ROA	Ratio of income before extraordinary items scaled by assets in the previous year. (Compustat)
SpecialItems	Special items scaled by assets in the previous year. (Compustat)
Volatility	The standard deviation of monthly stock returns over the fiscal year. (CRSP)
Return	The geometric sum of monthly stock returns over the fiscal year. (CRSP)
Tangibility	Gross property, plant, and equipment scaled by total assets. (Compustat)
CapEx	Capital expenditure divided by total assets. (Compustat)
Beta	CAPM beta calculated over one-year period. (CRSP)
Identification Strategy Variables	
MI	A dummy variable equal to one if a firm reports non-zero minority interest on its balance sheet and zero otherwise. (Compustat)
PNDIV	The proportion of conglomerates in each industry-year, where industries are defined based on the Fama-French 48 industry classification. (Compustat)
M&A	A dummy variable equal to one if a firm engaged in a merger or acquisition activity, for three years. (SDC)

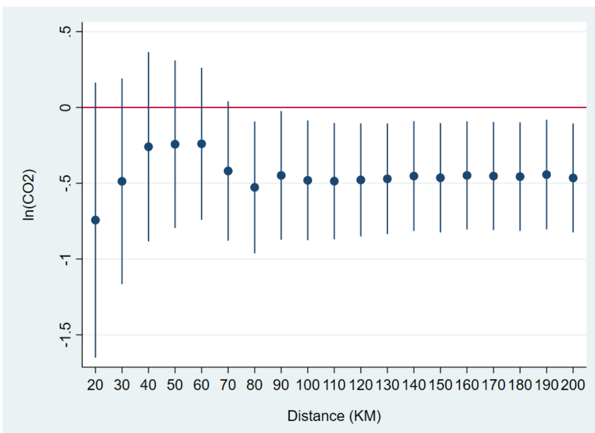
Table 4.1 - Continued

Variable	Definition and Data Source
Information Environment Variables	
Turnover	The sum of share trading volume over the fiscal year divided by the number of shares outstanding at the beginning of the year. (CRSP)
Analyst Forecast Error	Analyst consensus minus actual EPS divided by the stock price. (IBSES)
Price Nonsynchronicity	(1-R2), where R2 is the R^2 from a regression of a firm's daily stock returns on a constant, the CRSP value-weighted market return, and the return of the 3-digit SIC industry portfolio. (CRSP)
Cross-Sectional Variables	
Institutional Ownership	The fraction of the firm's shares outstanding owned by institutional investors. (Thomson-Reuters' Institutional (13f) Holdings Database)
Number of Analysts	The number of analysts following the firm who issue EPS forecasts. (I/B/E/S)
Managerial Intention	Proxied by Delta, defined as the change in the dollar value of the CEO's wealth for a one percentage point change in stock price. (Lalitha Naveen's Website)
Financial Outcome Variables	
Firm Value	Proxied by Tobin's Q, defined as the book value of total assets plus the market value of common stock minus the book value of common equity, divided by the book value of total assets. (Compustat)
Implied Cost of Equity Capital	A composite of characteristic based cost of capital measures. (Lee, So, and Wang, 2021)
Cost of Debt Capital	Total interest and related expenses scaled by total assets and multiplied by 100. (Compustat)
Readability Indices	
Flesch Kincaid	0.39 × (Number of words / Number of sentences) + 11.8 × (Number of syllables / Number of words) – 15.59
Fog Index	0.4 × (Avg number of words per sentence + Percent of complex words)
LIX	(Number of words / Number of sentences) + (Number of words over 6 letters × 100/ Number of words)
RIX	(Number of words with 7 characters or more) / (Number of sentences)
ARI	4.71 × (Number of characters / Number of words) + 0.5 × (Number of words / Number of sentences) - 21.43
SMOG	1.043 × sqrt (30 × Number of words with more than two syllables / Number of sentences) + 3.1291

