Essays in Empirical Corporate Finance

by

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Contents

List of Tables

List of Figures

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Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that one paper titled "Seeking Out Non-Public Information: Sell-side Analysts and the Freedom of Information Act", drawn from Chapter Two of this thesis, is co-authored with April Klein and Tao Li. A version of this chapter is under the revision process at the Accounting Review. Furthermore, the paper titled "The Spillover effect of Corporate Fraud: Evidence from Firm-Level Supply Chain Data", drawn from Chapter Four of this thesis, is co-authored with Zhou Zhang.

Bobo Zhang

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Abstract

This thesis consists of three essays in empirical corporate finance. In the first chapter co-authored with April Klein and Tao Li, we document that a number of sell-side healthcare analysts gain access to information outside the purview of management through Freedom of Information Act requests to the Food and Drug Administration for records on factory inspections, complaints, and drug and medical device applications. Using a difference-in-differences methodology, we find that buy (sell) recommendations and upgrades (downgrades) earn higher (lower) stock returns over the year following the receipt of FDA records. We also examine the type of information revealed in FDA factory inspection reports, and find that analysts are less likely to downgrade and are less pessimistic in their recommendations than the consensus recommendation when the information contained in the FDA report is not particularly severe. Our findings are consistent with a subset of analysts utilizing non-public information channels independent of management to gain value-relevant information about their covered firms.

The second chapter of the thesis studies corporate political transparency through the lens of shareholder engagements. We analyse factors explaining activist shareholders' target decisions and likelihood of successful engagements. Using hand-collected public announcements of engagement outcomes, we find that stock market reacts positively to successful engagements and negatively to a subset of unsuccessful engagements in politically active companies. Similar reactions are also found using institutional investors' holding data. Investors' aversion to hidden risk and

disciplinary effect of increased transparency could potentially explain the market reactions. Collectively, the results suggest that stock market investors value political transparency, especially in politically active companies.

In the third chapter co-authored with Zhou Zhang, we study the impact of corporate fraud revelation on linked firms along the supply chain. We show empirically that the revelation of corporate misconduct results in negative short-term market reactions for the stocks of suppliers and customers. The determinants of suppliers' and customers' abnormal returns are analysed to further uncover the main channel of shock propagation. In contrast to previous literature on production shocks, we do not find evidence in support of operation channel. Our results provide support for the reputation channel. We also find the negative shock is amplified by low-quality information environment. Overall, our research suggests that the revelation of corporate fraud imposes negative externalities on upstream and downstream firms, and enhanced corporate information environment and social capital accumulation could help alleviate them.

Chapter 1

Introduction

The thesis consists of three essays in empirical corporate finance. Chapter two documents that a subset of sell-side analysts utilizing non-public information channels independent of management to gain value-relevant information about their covered firms. Chapter three studies corporate political transparency through the lens of shareholder engagements. Chapter four investigates the impact of corporate fraud revelation on linked firms along the supply chain.

The importance of sell-side analysts in capital market has been extensively supported in both academic research and practice. They produce research reports and generate earnings forecasts and stock recommendations on covered firms, which move stock prices [Bradshaw, 2011] and create liquidity within the U.S. stock market [Kelly and Ljungqvist, 2012]. Even though most early studies concentrate on analysts' use of public, quantitative information (e.g., financial statements), a burgeoning area of research has emerged examining their acquisition of private and qualitative sources of information. A common theme in existing researches is that the channel of private information acquisition goes primarily from firm management to analyst. However, many sell-side analysts profess to engage in the acquisition of information outside the purview of management [Brown et al., 2015]. Yet, little has been known on how analysts gather and utilize data not generated by the firm, primarily because it is difficult for researchers to identify specific outside sources analysts use and the dates in which they receive these data.

In chapter two, we seek to bridge the gap by identifying a source of external information used by some healthcare analysts: Freedom of Information Act (FOIA) requests to the Food and Drug Administration (FDA) for FDA-generated records pertaining to healthcare firms. The healthcare industry provides an ideal setting for examining how analysts engage in private information searches. High R&D firms in general, and healthcare firms specifically, are difficult to value with public information only [Lehavy et al., 2011; Bushee et al., 2018; Lev and Zarowin, 1999]. Further, the information is generated by agency independent of company management. Therefore, FOIA requests to the FDA give healthcare analysts a vehicle to gather qualitative information to supplement their public and other private information about their covered firms.

Empirically, we find that buy (sell) recommendations and upgrades (downgrades) earn higher (lower) stock returns over the year following the receipt of FDA records. We also examine the types of information revealed in FDA factory inspection reports, and find that analysts are less likely to downgrade and are less pessimistic in their recommendations than the consensus recommendation when the information contained in the FDA report is not particularly severe. Our findings provide a new peek into a different "black box" of inputs used by sell-side equity analysts when formulating their stock recommendations.

With ever growing corporate political spending and recent regulatory changes on political spending, corporate political transparency (CPT) receives massive public attention. There are voices from politicians, academic scholars, and industry practitioners either supporting or criticising transparency of corporate political spending, as Securities and Exchange Commission (SEC) is considering the possibility to form related regulations in this area. However, until now, we still lack quantitative evidences in many aspects to understand corporate political transparency.

In chapter three, we explore the drivers and implications of corporate political transparency through the lens of shareholder engagements. We first find that there are many more successful shareholder engagements than previous literature have recognized. Most voluntary disclosure classified by previous literature are associated with successful shareholder engagements. They are mostly in the form of settlement agreements between activist shareholders and management. We then find that activist investors tend to target companies with political action committee and lower political transparency level. We also find evidence of repeated engagements. Consistent with institutional investors' superior ability to accumulate shares and coordinate with other investors, we find engagements launched by institutional investors are more likely to be successful. Among the domain of institutional activist investors, we find that SRI funds are best performers and labor unions are worst performers.

In terms of implication, we show that successful shareholder engagements indeed result in much bigger improvement in corporate political transparency, measured by CPA-Zicklin index, compared to unsuccessful engagements. Using market-based tests, we show that stock market reacts positively to successful engagements and negatively to a subset of unsuccessful engagements in politically active companies. Consistent with corporate political transparency lowering hidden risk to investors, the market reactions are stronger when political uncertainty is high. Consistent with the disciplinary effect of corporate political transparency, successful shareholder interventions result in a slower growth of PAC expenditure than unsuccessful interventions in politically active companies. Using quarterly institutional holding data, we find that institutional ownership of successfully engaged companies experiences an increase whilst that of unsuccessfully engaged companies experiences a decrease in medium to long-term, suggesting that institutional investors have a preference for corporate political transparency. Our findings provide support for corporate political transparency from a market perspective.

Corporate fraud revelation has been shown to be detrimental to accused firms themselves [Karpoff et al., 2008b,a]. In an interlinked economy, however, the impact of such revelation is not restricted to accused firms themselves. On the contrary, direct costs imposed on fraudulent firms may only constitute a small portion of overall economic impact of corporate fraud. Prior literature has examined the effect of corporate fraud on industry peers and household stock market participation [Goldman et al., 2012; Giannetti and Wang, 2016]. Given the growing corporate production network and its importance in the economy, it is also crucial to understand the implication of corporate fraud revelation for linked firms along the supply chain.

In chapter four, we study how the revelation of corporate misconduct affects upstream and downstream firms drawing on a large sample of corporate fraud events and corporate supplier-customer links. We show empirically that the revelation of corporate misconduct results in negative short-term market reactions for the stocks of suppliers and customers. We further validate this finding by showing that the effect is not driven by a particular firm at a specific period of time, industry trend, or business cycle. By analysing the cross-sectional determinants of suppliers' and customers' market reactions, we show that the negative market reactions are not attributed to operation channel, which is in contrast to previous literature on production shocks [e.g. Barrot and Sauvagnat, 2016; Wu, 2016]. Rather, we provide evidences in support of reputation channel. We also find that the negative shock is amplified by low-quality information environment. Our market-based tests provide support for the negative spillover effect of corporate fraud revelation on upstream and downstream firms. Our results also highlight the importance of distinguishing shock types in determining the main channels of shock propagation.

Chapter 2

Seeking Out Non-Public Information: Sell-side Analysts and the Freedom of Information Act

2.1 Introduction

Sell-side analysts are important to capital markets. They produce research reports and generate earnings forecasts and stock recommendations on covered firms, which move stock prices [Bradshaw, 2011] and create liquidity within the U.S. stock market [Kelly and Ljungqvist, 2012]. Bradshaw [2011] and Brown et al. [2015] refer to the process by which analysts use both public and private sources of information to generate their outputs as a "black box", and call for more research on understanding how analysts acquire and use various sources of information. Whereas most early studies concentrate on analysts' use of public, quantitative information (e.g., financial statements), a burgeoning area of research has emerged examining their acquisition of private and qualitative sources of information. These sources include management conference calls [Frankel et al., 1999][1], broker-sponsored conferences [Francis et al., 1997; Bushee et al., 2011; Green et al., 2014], analyst/investor days [Kirk and Markov, 2016], site visits [Cheng et al., 2016] and private meetings with management [Soltes, 2014].

A common thread running through these papers is that the channel of private information acquisition goes primarily from firm management to analyst. However, many sell-side analysts profess to engage in the acquisition of information outside the purview of management [Brown et al., 2015]. Yet, little has been written on understanding how analysts gather and utilize data not generated by the firm, primarily because it is difficult for researchers to identify specific outside sources analysts use and the dates in which they receive these data.

In this paper, we identify a source of external information used by some healthcare analysts: Freedom of Information Act (FOIA) requests to the Food and Drug Administration (FDA) for FDA-generated records pertaining to healthcare firms. The healthcare industry is an ideal setting for examining how analysts engage in private information searches. High R&D firms in general, and healthcare firms specifically, are difficult to value with public information only [Lehavy et al., 2011; Bushee et al., 2018; Lev and Zarowin, 1999]. Thus, FOIA requests to the FDA give healthcare analysts a vehicle to gather qualitative information to supplement their public and other private information about their covered firms.

Using our own FOIA requests to the FDA, we received a pdf file delineating all FOIA requests and outcomes made to the FDA between 1999 and 2014. The file contains over 180,000 requests; we are able to identify 873 of these requests as originating from sell-side analysts.[2] We use the full I/B/E/S database to identify

[1]Beginning on March 28, 2003, Regulation G requires public companies to furnish a Form 8-K to the SEC within five business days after issuing an earnings release. These releases are usually part of a conference call, suggesting that after this date, conference calls may be considered public rather than private information.

[2]To understand the extent that healthcare analysts use FOIA, we sent out similar FOIA requests

all healthcare analysts and classify them as FOIA analysts (treatment) and non-FOIA analysts (control) based on whether they made a FOIA request to the FDA. Consistent with Brown et al. [2015] that only a subset of analysts engage in the acquisition of outside private information, and with Grossman and Stiglitz's (1980) contention that the acquisition of private information is inversely related to the costs associated with acquisition (e.g., processing costs), we find that only 21% of our sample of healthcare analysts made at least one FOIA request for FDA records. A probit model explores cross-sectional differences in analyst traits associated with the propensity to make these requests.

We conduct two main analyses on FOIA analysts' efficiency in using these records. Our analysis concentrates solely on analysts' stock recommendations. Groysberg et al. [2011] show that analyst compensation is influenced heavily by whether the analyst is a "top stock picker" in his or her industry, and Brown et al.'s (2015) survey of what factors are important to analysts' compensation ranks the profitability of stock recommendations above accuracy and timeliness of earnings forecasts. Thus, using returns associated with stock recommendations aligns analysts' benefits with their incentives to acquire private information.