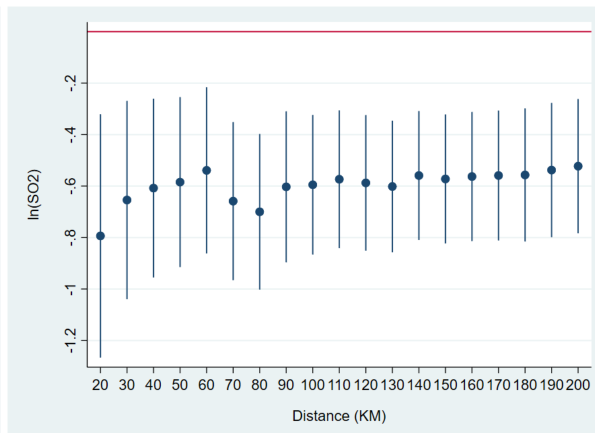
4.2. Chapter 2

Figure 4.1.
Robustness of Baseline Results to Geographical Distance of Control Group

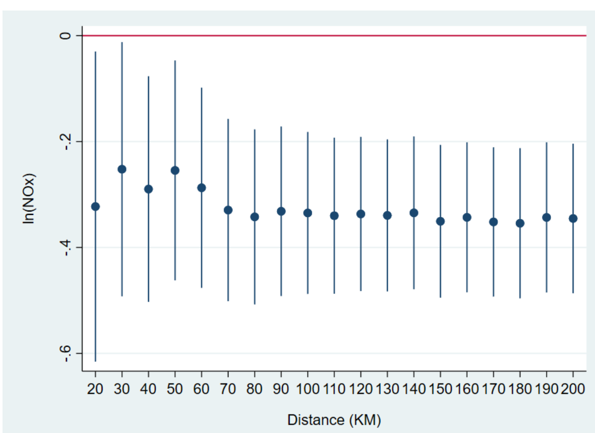
This figure depicts the robustness of baseline results to the choice of the geographical distance that is used to select the control group. Subfigures (a)-(d) show the robustness of results for CO2, SO2, NOx emissions, and electricity generation, respectively. Each subfigure plots estimated coefficients and their 95% confidence intervals.