In the first set of analyses, we do difference-in-differences (DiD) regressions of long-term stock returns for portfolios of buy (sell) recommendations for analysts covering the same company. In these regressions, the FOIA analyst and all non-FOIA analysts must have a buy (sell) recommendation both in the year before and after the FDA record receipt date. Thus, we keep analyst ability constant in both time periods, only varying the model by whether the treatment analyst has or does not have his/her requested FDA records. We control for analyst ability and effort, the information environment surrounding the firm, public information about the firm or the FDA record itself, and stock risk factors. Our regression

to the Federal Aviation Administration (airlines) and the Department of Energy (utilities and oil). From the pdf files they sent us, we found no analyst requests to the FAA and only 13 analyst requests to the DOE. We interpret this finding as indicative of analysts using different sources of information for different industries (see, for example Cheng et al. [2016]).

findings are consistent with buy portfolios following the receipt of FDA records outperforming buy portfolios of analysts without these records. We find similar results for portfolios of sell portfolios – portfolios of sell/hold recommendations perform worse after receipt of FDA records when compared to portfolios of sell/hold recommendations without these records. In economic terms, the extra monthly return on the buy portfolio is 1.69% per month, and the extra return on the sell/hold portfolio is -1.38% per month.

We also exploit our setting of healthcare firms and the FOIA request channel by creating new variables related to both. Similar to papers investigating analysts' backgrounds, for example, whether the analyst has a CFA or prior period industry experience [De Franco and Zhou, 2009; Bradley et al., 2017], we use LinkedIn to determine if treatment and control healthcare analysts have an MBA, a PhD in science, and/or an MD degree. In our DiD regressions, we find a positive association between stock picking and the PhD/MD degree, but no association with an analyst having an MBA degree. These results are consistent with De Franco and Zhou [2009], who find little to no evidence that a CFA aids analysts in forecasting earnings, and also with Bradley et al. [2017], who show a positive association between past industry experience and earnings forecasting accuracy for firms in that industry. We also create variables based on how FOIA healthcare analysts use the FOIA requesting process. Our findings are consistent with long-term stock returns being associated with analysts who frequently make FOIA requests to the FDA and with analysts who use the FOIA process to gain private information about other (non-covered) healthcare firms.

Although our stock return results are consistent with analysts using FDA records when issuing new recommendations, the evidence can be considered circumstantial. To somewhat remedy this criticism, our second analysis looks into the FDA records themselves to try to determine what information in these records is related to the likelihood that an analyst would downgrade the covered stock. We choose two types of ex ante “bad news” records to examine – Warning Letters and Forms 483, both containing a list of violations resulting from an FDA inspection of a firm's factory. Using two FOIA requests, we obtain copies of 39 usable FDA records that also were requested and received by our sample of analysts. We manually read each record and determine that the violations in these records can be classified generally into four general categories - product, manufacturing, testing, and documentation. Consistent with expectations that the first two categories might be more damaging to the firm than the latter two categories, we find evidence that (1) stock returns following the new stock recommendation are inversely related to whether the requested FDA record contains a manufacturing violation, and (2) the likelihood of a downgrade is inversely related to whether the record contains a documentation violation.

Our paper extends the current literature on analysts' acquisition of private information along several new dimensions. First, our setting differs from most previous papers in that FDA records are a source of information independent of management. Thus, this is the first paper to do an extensive examination into a process by which analysts gather private information from a source not emanating from the firm itself. In fact, a discussion with a FOIA analyst reveals that her main purpose for asking for FDA records is to evaluate the veracity of management's claims during conference calls and other face-to-face meetings.

To illustrate, on January 10, 2012, Hospira participated in a brokerage conference sponsored by J.P. Morgan, by giving a corporate presentation (see Bushee et al. 2011; and Green et al. 2014). The presentation was upbeat, but it also included a slide on a Form 483 issued by the FDA on January 4, 2012 on a factory located in Kansas.[3] Notably, the slide stated that the Kansas factory accounted for approximately 12% of net sales, that the FDA raised six “observations”, but that these observations “can be addressed with minimal or no disruption.” One week

[3] Hospira placed the 34 slides of its presentation on an 8-K filing prior to the presentation. This discussion is based on those slides as well as the records sent to us by the FDA in a FOIA request.

after the conference, a Citigroup analyst filed a FOIA request to the FDA asking for that particular Form 483. Our reading of the Form 483 reveals three manufacturing violations, including the "propagation of microbial contamination" within the factory's drug products. Prior to the request, the analyst's recommendation was a hold (IBES = 3). On February 16, 2012, shortly after receiving the Form 483, the analyst lowered his recommendation to a strong sell (IBES = 5).

Second, our setting is novel in that FOIA requests are private to the extent that each request is made by one analyst only, and unless another analyst sends in a FOIA request for the identities of previous requesters (we found none in the FDA pdf file), other analysts are not aware the FOIA request was made. These joint properties of privacy and being the sole recipient of the private information are similar to Soltes [2014], who examines private meetings between analysts, but differ from papers with settings involving groups of analysts or pre-announced meeting dates [Bushee et al., 2011; Green et al., 2014; Kirk and Markov, 2016; Cheng et al., 2016].

Third, our study extends the literature that uses content analysis to discern the types of private information analysts use in their outputs. Huang et al. [2018] analyze analyst reports using this approach. We use a subset of actual FDA records received by analysts to examine the types of information they use when making their first post-receipt stock recommendations.

Fourth, our study generally speaks to the costs and benefits of acquiring nonpublic information. One of the central tenets of Grossman and Stiglitz (1980) is that investors search for nonpublic information only if the benefits exceed the costs of finding the information. Our findings are consistent with their theory. Specifically, despite the fact that any analyst can make a FOIA request, only a minority of healthcare analysts avail themselves of this information channel, suggesting a cost to processing the information.[4] On the other hand, when the information is asso-

[4]The direct dollar costs of filing a FOIA request to the FDA are trivial. According to the FDA website, the current charges for filing a FOIA request are: search and review charges: $23.00,

ciated with a subsequent recommendation, the benefits, i.e., the stock returns, are economically significant. Therefore, even though our setting is analysts covering healthcare firms only, it is applicable to other industries or settings. For example, analysts can make FOIA requests to other public agencies, including the Securities and Exchange Commission (SEC) or state-level agencies [Bolton et al., 2018].

Like all research studies, this paper has its limitations. Its main limitation is that, although we can observe the timing and the source of non-public information, we cannot unambiguously map the direct link from FDA records to the analysts' stock recommendations. Unlike financial data or management forecasts, FDA records contain qualitative information about the firm and give no indication of the future economic effects that the FDA's decision or regulatory action will have on the firm. Further, we do not know the full extent of each analyst's information set about his/her covered firm prior to the receipt of the requested records. Thus, we are unable to place the contents of the FDA record(s) within the mosaic of the analyst's information. Despite these caveats, our study opens a new window into the realm of non-public information that analysts access to better value their covered firms.

2.2 FDA and FOIA Requests

The FDA is an agency within the U.S. Department of Health and Human Services. Since its creation in 1906, the U.S. Courts and Congress have expanded and contracted the scope of its oversight. Today, the FDA has three main roles: (1) oversight of the process leading up to the marketing of new products, particularly drugs and medical devices, (2) post-marketing monitoring of products, and (3) factory inspections.

$46.00 and $83.00 depending on the grade level of the FDA employee filling the request; duplication: $0.10 per page for standard-size paper or actual cost per page for odd-size paper, with no charge for the first 100 pages of duplication; certification: $10 each; computer charges: actual cost for time involved; electronic forms/formats: actual cost for form/format requested.

Under the FOIA, analysts may ask the FDA for a copy of any record(s) the agency holds pertaining to the requested firm. These reports are non-public in that firms are not required to share them with investors, analysts, or other individuals. The FDA, with discretion, places some of these records on its website. However, the timing and choice of which records to post are completely within the FDA's discretion, and are sporadic at best [Mullins and Weaver, 2013; Bruser and McLean, 2014].

Figure 2.1 describes the FDA drug approval process. The process begins with preclinical animal testing and winds it way through three separate human testing phases. If Phases I though III are each successful, the firm most likely will file an application with the FDA seeking approval to begin marketing the new drug. On average, the FDA takes approximately six months to a year to make its decision on the application.[5] The FDA decision issued to the company is called an "approval recommendation" (REC); it can be either (i) a rejection, (ii) a conditional approval or a non-approval (subject to further modifications, sometimes referred to as a Phase IV), or (iii) an approval for the firm to begin marketing its new drug. Only the REC is subject to a FOIA request; that is all documentation and records between firm and the FDA up to and including the application are deemed by the FDA to be proprietary and, therefore, are exempt from all FOIA requests.[6] [7]

As Figure 2.1 shows, the FDA has an elaborate post-marketing surveillance

[5] The FDA's vetting process is threefold. It first evaluates the results of the Phase I-III trials. Next, it examines drug labeling on dosage, usage, and side effects. Lastly, it inspects the facilities where the drug will be produced.

[6] In the FOIA, there are nine stated exemptions to the presumption of mandatory disclosure. These exemptions include breaches of national security, individual privacy, trade secrets, financial confidentiality, internal memoranda or letters that are privileged in civil litigation, confidential sources to law enforcement agencies, documents that are related to financial institution regulation, and, geological information. These exemptions have been upheld by various court decisions [Lurie and Zieve, 2006].

[7] Companies are not precluded from voluntarily providing information to the public. Examination of select pharmaceutical and biotech companies' Form 8-Ks reveals that some companies include selective information on the three clinical phases and/or their FDA applications in their earnings releases, or more rarely, in a stand-alone 8-K filing. We also find some but many fewer cases, in which the Form 8-K includes selective information about factory inspections and post-market surveillance records. Further, the FDA maintains a website, clinicaltrials.gov, in which pharmaceutical companies sometimes place their trial results [Capkun et al., 2017].

system. It maintains four databases of “adverse events,” based on either mandatory or voluntary reports by the firm, consumers, doctors, hospitals, or other individuals. These databases include records on drugs (FAERS), medical devices (MDR), food, dietary supplements, and cosmetics (CAERS), and vaccines (VAERS). Each record-type is subject to FOIA requests.

In 1938, the Federal Food, Drug, and Cosmetic (FD&C) Act of 1938 gave the FDA the authority to conduct factory inspections on food and drug companies. The 1953 Factory Inspection Amendment required the FDA to give manufacturers written reports of conditions observed during inspections and analyses of factory samples.

Figure 2.2 describes the factory inspection process [McDuffee, 2011]. Under the FD&C Act, registered domestic drug factories are to be inspected by the FDA at least once every two years. Notice is not required. Instead, an FDA inspector arrives at the factory with his/her credentials and a Form 482, the latter being a general form of what the inspector can and cannot examine. After the inspection, which can take several days or weeks, the FDA issues an Establishment Inspection Report (EIR) if the inspection produces no violations, or a Form 483, which is a list of violations. The firm has a right to remediate the violations or appeal to the FDA; often there will be correspondences between the firm and the FDA about either process. After the FDA determines all violations are corrected, it issues an EIR. Tangentially, the FDA issues Warning Letters (WL) to manufacturers about “significant” violations of FDA regulations, for example, a mislabeling of an ingredient in a drug or food supplement, or its inability to correct factory inspection violations. EIRs, Form 483s, warning letters and related correspondences between the company and the FDA are subject to FOIA requests.