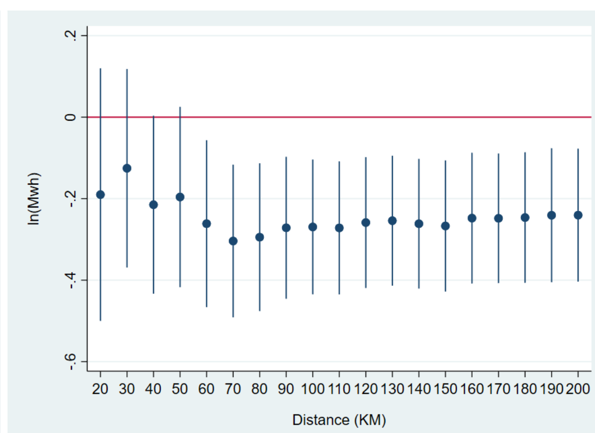
(a) CO2 emissions



(b) SO2 emissions



(c) NOx emissions



(d) Electricity Generation

Table 4.2.
Variable Definition

Variable	Definition and Data Source
ln(CO2)	Natural logarithm of 1 plus plant's total CO2 emissions in tons. (EPA's CAMD).
ln(SO2)	Natural logarithm of 1 plus plant's total SO2 emissions in tons. (EPA's CAMD).
ln(NOx)	Natural logarithm of 1 plus plant's total NOx emissions in tons. (EPA's CAMD).
ln(MWh)	Natural logarithm of 1 plus the net electricity generation in MWh (EIA-923).
$EnforceExposure_1$	For each power plant, it is calculated as the number of air enforcement actions that other power plants receive in the same county-year multiplied the share of plant's from total county capacity.
$EnforceExposure_2$	For each power plant, it is calculated as the number of air enforcement actions that other power plants receive divided by the total number of operating power plants in each county-year.
ln(Scrubbers)	Natural logarithm of 1 plus the number of scrubbers being used in power plants (EIA-860 and EIA-767). Data is only available for plants with steam-electric capacity of 10MW or more and this data is not available in 2006.
ln($Abatement)	Natural logarithm of 1 plus new structures and/or equipment purchased to reduce, monitor, or eliminate airborne pollutants during the year in million dollars (EIA-923). Data is only available for plants with steam-electric capacity of 10MW or more and this data is not available in 2006 and 2007.
ln(Generators)	Natural logarithm of one plus the number of newly constructed generators during the year (EIA-860).
ln(Steam)	Natural logarithm of one plus the number of newly constructed steam generators during the year (EIA-860).
ln(Gas Turbine)	Natural logarithm of one plus the number of newly constructed gas turbines during the year (EIA-860).
ln(Internal Combust.)	Natural logarithm of one plus the number of newly constructed internal combustion generators during the year (EIA-860).
ln(Combined Cycle)	Natural logarithm of one plus the number of newly constructed combined cycle generators during the year (EIA-860).
ln(Coal MMBTU)	Natural logarithm of 1 plus the total MMBTUs of heat from coal (EIA-923).
ln(Petro MMBTU)	Natural logarithm of 1 plus the total MMBTUs of heat from petroleum (EIA-923).
ln(Gas MMBTU)	Natural logarithm of 1 plus the total MMBTUs of heat from gas (EIA-923).
Coal Share	The ratio of coal heat input divided by the total heat input from all types of fossil fuels. (EIA-923).
Petro Share	The ratio of petroleum heat input divided by the total heat input from all types of fossil fuels.
Gas Share	The ratio of gas heat input divided by the total heat input from all types of fossil fuels.
ln(Fuel $/MMBTU)	Natural logarithm of 1 plus the average costs of fuel per unit of heat (EIA-923, EIA-423 and FERC-423).
ln(Sulfur)	Natural logarithm of 1 plus the total tons of sulfur (EIA-923 and EIA-767).
ln(Sulfur/MMBTU)	Natural logarithm of 1 plus the total lb of sulfur per MMBTU of heat (EIA-923 and EIA-767).
ln(Coal Sulfur/MMBTU)	Natural logarithm of 1 plus the lb of sulfur per MMBTU of coal heat (EIA-923 and EIA-767).
ln(Petro Sulfur/MMBTU)	Natural logarithm of 1 plus the lb of sulfur per MMBTU of petroleum heat (EIA-923 and EIA-767).

Table 4.2 - Continued
Variable Definition

Variable	Definition and Data Source
ln(MWh/MMBTU)	Natural logarithm of 1 plus the net electricity generation divided by total heat input (EIA-923).
ln(Coal MWh/MMBTU)	Natural logarithm of 1 plus the net electricity generation using coal divided by total heat input from coal (EIA-923).
ln(Petro MWh/MMBTU)	Natural logarithm of 1 plus the net electricity generation using oil divided by total heat input from oil (EIA-923).
ln(Gas MWh/MMBTU)	Natural logarithm of 1 plus the net electricity generation using gas divided by total heat input from gas (EIA-923).
Distance	The average distance in hundreds of kilometers between targeted plants and their siblings in the year of enforcement action. (EIA-860).
Siblings Coal Share	The ratio of the heat extracted from burning coal divided by total heat used in siblings. (EIA-923).
Siblings Petro Share	The ratio of the heat extracted from burning petro divided by total heat used in siblings. (EIA-923).
Siblings Gas Share	The ratio of the heat extracted from burning gas divided by total heat used in siblings. (EIA-923).
#Bank Branches	The number of bank branches located in the county of targeted plants in the year of enforcement action. (FDIC Summary of Deposits).
SB Loans	The total amount of small business loans (in million dollars) approved by the U.S. Small Business Administration in the year of enforcement action to all borrowers located in targeted plants' county. (U.S. Small Business Administration Website)
ln(Assets $ B)	Natural logarithm of 1 plus total assets of utility firms in billion dollars.
ln(Longterm Debt)	Natural logarithm of 1 plus long-term debts of utility firms divided by total assets.
ln(Operating Revenue)	Natural logarithm of 1 plus operating revenue divided by total assets.
ln(Production Expenses)	Natural logarithm of 1 plus production expenses divided by total assets.
ln(Operating Income)	Natural logarithm of 1 plus operating income divided by total assets.
ln($/MWh)	Natural logarithm of 1 plus the average price of electricity sold to different wholesale and retail customers.