2.3 Sample Selection and Summary Statistics

2.3.1 Analysts' Identities and FOIA Requests

On January 29, 2014, February 11, 2014, March 21, 2014, and June 10, 2015, respectively, we filed FOIA requests to the FDA. The information we requested was a list of all FOIA requests by outsiders to the FDA between January 1, 1999 and December 31, 2014. The FDA responded to our inquiries by giving us pdf files containing 182,149 individual requests. The information provided to us are (i) requester's identity [both person ("Signature") and company ("Requester"), if applicable]; (ii) date of request; (iii) outcome date; (iv) target firm or individual; (v) outcome of the request (e.g., sent, withdrawn, denied); and (vi) and a short description of which agency records were requested [8]

We identify FOIA analysts through the following process: First, we use "Requester" to identify all brokerage firms. Next, we manually use several Internet sites to determine the "Signature's" job at the time of the request. Most "Signatures" have both first and last names, although we have a few cases with last name but only an initial for the first name. Our first search engine is LinkedIn. If LinkedIn does not have the needed information, we turn to BrokerCheck, a website maintained by the Financial Industry Regulatory Authority (FINRA) containing background information on current and former FINRA-registered security industry professionals. If BrokerCheck does not have the needed information, we search Bloomberg, company websites and Zoominfo.com, the latter being a search engine that collects biographical data using publicly available information. These steps result in a file of 76 brokerage firms and 221 equity analysts, the latter including associates, assistants, or administrative assistants.

[8] We submitted the second and third requests to the FDA to better understand the dates provided by the FDA. What we call the request date, the FDA calls the "record date;" what we call the outcome date, the FDA calls the "close date." In both requests, the FDA's record and close dates align with our request and outcome dates, which was included in the FDA's file to us. We use our terminology for the sake of clarity.

Table 2.1, Panel A shows the 182,149 FOIA requests from 1999 through 2014 by year (column 6). We have 873 individual requests from the 221 sell-side analysts we identify from the FDA pfd file (column 2), with the 181,276 remaining requests coming from non-analysts, including hedge funds, insurance companies, public and private companies, hospitals, doctors, law firms, consulting firms, and individuals (column 5).

To derive our final sample, we manually match the 221 equity analysts from the pdf file to the I/B/E/S translation file[9] If the requesting person ("Signature") is on I/B/E/S, we keep that analyst. However, sometimes the "Signature" is not an analyst, but instead is an equity analyst associate, assistant or administrative assistant. In this case, we assume the "Signature" works for the chief analyst from the brokerage firm who covers the stock at the time of the FOIA request, and we include that chief analyst in our sample.

Our final sample contains 62 brokerage houses, comprising 199 equity analysts making 528 individual requests (column 3). Table 2.1, Panel B presents the identity and frequency of requests for all brokerage firms with 20 or more requests over our time period. As the panel shows, Favus Institutional Research (a private firm providing healthcare consulting services to institutional investors), Cowen and Company, and Collins, Stewart LLC (a mid-cap stockbroker before being acquired by Canaccord in 2012; Mundy 2011), are not in the I/B/E/S database. These three firms account for a reduction of 144 requests from the original FDA pdf file.

[9]The I/B/E/S translation file is for the year 2008. Thus, our matching criteria will not capture sell-side analysts working in the years 2009 through 2014 who are not already working as an analyst in 2008. Nor will it capture analysts working in earlier years who have left the field by 2008. To give the reader some idea of the possible temporal attrition, Panel A presents the percent of analysts included in I/B/E/S who we identify as sell-side analysts from the FDA pdf file. On average, the I/B/E/S match retains 60% of the FDA pdf file sell-side analysts. Interestingly, we do not see patterns of attrition from 2008 outwards – instead we see random deviations from the mean over time. However, one should not draw conclusions from these patterns since our sample selection does not allow us to examine the contra factual.

2.3.2 Analysts' Characteristics: FOIA Requesters and Non-FOIA Requesters

Using the I/B/E/S database, we identify 924 unique healthcare analysts covering each FOIA requested stock in our sample over 1999-2014. Of these analysts, 199 are FOIA requesters and 725 never used FOIA to request an FDA record. Thus, FOIA requesters represent 21.5% of our full sample of I/B/E/S analysts covering these specific healthcare stocks.

Table 2.2, Panel A contains descriptive statistics for FOIA and non-FOIA (control) analysts. All variable definitions are in Appendix A. FOIA analysts, on average, have 5.8 years of direct analyst experience, cover 8.6 stocks, work in brokerage firms with 82.7 analysts, and are designated Star Analysts 15.3% of the time. Table 2.2, Panel B reports summary statistics for a probit model on whether the analyst is a FOIA requester (*FOIA Requester = 1*) or a non-FOIA requester (*FOIA Requester = 0*) for any individual FOIA-requested stock in the year of the FOIA request.

Our probit findings are similar to previous studies in that an analyst's propensity to seek FDA records is positively related to analyst effort (*#Forecasts;* Barth et al. 2001; Kirk et al. 2014), to the resources available to the analyst (*#Analysts at Brokerage Firm;* Clement 1999), and to previous forecasts errors (*Past Forecast Error*). It is also negatively related to *Analyst Experience*, suggesting that newer analysts are more likely to request FDA records. New to this study, we consider both advanced degrees in business (*MBA*) and advanced degrees in biology, chemistry, other sciences, and medicine (*PhD /MD*) as being useful to healthcare analysts. We find no difference between groups. Finally, based on a private conversation with a biotech sell-side analyst, we predict and find that analysts are more likely to use FOIA requests to monitor firms after the issuance of more negative stock recommendations (*Past Recommendation*).[10]

[10]Stock recommendations are taken from the I/B/E/S numeric recommendation code, which as-

2.3.3 FDA Records Requested under FOIA

Table 2.3 contains summary statistics on FOIA analysts' FDA requests. Panel A presents a breakdown of record requests by type. (See Appendix B for definitions). Since many analysts request more than one FDA record-type, for example, an analyst may request an EIR and a Form 483 on the same date, the number of records exceeds the number of requests from Table 2.1. For our final sample of analysts, 226 out of 655 total requests are for a Form 483, a list of factory inspection violations. Other possibly adverse information documents requested are post market surveillance complaints (127), EIRs (54), and warning letters (57). As for potentially positive news, there are 65 requests for approval recommendation documents (RECs).

Panel B has the outcomes of these requests. The FDA can send all or some of the requested documents ("Sent" or "Partial Sent") or can deny the release of the document(s) to the requester ("Denial" or "Other Reason"). As the panel shows, 393 requests (385+8) were either fully or partially granted, which accounts for 74.4% of the total individual requests. The other 25.6% consists of requests in which the analyst received no information. To compare this with the full FDA population, we gather the percentage of requests granted (partial or full) from the FDA website for all processed requests over our time period. Full or partial grants, as a percentage of all processed requests are 74%, a number highly consistent with our sample.

Panels C and D present some cross-sectional data on how healthcare analysts use FOIA to obtain information. As Panel C shows, FOIA analysts, on average, made at least one request for 31.7% of their covered companies, which translates to approximately three out of 8.6 covered companies. However, there is variation in the percentage of requested firms across analysts, with the bottom quartile requesting FDA records on less than 9.1% of their covered firms and the top quartile making

signs recommendations on a scale of 1 through 5, representing strong buy, buy, hold, underperform, and sell.

FOIA requests on 41.7% of their covered firm portfolio.

As Panel D illustrates, analysts use FOIA requests in different ways. Some analysts target multiple stocks with simultaneous FOIA requests – 65 of the 199 FOIA analysts (32.7%) sent out multiple FOIA requests in any one month at least once. For example, in March 2002, a Goldman Sachs analyst sent out FOIA requests for AERs for Amgen and Johnson & Johnson, respectively. Some analysts are frequent FOIA users — 63 FOIA analysts (31.7%) made at least three FOIA requests to the FDA over our sample period. Some analysts use FOIA to make requests on healthcare stocks not covered by the analyst — 46 FOIA analysts (23.1%) made requests on non-covered stocks in the same industry. Of these 46 analysts, 17 requested FDA records on a company in which the analyst covered at a later time. Thus, even among our FOIA analysts, we observe variability in how and when analysts request FDA records.

2.3.4 Subsequent Recommendation Changes

Table 2.4, Panel A presents a breakdown of new stock recommendations by FOIA analysts occurring within one year after receipt of the requested record(s). The receipt of FDA records is associated with a subsequent upgrade, downgrade, or a new affirmation 46.3% of the time, with the percentages being 11.0% for upgrades, 15.3% for downgrades, and 20.0% for affirmations. Looking across record-types, most new recommendations fall within a 50% range, with the exception of REC, which elicits new recommendations only 33% of the time. RECs are the FDA's final decision as to whether the new drug or medical device has been approved for subsequent sale and marketing. Since 2007, the FDA requires pharmaceutical firms to register their clinical trials and to publish the results of these trials on the clinicaltrials.gov website within 12 months of completion.[11] Thus, for many trials,

[11] Enforcement of these rules, however, is weak with only 41% of trial results actually appearing on the website [Zarin et al., 2015; Capkun et al., 2017] and an even smaller percentage appearing within the 12 month window.

analysts have access to prior information leading up to FDA approval, which may explain the relatively small number of recommendation changes following the receipt of these RECs.

To better understand the frequencies in which FDA records are followed by new stock recommendations, we compare the percent changes from Panel A with percent changes in recommendation changes by analysts without FDA records. We provide three separate comparisons. Table 2.4, Panel B, column (1) shows the same percentages as the last column of Panel A - this is the treatment group where the analyst receives at least one FOIA-requested record from the FDA. In column (2), we keep the analyst and the stock the same, but we examine changes in recommendations made in year t-2 (year t-2 through year t-1) by that analyst for the same stock from column (1).[12] As the column illustrates, the overall percent of new recommendations made in year t-2 is 31.9%, compared to 46.3% in the year when the analyst receives the records; testing for differences in percentages yields a z-statistic of 4.44, significant at the 0.01 level. When examining upgrades/downgrades/affirmations, we see evidence that all three types of recommendation changes are significantly lower for the year in which the FOIA analyst did not have FDA records.

In column (4), we keep the analyst and the time period the same by examining the FOIA analyst's same-year recommendations for covered stocks in which the analyst did not make a FOIA request. For these stocks, the analyst issued new recommendations 29.3% over the same year, a percentage significantly lower than the 46.3% for the stocks in which FDA records were requested and received. When comparing the breakdown of upgrades/downgrades/affirmations, we see that this difference hails from downgrades and affirmations, but not from upgrades.

In column (6), we keep the stock and the time period the same by examining new recommendations by non-FOIA analysts who cover the same stocks as those in

[12]Using a two-year look-back period instead of the year immediately prior to the request year (year 0) allows us to better isolate the recommendation period from containing information that may have led the analyst to issue the FOIA request.

which the FOIA analyst receives the requested FDA records. For this group, we see a markedly lower percentage of new recommendations — 11.8% compared to the 46.3% for the FOIA-requesting analysts. The differences in new recommendations are significantly different for all three classifications of upgrades/downgrades/affirmations.

These comparisons support the view that some requested FDA records contain new information to the FOIA requester. FOIA requesters are more likely to issue new stock recommendations after receiving FDA records when compared to other stocks they cover over the same time period (column 4) and the same stock in a period prior to receiving the FDA records (column 2). Further, FOIA analysts are more likely to make new stock recommendations after receipt of FDA records when compared to analysts not receiving these records (column 6).

2.4 Stock Returns From Sell-side Analyst Stock Recommendations

In this section, we test whether healthcare analysts provide more timely stock recommendations after receiving requested FDA records. We measure timeliness by differences in stock returns generated in the year after a new recommendation is made.

2.4.1 Calendar Time Portfolio Approach

We employ a standard calendar time portfolio approach to measure stock returns [Fama, 1998; Lyon et al., 1999; Cohen et al., 2010]. We construct two treatment portfolios: (1) a BUY portfolio of stocks consisting of FOIA analyst upgrades to buy or strong buy from the previous recommendation, or initial coverage with a buy or strong buy rating, or reiterations of buy or strong buy recommendations, and (2) a SELL portfolio of stocks consisting of FOIA analyst downgrades to hold, underperform, or sell from the prior recommendation, or initial coverage with a hold, underperform, or sell recommendation, or reiterations of hold, underperform or sell recommendations. A stock is included in each portfolio only if a new recommendation appears within 12 months after receipt of FDA records.

We create two similar control sample portfolios for healthcare analysts covering the same stocks as the FOIA analysts, but who do not request (nor receive) FOIA FDA records. The main difference between the FOIA analysts' BUY (SELL) portfolios and the control analysts' BUY (SELL) portfolios is the timing as to when an analyst makes his/her respective stock recommendation. To illustrate, suppose a FOIA analyst receives an FDA record for Eli Lilly on June 1, 2010. If that analyst issues a buy recommendation on June 15, 2010, that buy recommendation would be included in the FOIA analysts' BUY portfolio. We next examine all other analysts covering Eli Lilly from June 1, 2010 forward, placing all buy recommendations from these non-FOIA requesting analysts in a separate BUY portfolio. For example, suppose a non-FOIA analyst issues a buy recommendation on July 10, 2010; that analyst's recommendation would be in the non-FOIA analyst's BUY portfolio. Thus, the difference between the two portfolios would be the timing of their buy recommendations. We use the same criteria to create two SELL portfolios – one for the FOIA requesting analysts and one for the non-FOIA requesting analysts.

Having created the BUY and SELL portfolios, we next accrue daily stock returns. Figure 2.3 demonstrates the time line following the FOIA analyst's receipt of FDA records on day t_0. Using a buy recommendation as an example, we designate day t_1 as the day in which the FOIA analyst upgrades, initiates or reiterates a buy or strong buy recommendation after receiving FDA records. Consistent with Cohen et al. [2010], we skip day t_1 and begin accruing returns on day $t_1 + 1$. We keep the stock in the portfolio only until the analyst downgrades it (day t_2) or until the end of one year after the receipt of FDA records (day t_0 + 1 year), whichever is shorter. If no new recommendation is issued over the year following day t_0, we do not include that stock in the portfolio. If more than one FOIA analyst covers the stock, we keep the duplicate stock in the portfolio and treat them as distinct stocks [Cohen et al., 2010]. Portfolio returns are equally weighted by calendar day; raw returns are calculated on a daily basis and averaged across all FOIA analysts.

We do the exact same procedure for non-FOIA (control) analysts, except that each control analyst's day t_1 is the day in that analyst issues the upgrade/buy recommendation. Because day t_1 differs between FOIA and non-FOIA analysts, our approach assesses the timing abilities of the FOIA analyst vis-à-vis the non-FOIA analyst covering the same stock after the FOIA analysts' receipt of FDA records.

We use the same approach to calculate raw stock returns prior to the receipt of FDA records. For a stock to be included in a specific portfolio, for example, the FOIA BUY portfolio, the same FOIA analyst must give a buy or strong buy recommendation on the same stock within one year prior to day t_0. As shown in Figure 2.3, we designate this new recommendation as day t_{-2}. We keep the stock in the FOIA BUY portfolio until the FOIA analyst either issues an opposite recommendation on day t_{-1}, or until day t_0. We follow the same procedure for the FOIA analyst's SELL portfolio and for the control analysts' BUY and SELL portfolios, respectively. Our approach creates a balanced sample in terms of having the same analyst and similar recommendation in both the pre- and post-receipt return portfolios.

2.4.2 Timing Differences

We calculate the average timing difference in days between FOIA and control analysts' first post-receipt date recommendations. For the BUY portfolio, the mean (median) difference is 104 (92) days, consistent with FOIA analysts providing more timely recommendations than non-FOIA analysts following the receipt of an FDA record. For the SELL portfolio, the mean (median) is 95 (69) days, a finding also consistent with FOIA analysts issuing more timely recommendations following the receipt of an FDA record.

2.4.3 Univariate Comparisons of Stock Returns

Table 2.5, Panel A presents monthly calendar time portfolio stock returns and their differences across analyst-type or time period. These statistics are descriptive because we do not control for differences in risk, analyst characteristics, firm characteristics, or other available information. For the BUY portfolios, post-receipt date returns across analysts with and without FOIA records produces an average difference in monthly returns of 1.21% (t-statistic = 2.22), which translates into a yearly return of 14.52%. Since each portfolio is predicated on the analyst providing a buy/strong buy recommendation and/or an upgrade, the primary difference between the two portfolios is the receipt of information. In contrast, we cannot reject the hypothesis of no difference in post-receipt date returns for SELL portfolios between requesting FOIA Analysts and our sample of control analysts. The difference in post-receipt date returns between FOIA and non-FOIA analysts is -0.45% (t-statistic = -0.96).

2.4.4 Multivariate Analyses

To examine whether our univariate results are driven or affected by other factors, we employ a difference-in-differences regression methodology. The regressions are run on daily stock returns (*Return*), but consistent with Cohen et al. [2010], the coefficients on all independent variables are adjusted to represent monthly returns. Variable definitions are in Appendix 2.A. For the portfolio of BUYS or SELLS, respectively, we estimate the following regression:

$$
\begin{aligned}
Return = {} & \alpha + \beta_1 \, FOIA\ Analyst + \beta_2 \, Post + \beta_3 (FOIA\ Analyst \times Post) + \beta_4 \, Firm\ Size + \beta_5 \, B/M \\
& + \beta_6 \, Momentum + \beta_7 \, Analyst\ Experience + \beta_8 \, Ln(\#\ Stocks\ Covered) \\
& + \beta_9 \, Ln(\#Analysts\ at\ Brokerage\ Firm) + \beta_{10} \, PhD/MD + \beta_{11} \, MBA + \beta_{12} \, Star\ Analyst \\
& + \beta_{13} \, Frequent\ FOIA\ Requester + \beta_{14} \, FOIA\ Industry\ Expertise + \beta_{15} \, Forecast\ Dispersion \\
& + \beta_{16} \, Institutional\ Ownership + \beta_{17} \, Ln(\#\ News\ Articles) + \beta_{18} \, Previous\ 8K\ Filing \\
& + \beta_{19} \, Multiple\ FOIA\ Requests\ on\ Stock + FE + \varepsilon
\end{aligned}
\tag{2.1}
$$

FOIA Analyst is one if the analyst receives FDA records, and zero otherwise. *Post* is one if the stock recommendation is made after the FDA receipt date, and zero otherwise. The interaction between *FOIA Analyst* and *Post* tests whether stock returns after the receipt of the FDA records are different for analysts with and without these records.

We create two new analyst ability measures based on how FOIA analysts use FOIA to request FDA records. Presumably, frequent FOIA requesters find FDA records to be useful. *Frequent FOIA Requester* is an indicator if the analyst filed at least three FOIA requests over our time period.[13] According to Brown et al. [2015], 83.42% of surveyed sell-side analysts consider "industry knowledge" to be an important input when making stock recommendations; *FOIA Industry Expertise* is an indicator if the analyst made at least one FOIA request to the FDA for an uncovered healthcare stock. We interpret this practice as the FOIA analyst seeking out information on competing firms, or more broadly, on his/her covered industry.

PhD/MD and *MBA* measure whether an analyst has these post-graduate degrees, respectively. To control for the timeliness of the information contained in the FDA record, we include *Previous 8K Filing* as an independent variable. For our sample of FOIA receipts, 208 (39%) Form 8-Ks were filed with the SEC prior to the request with some information about the requested FDA record. On average,

[13] Conversely, we create an indicator if the FOIA analyst request is the first FOIA request to the FDA. Because this indicator and *Frequent FOIA Requester* are highly negatively correlated, we re-do our analyses with this indicator instead of *Frequent FOIA Requester*. The empirical results are qualitatively the same with either variable and therefore, we only show the empirical results with *Frequent FOIA Requester*.

these Form 8-Ks preceded the formal FOIA request by 10.3 days, with a median lead-time of 7.0 days. To understand the contents of these filings, we manually downloaded and read through each 8-K filing. Notably, the filings do not contain the FDA record itself, but only reveal the existence of the record. Thus, the FDA record itself contains more information than what is on the 8-K filing. *Multiple FOIA Requests on Stock* is an indicator if at least two separate analysts placed FOIA requests with the FDA on the same stock within a month of each other.

Our multivariate regression includes many controls based on the prior literature on stock returns (*Firm Size*, *B/M*, *Momentum*) and analysts' recommendations or forecast errors. We control for analyst's ability and available resources (*Analyst Experience*, *#Stocks Covered*, *#Analysts at Brokerage Firm*, and *Star Analyst*), and for the firm's information environment (*Forecast Dispersion*, *Institutional Ownership*, and *#New Articles*). We include fixed effects (FE) for month and for firm.[14] Table 2.5, Panel B presents covered firms' characteristics. Other variables are in Tables 2.2 and 2.3.

Column (1) of Table 2.6 presents the regression results for BUYS. The coefficient on (*FOIA Analyst* $\times$ *Post*) is significantly positive at the 0.05 level. In economic terms, the 0.0169 coefficient is the extra monthly return a BUY portfolio earns after a FOIA analyst receives the requested FDA records. Thus, after controlling for equity risk, analyst characteristics, and the firm's information environment, we find evidence consistent with FDA records providing value-relevant information to FOIA requesting analysts.

We find a significantly positive coefficient on *PhD/MD*, consistent with analysts with terminal science or medical degrees leveraging their specialized knowledge to better assess future stock values for healthcare companies. This finding is con-

[14]Alternatively, we include a fixed effect for the analyst. With this FE, we cannot include time invariant analyst characteristics such as MBA or PhD/MD into the regression equation. The empirical results with this FE are qualitatively the same as those without the analyst FE. Specifically, the coefficients on *FOIA Analyst* $\times$ *Post* are qualitatively the same and remain significant at the same levels.

sistent with Bradley et al. [2017], who find that analysts with prior experience in their covered industries are better predictors of future earnings. In contrast, having an *MBA* degree provides no significant additional expertise, a finding somewhat consistent with De Franco and Zhou [2009], who find weak evidence that having a CFA improves analyst's ability to forecast earnings.

The significantly positive coefficient on *Multiple FOIA Requests on Stock* supports the view that FOIA analysts interpret the requested FDA record(s) in similar ways. The statistically negative coefficient on *Prior 8K Filing* is consistent with an 8-K filing muting an analyst's advantage in using the information contained in the requested FOIA record. *Frequent FOIA Requester* has a significantly positive coefficient, consistent with the view that analysts who use FOIA requests more frequently are the ones who benefit most from these records. The coefficient on *FOIA Industry Expertise*, however, is insignificantly different from zero. The other variables support those found in prior literature (*Firm Size*, *B/M*, *Momentum*, *Analyst Experience*, *#Stocks Covered*, *Forecast Dispersion*, *Institutional Ownership*, *#News Article*).

Column (2) contains the regression results on stock returns on SELL portfolios. Stock returns are negatively related to the receipt of FDA records by requesting analysts, as seen by the significantly negative coefficient on (*FOIA Analyst* $\times$ *Post*), (p-value < 0.10). In economic terms, FOIA analysts issuing sell recommendations after the receipt of a requested FDA record, on average, avoid a monthly loss of 1.38% when compared to analysts without these records.

Similar to BUY portfolios, stock returns on SELL portfolios are significantly related to the risk factors *Firm Size*, *B/M*, and *Momentum.* SELL portfolios earn more negative stock returns for analysts with science or medical knowledge (*PhD/MD*) or have an expertise with respect to the FOIA process (*Frequent FOIA Requester*). We also find that returns on sell recommendations are associated with a better information environment in general (*Forecast Dispersion*, *Institutional Own-*

ership), with *#News Articles*, and with other analysts requesting the same FDA record (*Multiple FOIA Requests on Stock*). Similar to the results on BUY portfolios, the filing of a Form 8-K prior to the receipt of the FDA record mutes the negative return on the SELL portfolios. The other independent variables are insignificantly different from zero. In summary, Table 2.6 presents evidence consistent with analysts finding FOIA requested FDA records to be informative in making their future stock recommendations.