Table 4.3.
Emission Intensity

This table reports the effect of EPA enforcement on emission intensity defined as tones of emission emitted per GWh of electricity production. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The control group consists of plants within 100 kilometers radius around the treated ones, but neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equal 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. Table A1 details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(CO2/GWh)	ln(SO2/GWh)	ln(NOx/GWh)
	(1)	(2)	(3)
Post × Treated	-0.132	-0.163***	-0.057**
	(-1.27)	(-4.19)	(-2.19)
Observations	12820	12820	12820
Adjusted R^2	0.824	0.852	0.840
Cohort × Year FE	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes

Table 4.4.
Plant Share, Capacity Factor, and EPA Enforcement Action

This table reports the effect of EPA enforcement on Plant Share and Capacity Factor of targeted power plants. Plant Share is defined as plant's electricity generation divided by the parent utility firm's generation. CapFactor is equal to the ratio of the electricity that is generated throughout the year to the maximum amount of the electricity that could be generated using 100% of capacity. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The control group consists of plants within 100 kilometers radius around the treated ones, but neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equal 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Plant Share	CapFactor
	(1)	(2)
Post × Treated	-0.014	-0.043***
	(-0.95)	(-3.56)
Observations	12820	12820
Adjusted R^2	0.873	0.848
Cohort × Year FE	Yes	Yes
Cohort × Plant FE	Yes	Yes

Table 4.5.
Baseline Results for the Subsample Used in Instrumental Variable Analysis

This table reports shows baseline results for the subsample that has been used in Table **2.3** in which controls plants located in the same county as the treated ones are excluded. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The control group consists of plants within 100 kilometers radius around the treated ones, but neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equal 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. Table A1 details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.395*	-0.553***	-0.324***	-0.263***
	(-1.95)	(-3.90)	(-4.22)	(-3.16)
Observations	11715	11715	11715	11715
Adjusted R^2	0.857	0.906	0.919	0.901
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 4.6.
Plants' Age and EPA Enforcement Actions

This table reports how a plant's age impacts the effectiveness of EPA enforcement actions on multi-plant utility firms. Plant's age is calculated as the average age of all operating generators. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The control group consists of plants within 100 kilometers radius around the treated ones, but neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equals 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated × Age	-0.060***	-0.059***	-0.038***	-0.035***
	(-5.58)	(-8.31)	(-9.27)	(-7.06)
Post × Treated	1.209***	1.063***	0.732***	0.719***
	(3.04)	(4.83)	(6.38)	(5.51)
Observations	12820	12820	12820	12820
Adjusted R^2	0.855	0.905	0.920	0.903
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 4.7.
Robustness of Results to the Choice of Control Group