2.4.5 Information or Better Skill: Alternative Control Sample

An alternative explanation is that FOIA analysts are better stock pickers than non-FOIA analysts. That is, even though we control for many analyst characteristics, we cannot rule out the possibility that omitted analyst characteristics might be driving our results. To examine this alternative explanation, we create a second control sample and re-do our difference-indifferences regression analysis. Specifically, we gather all FOIA requests that were rejected by the FDA (see Table 2.3) and examine differences in subsequent stock returns between FOIA analysts receiving their requested FDA records (treatment) and FOIA analysts not receiving their requested FDA records (new control). Since both samples contain FOIA analysts only, the primary difference between the two groups is the receipt/non-receipt of requested FDA record(s).

We create a new indicator variable, *Receipt of FOIA Request*, if the FOIA analyst received his/her requested record(s). We interact this variable with *Post*, thus testing for differences in stock returns on BUY (SELL) portfolios before and after receipt of FDA records. The regressions control for equity risk, the overall information environment of the firm, the number of news stories, and the information environment surrounding the FDA record itself. Since our sample includes only those analysts making FOIA requests, we omit the analyst experience and ability variables in our regression specifications.

Table 2.7 contains the regression results. The empirical findings are consistent with the information hypothesis associated with the receipt of the FDA records. Specifically, the coefficient on (*FOIA Analyst* $\times$ *Post*) is significantly positive at the 0.05 level for the regressions on BUY portfolios and is significantly negative at the 0.10 level for the regressions on SELL portfolios. In economic terms, FOIA analysts earn, on average, 2.32% higher monthly returns on their BUY portfolios and avoid 1.70% lower monthly returns on their SELL portfolios when in possession of the FDA records. The equity risk variables and some of the information environment variables remain significantly different from zero. In sum, Table 2.7 provides evidence consistent with FDA records providing valuable information to requesting analysts.

2.5 Inside the FDA Records

Our large sample stock return results are consistent with FOIA records providing value-relevant information to FOIA analysts. However, they do not lend much insight into the type of information FOIA analysts use in revising their recommendations. In this section, we go inside a subset of FDA records and examine (1) the content of these records and (2) the types of information within these records most associated with analysts' revised stock recommendations.

To gain access to FDA records, we filed two separate FOIA requests to the FDA in July 2017 asking for a subset of Form 483s and Warning Letters sent to our FOIA analysts. Form 483s and most warning letters contain a list of factory violations only. We select these two record-types because they are relatively easy (for us) to read and understand when compared to EIRs or RECs, and the information contained in these records are similar across records allowing us to classify the information into various "buckets."

To keep our sample manageable, we randomly selected 46 of the 92 Forms

483 and all 16 Warning Letters from our initial sample that resulted in a post-receipt recommendation by the FOIA analyst. The FDA sent us files on all our requests. However, only 41 of the requested files contained all of the needed information for this analysis — a record of the analyst's request letter, a record of the FDA's reply to the analyst, and the FDA Form 483 or warning letter itself. Two of the warning letters were not related to factory inspections, and therefore, were not used. Most of the missing records are from requests by the analyst prior to 2011, leading us to infer that the FDA only sent us records from their computer bank. Our final sample has 27 Form 483s and 12 warning letters.

We printed and manually read each of the 39 FDA records. After a joint consultation, we classified the factory violations into four distinct types: product, manufacturing, testing, and documentation.[15] A product violation is a mention of a substandard drug or medical device. A manufacturing violation refers to a defect in a factory's manufacturing process. A test violation is when the firm fails to establish a mandated test to monitor its processes or products, or receives a criticism as to how a test was conducted. A documentation violation occurs when the firm fails to adequately document its procedures or test results.

Appendix 2.C contains snapshots from the records the FDA sent us. The blackened parts are redactions by the FDA. We classify the excerpt from the Thoratec Corporation Warning Letter as a product violation because it refers to a medical device that "may have caused or contributed to a [patient's] death." The excerpt from the Hospira Form 483 is a manufacturing violation because it discusses how a factory "promotes the propagation of microbial contamination." The Alpharma Form 483 includes a "failure to perform the preparatory test for the validation of the

[15]The categorization of violations mirrors the standard operating process of typical pharmaceutical and food companies. The product or device is fist designed (*product*) and then manufactured by affiliated factories (*manufacturing*). In order to make sure the product or device reaches certain criteria, testing procedures are implemented along the way to oversee the manufacturing processes or product usage (*testing*). The activities in manufacturing and testing process are also recorded for future reference (*documentation*). The categorization is consistent with key building blocks of Quality System (QS) employed by FDA. It is able to capture all inspection violations from our reading and analysis of FDA records.

membrane filtration method…" and, therefore, is classified as a testing violation. The Genzyme Form 483 disclosure is an example of a documentation violation in that it states that "activities performed during drug substance manufacture are not adequately documented."

Table 2.8, Panel A contains a numeration of our violation categories. On average, each record contains 9.82 violations, with a range of 1 to 25 violations [untabulated]. The two most prevalent violations relate to testing and documentation, with 82% and 74% of the records having at least one testing or documentation violation, respectively. Manufacturing (44%) and product (33%) violations also are commonly found. We further note that 21% of the records use the existence of a current or previous complaint as an example of a product violation and therefore we include it as a separate category.

Ex ante, we expect product, manufacturing, and complaints to be associated with more negative news, as these violations may be indicative of more severe and possibly more expensive problems within the firm. Conversely, we expect testing and documentation violations to be less costly to the firm, thus being indicative of less negative or problematic news.[16] [17]

Regression Results We regress two measures of FOIA analysts' post-receipt stock recommendations on the number and type of each violation. *NegConsensus* is an indicator if the FOIA analyst's first post-receipt recommendation is more neg-

[16]If there are violations in product design and manufacturing process, then final products are almost certainly flawed. By contrast, if testing procedure are not properly conducted or the documents are not appropriately maintained, the likelihood of final products being flawed will be substantially lower. Meanwhile, settlement costs and potential reputation damage brought by product, manufacturing violations and complaints are much larger than those of testing and documentation violations.

[17]Anecdotally, in 2014, an analyst at Leerink Partners wrote in a "research note" that she is not changing her "outperform" rating on HeartWare after the company released a statement announcing the receipt of a warning letter related to its Florida manufacturing facility [Seiffert, 2014]. Notably, the warning letter found issues with the plant's "procedures for validating device design, procedures for implementing corrective and preventive action, maintaining records related to investigations and validation of computer software." [Seiffert, 2014] We would classify these issues as testing and documentation violations.

ative than the consensus recommendation on that date for all non-FOIA analysts. *Downgrade* is an indicator if the FOIA analyst's first post-receipt recommendation is a downgrade from his/her previous stock recommendation. If our ex ante expectations are correct about the relative costs of correcting these violations, and if the analyst is using this information, we would expect to see positive associations between *NegConsensus* (*Downgrade*) and product, manufacturing, or complaint violations, and negative associations with testing or documentation violations.

Table 2.8, Panel B contains the regression results on *NegConsensus*. In column (1), we find no association between *NegConsensus* and the number of violations contained in the FDA record, suggesting that the number of violations itself does not influence the FOIA analyst's post-receipt recommendation. However, in column (2), we find evidence that the severity of the information contained in the FDA records is associated with the FOIA analyst's first post-receipt recommendation, as evidenced by the significantly negative coefficient on *Documentation* and the significantly positive coefficient on *Complaint*. Further, we note that the R-squared value for the regression in column (2) is 0.19, explaining about 19% of variation in *NegConsensus*. In Panel C, we present the regression results on *Downgrade*. The results are consistent with FOIA analysts being less likely to downgrade stocks with *Documentation* violations, as evidenced by its significantly negative coefficient in column (2).[18] Both panels support our expectations about associations between recommendation revisions and the severity of the listed violations.

Finally, we discover that 7 of the 39 records resulted in subsequent class action lawsuits in which plaintiffs specifically accuse the firm of hiding adverse information from investors by not revealing the existence or contents of the Form

[18]We also regress individual one-year stock returns following the first post-receipt recommendation on the number of violations and the type of violations, respectively for each record. Wong et al. [2017] do a similar type of analysis for earnings forecast accuracy in China based on the content of home based/international based analyst reports. Our results are consistent with our analyst recommendation results in that we find significantly negative coefficients on *ln(number of violations)* and on *Manufacturing*, respectively. That is, we find valuation effects associated with the severity of the violations stated in the Form 483/Warning Letter.

483 or warning letter. To see if FOIA analysts anticipate the ramifications surrounding this negative event, we create an indicator (*Lawsuit*) for these 7 firms. As column (3) of Panels B and C show, FOIA analysts are more likely to have a negative post-receipt stock recommendation vis-à-vis the consensus recommendation (Panel B) and are more likely to downgrade the firm's stock (Panel C) for firms that ultimately are sued for not disclosing the contents of these specific records. In summary, this section presents evidence consistent with analysts differentiating among violation types when making their subsequent recommendations.

2.6 Additional Analyses

As we emphasized in the introduction, we focus mainly on analysts' stock recommendations as they best align analysts' benefits with their incentives to acquire private information [Groysberg et al., 2011; Brown et al., 2015]. In unreported results, we also examined analysts' one-year ahead and two-year ahead earnings and revenue forecast error both before and after the receipt of FDA records.[19] We find that FOIA analysts' earnings and revenue forecasts are more accurate after the receipt of FDA records, both compared to non-FOIA analysts and FDA-denied FOIA analysts. The results hold for both one-year and two-year ahead forecasts.

We conducted a quasi-placebo test in which we examine stock returns (Return) following two types of records – *RECs* and *All Other Records*. This division divides our FDA records into ex ante good news (*RECs*) and ex ante bad news (*All Other Records*). The main difference between this test and what we have done already is that we do not condition these two portfolios on analysts' stock recom-

[19] There are some cases in which companies issue 8-K filings related to requested FDA records after analysts requesting the information. To gain a better understanding of how and when FDA records affect future earnings and revenues, we manually downloaded and read those 8-K filings. From our reading, we find that form 8-K filings almost never provide a timeframe connecting the requested FDA record to its expected resolution; instead, they contain brief mentions of actual resolutions. Further, resolutions of FDA violations or the time for a firm to roll out a new drug/medical device varies substantively across events and can have a fairly long time horizon. Because of the varying timeframes, we do our analyses on two forecasting windows: one-year and two-year ahead forecasts.

mendations. Thus, our quasi-placebo test aims to examine if the existence of the record-type *per se* gives us the same stock return results as our BUY/SELL findings. If the results with these two portfolios are the same as those found in Table 2.6, we can infer that learning about the existence of the record itself generates positive or negative stock returns – that is, there is no added value to the analyst examining the content of FDA records. By examining returns spanning one-year prior to and one-year after receipt date, we find that knowledge of an ex ante good (bad) news FDA record does not, *per se*, result in subsequent positive (negative) stock returns. Thus our findings are consistent with FOIA analysts examining the content of FDA records and using requested FDA records in a timely fashion when issuing their stock recommendations.

2.7 Concluding Remarks

This paper adds to the literature on sell-side analysts' search for private information by examining a source of not readily accessible information — FOIA requested FDA records. We obtain our data through our own FOIA requests, asking the FDA to send us information on past FOIA requests as well as copies of some specific records sent to analysts.

Our findings are consistent with healthcare analysts using FOIA-requested FDA records to make more timely (profitable) stock recommendations. We also present evidence that these FOIA analysts revise their stock recommendations more frequently and sooner than healthcare analysts not receiving FDA records. Further, a content analysis of specific FDA records on factory inspections provides evidence consistent with more serious violations (e.g., product or manufacturing) being more aligned with downward recommendation revisions than less serious violations (e.g., testing or documentation).

Our study is the first to do an extensive analysis into the process by which analysts gather qualitative, non-public information from a source outside of firm management. As such, it complements prior studies on analysts' search for private information by providing a new peek into a different "black box" of inputs used by sell-side equity analysts when formulating their stock recommendations.

Appendix 2.A Variable Definitions

	Definition
Dependent Variables	
FOIA Requester	Indicator equal to 1 for an analyst who filed FOIA requests to the FDA, and 0 otherwise.
Returns	Daily stock returns as reported by CRSP.
NegConsensus	Indicator equal to 1 if a FOIA analyst's first post-receipt recommendation is more negative than the consensus recommendation on that date for all non-FOIA analysts.
Downgrade	Indicator equal to 1 if an FOIA analyst's first post-receipt recommendation is a downgrade.
FOIA Variables	
FOIA Analyst	Indicator equal to 1 for an analyst who receives requested FOIA records, and 0 otherwise.
Post	Indicator equal to 1 for periods after the FOIA receipt date, and 0 otherwise.
Receipt of FOIA Request	Indicator equal to 1 if the FDA sends the FOIA requested record to the requesting analyst; 0 if the FDA denies the request.
Analyst Characteristics	
Analyst Experience	Number of years the analyst has made recommendations as recorded in I/B/E/S.
Distance	Number of years between the forecast and the earnings announcement as recorded in I/B/E/S.
#Forecasts	Number of the analyst's forecasts on the FOIA stock within one year before the FOIA request as recorded in I/B/E/S.
#Stocks Covered	Number of stocks covered by the analyst from I/B/E/S.
Past Earnings FE	The analyst's last one-year earnings forecast error for the previous fiscal year from I/B/E/S.
Past Recommendation	The last stock recommendation prior to the FOIA analyst's request. It is equal to 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform, and 5 for Sell; from I/B/E/S.
PhD/MD (MBA)	Indicator equal to 1 if the analyst has a PhD/MD (MBA) degree, and 0 otherwise from LinkedIn and other websites.
Star Analyst	Indicator equal to 1 if the analyst is voted an all-American star analyst in the October issue of *The Institutional Investor* magazine for the given year, and 0 otherwise.
#Analysts at Brokerage Firm	Number of analysts at the analyst's brokerage firm as recorded from I/B/E/S.

FOIA Characteristics	
FOIA Industry Expertise	Indicator equal to 1 if the analyst filed FOIA requests on uncovered stocks in the same industry, and 0 otherwise.
Frequent FOIA Requester	Indicator equal to 1 if the analyst filed at least three FOIA requests to the FDA, and 0 otherwise.
Multiple FOIA Requests on Stock	Indicator equal to 1 if there were more than one FOIA request on the same stock within a month of each other, and 0 otherwise.
Prior 8K Filing	Indicator equal to 1 if the FOIA request is preceded by a Form 8-K filing with some information about the FDA record, and 0 otherwise.
FDA Record Violations	
Number of Violations	Number of violations identified in the FDA record.
Product	Indicator equal to 1 if a FDA record mentions a substandard drug or medical device.
Manufacturing	Indicator equal to 1 if the FDA record refers to a defect in a factory's manufacturing process.
Testing	Indicator equal to 1 if the FDA record refers to the firm's failure to establish a mandated test to monitor its processes or products, or received a criticism as to how a test was conducted.
Documentation	Indicator equal to 1 if the FDA record mentions a failure to adequately document its procedures or test results.
Complaint	Indicator equal to 1 if the FDA record refers to the existence of a current or previous consumer complaint as an example of a product violation.
Lawsuit	Indicator equal to 1 for a subsequent class action lawsuit in which the plaintiffs specifically accuse the firm of hiding adverse information from investors by not revealing the existence or contents of the Form 483 or warning letter.
Other Independent Variables	
B/M	Ratio of the book value of equity to the market value of equity from Compustat.
Firm Size	Natural logarithm of lagged market capitalization in millions of dollars from CRSP.
Forecast Dispersion	Standard deviation of the current two-year ahead EPS forecasts from I/B/E/S.
Institutional Ownership	Proportion of shares held by institutional investors as reported by the Thomson Reuters Ownership Database.
Momentum	Firm's buy-and-hold return in the past 12 months as reported from CRSP.
#News Articles	Number of daily newspaper articles by Dow Jones Newswires as reported by RavenPack.

Appendix 2.B FDA Record Types

Factory Inspections	
Establishment Inspection Report (EIR)	Upon completion of an inspection, an EIR is written which details inspection findings.
Form 483	A Form 483 is issued to firm management at the conclusion of an inspection when an investigator has observed any conditions that may constitute violations of the Food Drug and Cosmetic (FD&C) Act and related Acts.
Post-market Surveillance Databases	
FDA Adverse Event Reporting System (FAERS)	FAERS is a database that contains information on adverse e drug reactions (ADR) and medication error reports submitted to FDA. It supports the FDA's post-market safety surveillance program for all approved drugs and therapeutic biologics.
Medical Device Reporting (MDR)	MDR is FDA's post-market surveillance tool to monitor device performance, detect potential device-related safety issues, and contribute to benefit-risk assessments of these products. Both mandatory and voluntary reports are included.
Center for Food Safety and Applied Nutrition (CFSAN) Adverse Event Reporting System (CAERS)	CAERS are reports about adverse health events and product complaints related to CFSAN-regulated products, including conventional foods, dietary supplements and cosmetics. Reports are mandatory and voluntary for dietary supplements, and are voluntary for all other products.
Vaccine Adverse Event Reporting System (VAERS)	The purpose of VAERS is to detect possible signals of adverse events associated with vaccines. Reports are voluntary only.
Warning Letter (WL)	When the FDA finds that a manufacturer has significantly violated FDA regulations, it notifies the manufacturer in the form of a warning letter.
Approval Recommendation (REC)	Approval recommendations (RECs) contain the FDA's decisions on New Drug Application (NDA) and Biologic License Application (BLA). The NDA application is the vehicle through which drug sponsors formally propose to the FDA approval of the sale and marketing in the U.S of a new drug. BLA is a request for permission to introduce, or deliver for introduction, a biologic product into interstate commerce.
Other	Includes company responses to FDA reports, correspondence, meeting minutes, alert, safety review and Notices of Inspection (Form 482).

Appendix 2.C Examples of Types of Disclosures in Warning Letters and Forms 483 (Factory Inspections)

1. Product Violation: Thoratec Corporation Warning Letter (January 3, 2012)

1. Failure to report to the FDA no later than 90 calendar days after the day that your firm received or otherwise became aware of information, from any source, that reasonably suggests that a device that it markets may have caused or contributed to a death or serious injury, as required by 21 CFR 803.50(a)(1). Under the authority of 21 CFR Part 803.19(e), your firm was granted an exemption from the 30 calendar day reporting timeframe required by 21 CFR 803.50(a)(1) for events that your firm receives from the INTERMACS Registry. However, your firm did not submit an MDR to FDA within the 90 calendar day timeframe for the following:

Complaint 201 008-0145 indicates that your firm's device may have caused or contributed to the patient's death. Your firm became aware of this event on April 30, 2010, and the MDR was received by FDA on August 17, 2010, which is beyond the 90 calendar day timeframe.

2. Manufacturing Violation: Hospira Form 483 (January 4, 2012)

OBSERVATION 2

Procedures designed to prevent microbiological contamination of drug products purporting to be sterile are not established and written.

Specifically,

The design of the personnel entryway, personnel and material traffic flow, and gowning practices promotes the propagation of microbial contamination. The following was observed during the entirety of the inspection 11/28/11-1/4/12. This is applicable to all drug products, ~[redacted] different pharmaceutical configurations.

Procedure MF0101.01 General Rules and Regulations: Aseptic Areas (effective Dec 16 2011) states "***The McPherson Aseptic Manufacturing areas are the most critical manufacturing locations in our site operations.***" Training Course Plan PRT0106 attachment 2 under Importance of Correct Gowning (bullet 2) states "***Protecting the product from particulate and microbial contamination.***" Dedicated plant clothing is intended to mitigate the ingress of dirt, debris and microorganisms into the cleaner areas of the plant. However, it was observed aseptic filling room personnel are allowed to frequent common public area's such as administrative offices, restrooms, and the cafeteria without being required to change out of dedicated plant scrubs and shoes which are then worn back into aseptic fill rooms under aseptic gowning. There is common interaction and comingling of personnel in street clothing and those performing manufacturing in the aseptic core.

Failure to mitigate the ingress of dirt, debris and microorganisms is exampled by:

- men and women's locker rooms and personal area required to don factory attire and factory dedicated shoes prior to entering into the manufacturing areas is not delineated to avoid cross contamination of street clothing to factory clothing. Lockers where street clothing/shoes and plant shoes are kept are shared.
- There is no record or document which dictates factory shoes are cleaned/sanitized on a routine basis.
- Aseptic personnel are required to don factory attire and dedicated shoes used to reduce the ingress and presence of objectionable microorganisms yet employees can and do access the production staging warehouse, cafeteria, restrooms and office corridors which are uncontrolled environments.
- Aseptic personnel are required to don a disposable lab coat prior to entering the cafeteria in order to protect their plant uniform. However, they disposable coats can be reused up to [redacted] days.

3. Testing Violation: Form 483: Alpharma Form 483 (September 27, 2001)

5. Failure to perform the preparatory test for the validation of the membrane filtration method used in microbial limits testing of the following products:

Epinephrine Mist;
Oxymetazoline HCl (12 hr Nasal spray);
Lindane 1% Shampoo; and,
Povidine Surgical Scrub.

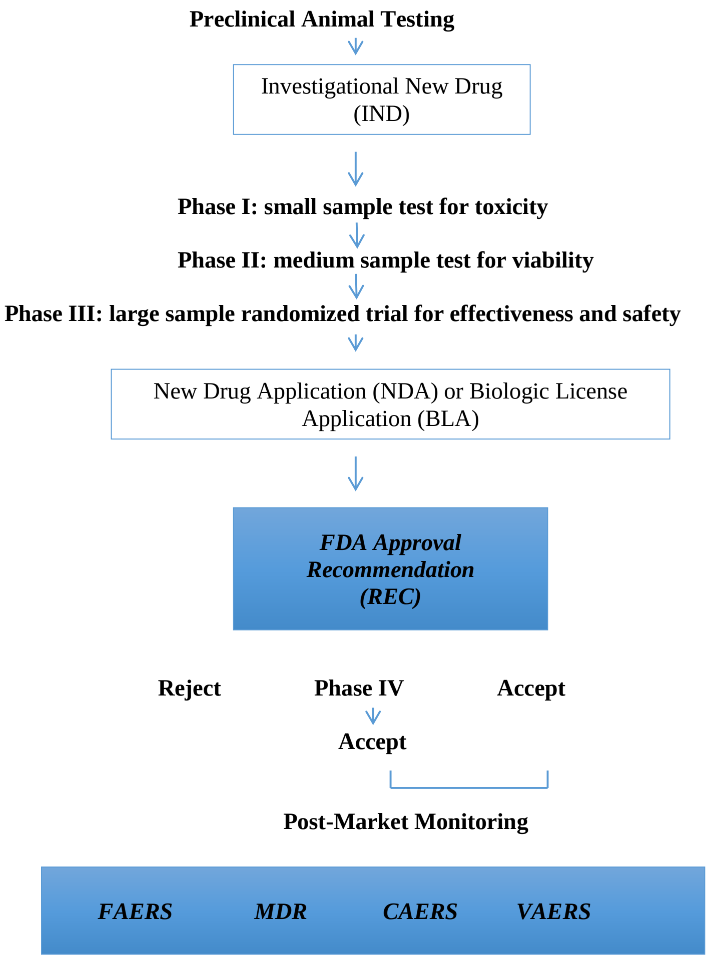
4. Documentation Violation: Genzyme Form 483 (October 10, 2008)

4. A. Activities performed during drug substance manufacture are not adequately documented. For example:

- When performance of an activity is optional at a given time point (b) (4) (b) (4) there is frequently no place in the batch record to record whether the activity was performed.
- Dated and signed crossing-out of optional activities that are not performed is not used consistently in the batch record.
- Additional activities may be performed during manufacture of some commercial batches as part of a study. These activities are not always reflected in the batch record.
- Data are recorded in incorrect units.