This table reports the robustness of baseline finding to different control group choices. In Panel A, control group consists of three power plants with the closest nameplate capacity in the same state as targeted plants. In Panel B, control group consists of three power plants that are located in the same state as the targeted one and have the highest fuel mix similarity measured by Cosine Similarity ratio. In Panel C, control group consists of three power plants that are located in the same state as the targeted one and are closest in terms of age. In Panel D, control group consists of all power plants that are located in the same state as the targeted one and are similar to the targeted plant in terms of having or not having a coal- or oil-fired steam generator. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The Post dummy equals 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants matched to it. All continuous variables are winsorized at the 1st and 99th percentiles. Table A1 definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Control Group Based on Nameplate Capacity			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.468***	-0.513***	-0.382***	-0.251***
	(-2.69)	(-4.41)	(-5.54)	(-3.19)
Observations	8251	8251	8251	8251
Adjusted R^2	0.871	0.929	0.920	0.875
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel B: Control Group Based on Fuel Mix Similarity			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.349*	-0.482***	-0.366***	-0.245***
	(-1.93)	(-3.63)	(-5.35)	(-3.21)
Observations	8190	8190	8190	8190
Adjusted R^2	0.876	0.917	0.931	0.893
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 4.7 - Continued
Robustness of Results to the Choice of Control Group

	Panel C: Control Group Based on Age			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.205	-0.343***	-0.315***	-0.198**
	(-1.34)	(-3.29)	(-5.11)	(-2.02)
Observations	8260	8260	8260	8260
Adjusted R^2	0.910	0.938	0.936	0.827
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel D: Control Group Based on Coal-/Oil-fired Steam Generation			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.437**	-0.306**	-0.153**	-0.079
	(-2.16)	(-2.14)	(-2.01)	(-0.94)
Observations	18866	18866	18866	18866
Adjusted R^2	0.878	0.906	0.940	0.913
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

Table 4.8.
Robustness to Enforcement Actions' Penalty Size

This table reports the robustness of baseline finding to inclusion of enforcement actions with different penalty sizes. In Panel A and B, I include all enforcement actions with a total penalty greater than \$0 and \$10,000, respectively. The Treated dummy equals 1 if the plant receives an enforcement action and 0 otherwise. The control group consists of plants within 100 kilometers radius around the treated ones, but neither received any enforcement action themselves nor experienced any in one of their siblings. The Post dummy equal 1 after the first enforcement action. Each cohort consists of one treated plant and the control plants surrounding it. All continuous variables are winsorized at the 1st and 99th percentiles. The appendix details the definition of all the variables. t-statistics are reported in parentheses. Standard errors are clustered at the plant-cohort level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Enforcement Actions with higher than \$0 Penalty			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.334*	-0.467***	-0.224***	-0.194**
	(-1.86)	(-3.72)	(-3.27)	(-2.54)
Observations	13953	13953	13953	13953
Adjusted R^2	0.842	0.897	0.921	0.912
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

	Panel B: Enforcement Actions with higher than \$10,000 Penalty			
	ln(CO2)	ln(SO2)	ln(NOx)	ln(MWh)
	(1)	(2)	(3)	(4)
Post × Treated	-0.418*	-0.610***	-0.395***	-0.318***
	(-1.87)	(-3.85)	(-4.61)	(-3.25)
Observations	11664	11664	11664	11664
Adjusted R^2	0.846	0.912	0.917	0.894
Cohort × Year FE	Yes	Yes	Yes	Yes
Cohort × Plant FE	Yes	Yes	Yes	Yes

4.3. Chapter 3

Table 4.9.
Definition for Different Types of Proposals

This table reports the definition and selection criteria for different subsamples of proposals based on their types and context. These categories are not mutually exclusive and some items can exist in more than one group. ISSAgendaItemIDs of items included in each category are provided in parentheses.