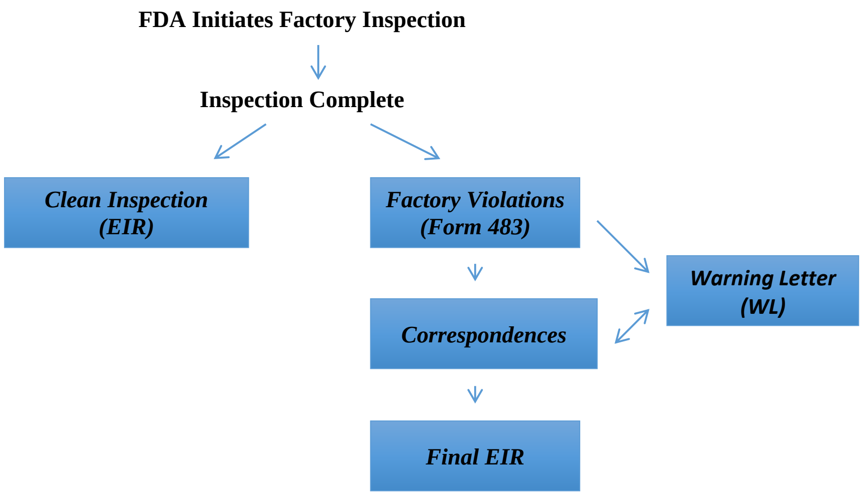
Appendix 2.D Figures

Figure 2.1: FDA Drug Approval Process and Post-Market Monitoring



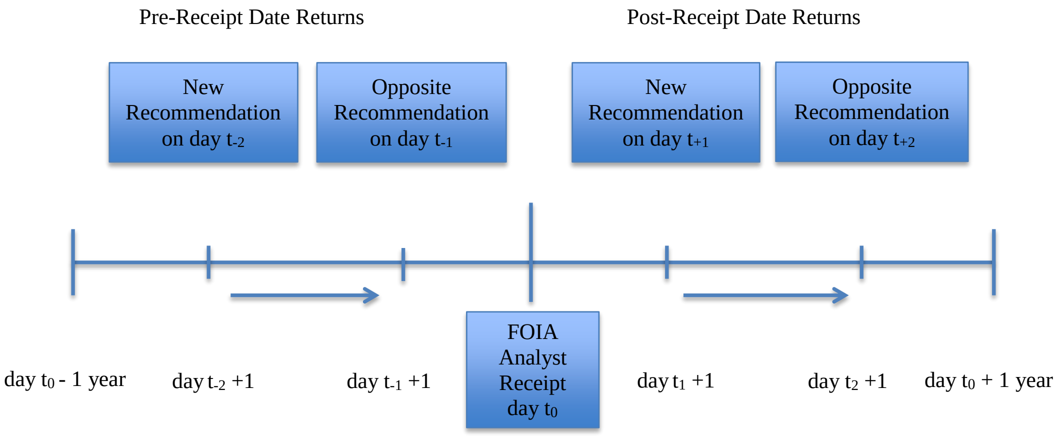
*****The shaded rectangles contain all FDA records subject to FOIA requests [REC, FAERS, MDR, CAERS, VAERS]. Everything above REC is not subject to FOIA requests. See Appendix B for a description of the FOIA-eligible FDA records.

Figure 2.2: Factory Inspection Process



***** The shaded rectangles contain all records subject to FOIA requests. See Appendix B for a description of the FOIA FDA records.

Figure 2.3: Time Frames for Accruing Raw Stock Returns



Appendix 2.E Tables

Table 2.1: FOIA Requests to the FDA

Year	Requests in FDA pdf File	Requests with Analysts in I/B/E/S	Percent of FDA pdf file in I/B/E/S	Requests from Non-Analysts	Total Requests
(1)	(2)	(3)	(4)	(5)	(6)
1999	3	0	0%	3,637	3,640
2000	6	4	67%	3,963	3,969
2001	7	3	43%	4,540	4,547
2002	45	24	53%	19,629	19,674
2003	17	9	53%	16,586	16,603
2004	19	12	63%	19,959	19,978
2005	32	24	75%	17,458	17,490
2006	37	23	62%	18,394	18,431
2007	31	15	48%	10,946	10,977
2008	31	18	58%	8,942	8,973
2009	70	47	67%	9,980	10,050
2010	73	57	78%	9,330	9,403
2011	102	77	75%	9,341	9,443
2012	133	68	51%	8,783	8,916
2013	155	77	50%	9,830	9,985
2014	112	70	63%	9,958	10,070
Total	873	528	60%	181,276	182,149

Panel B: Most Frequent Analyst Requests (Over 20 Requests)

Brokerage House	No. of Requests	Rank	No. of Requests in Final Sample
Favus Institutional Research	87	1	0
RBC Capital Markets	61	2	54
Jefferies & Co	57	3	45
Wells Fargo Securities	57	3	49
Merrill Lynch	34	5	32
Leerink Swan & Co	32	6	21
Cowen and Company	32	6	0
Morgan Stanley	29	8	21
Northcoast Research	29	8	19
Robert W Baird & Co	28	10	18
Collins Stewart LLC	25	11	0
Sanford Bernstein & Co	23	12	17
Citigroup	23	12	15
Deutsche Bank	22	14	18
JP Morgan	21	15	16
UBS	20	16	11
Stifel Nicolaus & Co	20	16	12

Panel A presents the number of requests by year. *Requests in FDA pdf File* are requests from sell-side analysts identified in the FDA pdf file. *Requests with Analysts in I/B/E/S* are requests from sell-side analysts in the FDA pdf file matched with the I/B/E/S database. *Percent of FDA pdf File in I/B/E/S* is *Requests with Analysts in I/B/E/S* divided by *Requests in FDA pdf File*. *Requests from Non-Analysts* include public and private companies, hospitals, doctors, law firms, consulting firms and individuals. *Year* is the year the request was made. Panel B ranks the brokerage or research firm by the number of FOIA requests.

Table 2.2: Analysts' Characteristics

Panel A: Analysts' Characteristics

	FOIA Analysts		Control Analysts		Difference with Control Analysts	
	Average	**Std. Dev.**	**Average**	**Std. Dev.**	**Diff. in Avg.**	***t*-stat. of Diff.**
Analyst Experience	5.798	4.055	7.580	4.492	-1.782***	-6.74
#Stocks Covered	8.606	4.279	8.365	5.358	0.241	0.86
Star Analyst	15.3%	32.6%	10.4%	29.7%	4.9%**	2.32
MBA	52.6%	49.2%	48.3%	49.8%	4.3%	1.34
PhD/MD	26.2%	44.0%	31.4%	46.1%	-5.2%*	-1.82
#Forecasts	6.208	2.811	5.002	2.924	1.206***	6.59
Past Recommendation	2.437	1.037	2.216	0.937	0.221***	3.29
Past Forecast Error	0.006	0.017	0.004	0.012	0.002**	2.33
#Analysts at Brokerage Firm	82.669	70.077	70.988	62.192	11.681**	2.57

Panel B: Probit Model for the Prediction of FOIA Requests

Dependent Variable: FOIA Requester	**Coefficient**	***t*-statistic**	**Marginal Probability**
Analyst Experience	-0.049***	-5.61	-0.3%
Ln (#Stocks Covered)	0.021	0.52	0.1%
Star Analyst	0.099	1.03	0.6%
MBA	0.095	1.58	1.0%
PhD/MD	-0.111	-1.60	-1.0%
Ln(# Forecasts)	0.343***	6.03	2.0%
Past Recommendation	0.099***	3.25	0.6%
Past Forecast Error	4.374**	2.35	25.5%
Ln (#Analysts at Brokerage Firm)	0.082**	2.54	0.5%
Observations	7,253		
Pseudo R-squared	0.06		

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). Panel A presents characteristics of FOIA analysts and control analysts, respectively. Panel B presents a probit model for predicting FOIA requests. We report coefficients, their heteroscedasticity-robust *t*-statistics, and the marginal probability change induced by a one-unit change in the value of specific covariate from its sample average. See Appendix A for variable definitions.

Table 2.3: FOIA Requests to FDA

Panel A: Types of FDA Records Requested by Analysts under the FOIA

Year	Establishment Inspection Report (EIR)	Form 483	Post Market Surveillance Database	Warning Letter (WL)	Approval Recommendation (REC)	Other	Total
Total	54	226	127	57	65	126	655

Panel B: Outcomes of Requests by Analysts for FDA Records

	Sent	Partial Sent	Denial	No Record	Withdrawn	Other Reason	Pending	Total
Total	385	8	18	52	37	25	3	528

Panel C: Percent of Unique Firms in the FOIA Analyst's Portfolio with FOIA Requests

Average	25 percentile	Median	75 percentile	Std. Dev.
31.7%	9.1%	16.7%	41.7%	31.8%

Panel D: Variations in FOIA Requests with Receipts

	Number of Analysts	Percent of all FOIA Analysts	Number of Requests
FOIA Requests on Multiple Stocks in at Least One Month	65	32.7%	218
Analyst's Requests ≥ 3	63	31.7%	234
Requests on Non-Covered Stocks	46	23.1%	66
Of Which Covered Later	17	8.5%	20

This table presents descriptive data on the type of FDA records analysts request under the FOIA (Panel A) and the outcomes of these requests (Panel B). For Panel A, see Appendix B for a description of each FDA report type. *Post Market Surveillance Database* is a combination of FAERS, MDR, CAERS, and VAERS. In Panels B *Sent* is when the FDA grants FOIA information to the investment company requester, *Partial Sent* is when at least one, but not all, of the requested records is sent, *Denial* is when no record is sent, *No Record* is when the FDA's response is that the requested record does not exist, *Withdrawn* involves cases in which the requester voluntarily withdraws its FOIA request, and *Other Reason* refers to cases when the request is closed due to other reasons and no information is released to the requester. A single FOIA request may cover multiple categories. Panel C reports the percent of unique firms in the FOIA analyst's portfolio with FOIA requests. Panel D reports variations in how FOIA analysts use FOIA to make their requests.

Table 2.4: Analysts' Stock Recommendations Following Receipt of FDA Records

Panel A: Number of New Recommendations After Receipt of FDA Records

Direction of First New Recommendation	EIR	Form 483	Complaints	WL	Other	REC	Total/ Percent of Total
Upgrade	6	25	4	4	8	2	49/11.0%
Downgrade	3	27	12	6	15	5	68/15.3%
Affirmation	6	40	14	6	17	6	89/20.0%
Total	15	92	30	16	40	13	206/46.3%
Number of Receipts	27	190	61	32	96	39	445/100.0%

Panel B: Comparisons of Percent of New Recommendations by Whether Analyst Received or Did Not Receive FOIA Requested Records

Direction of First New Recommendation	FOIA Analysts FOIA Stocks (Year 0)	FOIA Analysts FOIA Stocks (Year -2)	z-stat of (1) – (2)	FOIA Analysts Non-FOIA Stocks (Year 0)	z-stat of (1) – (4)	Non-FOIA Analysts FOIA Stocks (Year 0)	z-stat of (1) – (6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upgrade	11.0%	6.3%	2.51**	10.4%	0.39	3.9%	4.76***
Downgrade	15.3%	11.2%	1.78*	8.8%	3.68***	4.7%	6.19***
Affirmation	20.0%	14.4%	2.23**	10.1%	5.05***	3.2%	8.82***
Total Percent	46.3%	31.9%	4.44***	29.3%	6.85***	11.8%	14.49***

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). Panel A describes the direction of the first new stock recommendation by FOIA analysts after receiving FDA records. See Appendix B for a description of the record types. Panel B presents the percentages of the first new recommendation and compares them to (a) FOIA analysts' recommendation changes on the same stocks in the year t-2, (b) FOIA analysts' recommendation changes on other stocks covered by FOIA analysts in the same year as the FOIA stocks, and (c) Non-FOIA analysts' recommendation changes on FOIA stocks during the same year as the FOIA analysts' new recommendations.