Item Type	Definition
Say-On-Pay Freq.	Shareholders' advisory votes on Say on Pay frequency. (M0552)
Auditor	Votes on ratification of auditors. (M0101)
Compensation	Compensation related items are those that contain any of the following keywords in their description: "COMPENSATION", "STOCK PLAN", "BONUS PLAN", "STOCK PURCHASE PLAN", "STOCK OPTION PLAN", "DIRECTOR STOCK AWARDS", "DOUBLE TRIGGER ON EQUITY PLANS", "PAY FOR SUPERIOR PERFORMANCE", and "APPROVE REPRICING OF OPTIONS". (M0550, M0524, M0522, M0535, M0512, S0517, M0510, S0527, M0599, M0598, S0511, M0503, M0548, S0520, M0516, M0526,M0501,M0509, M0514, M0547, S0504, M0597, M0507, S0508, M0596, M0538, M0525, S0503, M0554, M0555, S0515, S0531, S0521, S0532, M0558, S0526, M0556, S0204, M0506, M0588, and M0504)
E&S	It includes items related to corporate environmental and social practices. These items are identified by search the follow keywords in item descriptions: "HUMAN RIGHT", "EMISSIONS", "TOXIC", "CLIMATE CHANGE", "SOCIAL", "ENVIRONMENAL", "SEXUAL", "REPORT ON EEO", "GENDER", "DISPARITY", "DIVERSITY", "RECYCLING", "RENEWABLE", "HEALTH", "SAFETY", "ANIMAL", "DISCRIMINATION", "TOBACCO", "WEAPONS", "DRUG PRICING", "FAIR LENDING", "NUCLEAR", "ENERGY", "PROTECTED AREAS", "WOOD", "GLASS CEILING", "CHARITABLE", "CERES PRINCIPLES", and "POLITICAL". (S0807, S0808, S0999, S0414, S0743, S0742, S0911, S0510, S0811, S0812, S0817, S0809, S0507, S0227, S0206, S0781, S0779, S0735, S0806, S0738, S0412, S0890, S0891, S0224, S0815, S0734, S0725, S0729, S0710, S0602, S0709, S0703, S0892, S0733, S0780, S0745, S0741, S0778, S0708, S0814, S0737, S0732, S0704, M0127, S0711, S0728, and S0416)
Entrenchment	It includes all items related to board declassification, supermajority voting, independent board chair, poison pill, and golden parachute provisions. (S0107, S0201, S0311, M0566, S0302, M0609, S0332, M0605, M0606, M0607, S0303, and M0559)
Disclosure	It includes items that are related to companies information disclosure. These items encompass disclosure regarding political contributions (S0807), political lobbying (S0808), executive compensation (S0503), and proxy voting (S0308).
Lobby Disclosure	Votes on political lobbying disclosure (S0808).
Political Contribution Disclosure	Votes on political contribution disclosure. (S0807)
Executive Compensation Disclosure	Votes regarding the increase in disclosure of executive compensation (S0503).
Proxy Voting Disclosure	Votes on proxy voting disclosure (S0308).

Table 4.10.
Variable Definition

Variable	Definition
VoteWithMgmt	A dummy variable that equals 1 if mutual funds follow management recommendation and zero otherwise.
Connected	A dummy variable that equals 1 if a fund-firm pair have a common lobbyist and zero otherwise.
MgmtSponsored	A dummy variable that equal 1 if a proposal is sponsored by management and zero otherwise.
#Common Lobbyists	The number lobbying firms that are simultaneously hired by the mutual funds and their portfolio firms in a given quarter.
Family Lobby Expense	Total monetary amount (in $100,000) that is paid by each fund family to common lobbyists in a given quarter.
Firm Lobby Expense	Total monetary amount (in $100,000) that is paid by each firm to common lobbyists in a given quarter.
Analysts Forecast Error	The absolute value of the difference between median analysts forecast and the actual annual EPS for the last fiscal year divided by the stock price.
#Analysts	The number of analysts issuing annual EPS forecast for the last fiscal year.
Volatility	Volatility of daily stock return over the last fiscal year before the meeting.
Amihud Illiquidity	Average daily Amihud illiquidity over the last fiscal year before the meeting. Following Amihud (2002), this measure is calculated as absolute return divided by trading volume multiplied by 10^6.
Bid-Ask Spread	Average daily bid-ask spread over the last fiscal year before the meeting.
Intangibility	Calculated as intangible assets divided by total assets at the end of last fiscal year before the meeting.
Analysts Forecast Error	Defined as the difference between the analyst consensus forecast and actual earnings per share divided by the stock price for the last fiscal year.
E-Index	Entrenchment Index calculated following Bebchuk, Cohen, and Ferrell (2008). It shows what number of the six more important governance provisions exist in a given firm. These provisions include Staggered board, Limits to amend bylaws, Limits to amend charter, Supermajority voting requirement, Golden parachutes, and Poison pill.
Board Indep.	Number of independent board members divided by board size.
Dual Class Shares	A dummy variable that is equal to 1 if a firm has dual class shares and zero otherwise.
UD Law	A dummy variable that equals 1 if the firm is incorporated in any of the states with Universal Demand law (GA, MI, FL, WI, MT, VA, UT, NH, MS, NC, AZ, NE, CT, ME, PA, TX, WY, ID, HI, IA, MA, RI, SD) and zero otherwise.
Contentious	A dummy variable that is equal to 1 if management recommends For a proposal but ISS does not and vice versa.
Contested	A dummy variable that equals 1 if the level of support is within 10% of the threshold that passes the item and zero otherwise.
Mgmt Favorite Outcome	A dummy variable that equals 1 when the result of the voting is aligned with management's recommendation (i.e., if a proposal passes when management recommends For and not passes when management does not.)
Mgmt Unsuccessful	A dummy variable that equals 1 when the voting outcome is against management's recommendation.
Pct of Funds Connected	The ratio of voting funds that are connected to firm.
Pct of withMgmt	The proportion of connected funds that vote with management.
Size	Natural logarithm of 1 plus market capitalization at the end of last fiscal year before the meeting.
ROA	Ratio of income before extraordinary items scaled by lagged assets during the last fiscal year before the meeting.
MB	Market value of equity over the book value of common equity at the end of last fiscal year before the meeting.
Leverage	Long-term debt plus short-term debt scaled by total assets at the end of last fiscal year before the meeting.
Stock Return	The geometric sum of monthly stock returns over the last fiscal year before the meeting.
Tangibility	Gross property, plant, and equipment scaled by total assets at the end of last fiscal year before the meeting.
Age	The number of years since the first time that the firm appeared in Compustat.
IO	The proportion of shares outstanding that is owned by institutional investors.

Table 4.11.
Robustness to Different Sample Section Criteria

This table reports the definition and selection criteria for different subsamples of proposals based on their types and context. These categories are not mutually exclusive and some items can exist in more than one group. ISSAgendaItemIDs of items included in each category are provided in parentheses.

	Panel A: All Votes				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0280***	0.0292***	0.0279***	0.0071***	0.0070***
	(11.15)	(29.41)	(11.12)	(7.59)	(7.49)
MgmtSponsored	0.2806***	0.2648***		0.2805***	
	(73.31)	(68.32)		(73.21)	
Observations	23073505	23073506	23073504	23073499	23073498
Adjusted R^2	0.201	0.140	0.443	0.257	0.500
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes
	Panel B: Including Firms and Mutual Funds with at Least One Connection				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0273***	0.0227***	0.0272***	0.0047***	0.0046***
	(10.89)	(28.12)	(10.86)	(6.07)	(5.96)
MgmtSponsored	0.2652***	0.2590***		0.2652***	
	(60.22)	(58.33)		(60.15)	
Observations	9535181	9534797	9535168	9534796	9534783
Adjusted R^2	0.194	0.165	0.421	0.255	0.484
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes
	Panel C: Including Prposals and Mutual Funds with at Least One Connection				
	(1)	(2)	(3)	(4)	(5)
Connected	0.0276***	0.0162***	0.0275***	0.0020***	0.0019***
	(11.09)	(23.75)	(11.06)	(3.33)	(3.17)
MgmtSponsored	0.2500***	0.2447***		0.2500***	
	(59.20)	(57.43)		(59.13)	
Observations	6532462	6531833	6532462	6531833	6531833
Adjusted R^2	0.182	0.169	0.408	0.250	0.478
Firm × Year FE	Yes			Yes	
Fund × Year FE		Yes		Yes	Yes
Proposal FE			Yes		Yes