Table 2.5: Descriptive Statistics

Panel A: Monthly Stock Returns Before and After the Receipt Date

	BUY Portfolios			SELL Portfolios		
	Pre-Receipt Date	Post-Receipt Date	Difference	Pre-Receipt Date	Post-Receipt Date	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
FOIA Analysts	0.61%	2.71%***	2.10%***	1.14%**	1.86%***	0.72%
	[1.10]	[5.12]	[2.73]	[2.13]	[4.13]	[1.03]
Control Analysts	1.04%***	1.50%***	0.46%***	1.54%***	2.31%***	0.77%***
	[9.06]	[11.41]	[2.64]	[11.87]	[17.90]	[4.21]
Difference	-0.43%	1.21%***		-0.40%	-0.45%	
	[-0.76]	[2.22]		[-0.73]	[-0.96]	

Panel B: Firm Characteristics

	Average	Median	Std. Dev.
Market Capitalization ($Billion)	23.76	6.43	44.43
B/M	0.61	0.34	1.89
Momentum (Buy, Past 12 Months)	28.99%	12.71%	64.73%
Momentum (Sell, Past 12 Months)	16.35%	7.79%	50.50%
Forecast Dispersion	0.29	0.17	0.34
Institutional Ownership	68.45%	78.30%	29.20%
# News Articles	0.67	0	1.38

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). Panel A shows the average calendar-time monthly returns of stocks based on buy or sell recommendations. BUY encompasses both buys and upgrades in columns (1) through (3); SELL has holds/sells and downgrades in columns (4) through (6). Panel B presents summary statistics for firm characteristics. See Appendix A for variable definitions.

Table 2.6: Regressions on BUY and SELL Portfolios

Dependent Variable	**Returns on BUY Portfolios**	**Returns on SELL Portfolios**
	(1)	**(2)**
FOIA Analyst	-0.0026	-0.0077
	[-0.33]	[-1.10]
Post	0.0099	0.0184*
	[1.11]	[1.95]
FOIA Analyst × Post	0.0169**	-0.0138*
	[2.38]	[-1.89]
Firm Size	-0.0085***	-0.0407***
	[-4.12]	[-4.42]
B/M	0.0053**	0.0151**
	[2.05]	[2.41]
Momentum	-0.0904***	-0.5827***
	[-3.11]	[-6.35]
Analyst Experience	0.0005*	0.0005
	[1.64]	[1.02]
Ln (# Stocks Covered)	-0.0090**	0.0031
	[-2.44]	[1.21]
Ln (#Analysts at Brokerage Firm)	0.0010	-0.0002
	[0.57]	[-0.15]
PhD/MD	0.0101**	-0.0189***
	[2.56]	[-2.69]
MBA	-0.0009	-0.0012
	[-0.35]	[-0.36]
Star Analyst	-0.0015	-0.0089
	[-0.31]	[-0.60]
Frequent FOIA Requester	0.0229**	-0.0472***
	[2.10]	[-2.70]
FOIA Industry Expertise	0.0034	-0.0064
	[0.26]	[-0.22]
Forecast Dispersion	-0.0292***	0.0548**
	[-3.16]	[3.69]
Institutional Ownership	0.0190**	-0.0465***
	[2.48]	[-3.00]
Ln (# News Articles)	0.0145*	-0.0577***
	[1.69]	[-3.94]
Previous 8K Filing	-0.0104***	0.0130*
	[-3.55]	[1.66]
Multiple FOIA Requests on Stock	0.0117**	-0.0783***
	[2.40]	[-2.60]
Constant	0.0556***	0.0470
	[6.63]	[0.55]
Month and Firm FEs	Yes	Yes
Observations	363,234	352,931
R-squared (%)	0.88	0.93

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). This table presents regression results on daily stock returns for BUY and SELL portfolios. *t*-statistics are in parentheses. Returns are winsorized at 0.01%, and standard errors are clustered at the month level. See Appendix A for variable definitions.

Table 2.7: Regressions on Alternative Control Sample

Dependent Variable	**Stock Returns on BUY Portfolios (1)**	**Stock Returns on SELL Portfolios (2)**
Receipt of FOIA Request	-0.0040	-0.0032
	[-0.38]	[-0.33]
Post	0.0131	0.0157**
	[1.01]	[2.34]
Receipt of FOIA Request × Post	0.0232**	-0.0170*
	[2.12]	[-1.71]
Firm Size	-0.0091***	-0.0164***
	[-2.71]	[-4.19]
B/M	0.0322***	0.0072*
	[3.96]	[1.73]
Momentum	-0.1399**	-0.7285***
	[-3.29]	[-8.46]
Forecast Dispersion	-0.0146	0.0550***
	[-1.38]	[2.98]
Institutional Ownership	0.0070	-0.0546***
	[0.50]	[-3.69]
Ln(# News Articles)	0.0528***	-0.0926***
	[3.51]	[-4.46]
Multiple FOIA Requests on Stock	0.0034	-0.0244**
	[0.25]	[-2.05]
Constant	0.1675***	0.2972***
	[4.11]	[5.29]
Month and Firm FEs	Yes	Yes
Observations	24,987	33,497
R-squared (%)	0.58	0.84

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). This table presents regression analyses of daily stock returns on BUY and SELL portfolios. The control sample consists of FOIA analysts who did not receive a requested FDA record. *t*-statistics are in parentheses. Stock returns are winsorized at 0.01%, and standard errors are clustered at the month level. See Appendix A for variable definitions.

Table 2.8: Information Contained in Warning Letters and Form 483s

Panel A: Types of Violations

	Mean Total Violations	Product Violation	Manufacturing Violation	Testing Violation	Documentation Violation	Complaint
Full Sample						
Number	9.82	13	17	32	29	8
%		33%	44%	82%	74%	21%
Warning Letters		7	5	12	6	5
Form 483s		6	12	20	23	3

Panel B: FOIA Analyst First Post-Receipt Recommendation is More Negative than Consensus Recommendation

Dependent Variable		**NegConsensus**	
	(1)	**(2)**	**(3)**
Ln (Number of Violations)	0.0376		
	[0.46]		
Product		0.0588	
		[0.29]	
Manufacturing		0.0310	
		[0.12]	
Testing		0.0234	
		[0.07]	
Documentation		-0.4754**	
		[-2.45]	
Complaint		0.3133*	
		[1.66]	
Lawsuit			0.6240**
			[2.09]
Constant	0.5678***	0.9530***	0.6800
	[2.82]	[2.87]	[7.02]
Observations	39	39	39
R-squared	0.01	0.19	0.05

Panel C: FOIA Analyst's First Post-Receipt Recommendation is a Downgrade

Dependent Variable:		**Downgrade**	
	(1)	**(2)**	**(3)**
Ln (Number of Violations)	0.0872		
	[0.90]		
Product		-0.3187	
		[-1.60]	
Manufacturing		-0.0060	
		[-0.02]	
Testing		0.1129	
		[0.34]	
Documentation		-0.5730***	
		[-2.69]	
Complaint		0.1109	
		[0.33]	
Lawsuit			0.4583***
			[4.32]
Constant	0.5422**	1.0146***	0.5417***
	[2.39]	[2.73]	[5.11]
Observations	39	39	39
R-squared	0.01	0.29	0.04

*, **, *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively (two tailed). *t*-statistics are in parentheses. Panel A has a numeration of the types of violations (See Appendix A for definitions). Panel B presents summary statistics for regressions on whether the FOIA analyst's post-receipt first stock recommendation is more negative than the consensus stock recommendation. Panel C presents summary statistics for regressions on whether the FOIA analyst downgraded the stock recommendation after receipt of FOIA-requested FDA records.

Chapter 3

Shining Light on Corporate Political Spending: Evidence from Shareholder Engagement

3.1 Introduction

In 2016 election cycle, record-breaking $6.8 billion were spent on presidential and congressional elections.[1] Although it is difficult to pin down the exact number, a large fraction of these election funding comes from U.S. public companies and their employees. For instance, the Political Action Committee (PAC) of Honeywell International spent $9.2 million.[2] Should public companies give shareholders the right to know their political spending? Some argue that companies' political spending may not be in the best interest of shareholders and therefore should be disclosed to shareholders.[3] Others argue that disclosing political spending to shareholders

[1]See CBS news. https://www.cbsnews.com/news/election-2016s-price-tag-6-8-billion

[2]See Center for Responsive Politics Website.
https://www.opensecrets.org/pacs/lookup2.php?strID=C00096156&cycle=2016

[3]Bebchuk and Jackson(2013) provides this kind of argument. Some other public figures expressed this kind of concern as well. For example, U.S. Senators Richard Blumenthal and Chris Murphy joined a letter, led by U.S. Senator Bob Menendez, to the new SEC Chair and reintroduced the Shareholder Protection Act—two actions aimed at requiring public companies to disclose political

would merely incur additional costs and would put the company at a disadvantage by revealing confidential corporate strategy.[4] Currently this is under heated debate as Securities and Exchange Commission (SEC) is considering the possibility to form regulations requiring public companies to disclose their political spending. However, until now, we still lack quantitative evidences in many aspects to understand corporate political transparency (CPT).

In this paper, we explore the drivers and implications of corporate political transparency (CPT) through the lens of shareholder engagements. The rise of shareholder engagements on corporate political transparency began in recent decade.[5] They usually file shareholder proposals with targeted companies in order to pursue changes.

We first document that there are substantial amount of successful shareholder engagements. Past research [e.g. Bebchuk and Jackson Jr, 2012; Cohn et al., 2016; Copland and O'Keefe, 2016] generally focuses on the low success rate of CPT-related shareholder proposals in shareholder meeting. They classify the sudden disclosure of political spending by companies as "voluntary". We find that in those cases, shareholder proponents and company management reach agreement before the meeting, leading to withdrawal of shareholder proposals in exchange for improved corporate political transparency. This finding echoes the widespread behind-the-scenes intervention documented in the literature [e.g. McCahery et al., 2016]. Our finding shows the importance of shareholder democracy in driving corporate political

spending to their shareholders. They wrote "...it is imperative that the SEC move swiftly to provide investors and the public with transparency about corporate political spending. Without this disclosure, executives will remain free to spend corporate funds to influence election and policy outcomes without any accountability or oversight."

[4]For example, Warren Buffett's Berkshire Hathaway has been continuously objecting shareholders' effort in improving corporate political transparency. In the 2017 proxy statement, the board replied "...To the contrary, the Board of Directors believes the adoption of the reporting being proposed, in addition to creating unnecessary administrative costs, could expose Berkshire subsidiaries to competitive harm without commensurate benefit to our shareholders." Some other public figures, such as Tom Quaadman, executive vice president of U.S. Chamber Center for Capital Markets Competitiveness, also expressed similar views.

[5]This is also reported by mainstream media. Figure 3.8 in the appendix gives two examples of media coverage.

transparency.

We then analyse activist shareholders' target decisions. We find that activist shareholders tend to target companies with PAC committee, suggesting that PAC activities influence shareholders' perception of corporate political activism. Target companies have lower political transparency level than non-target companies in all dimensions. Consistent with literature on governance-related shareholder proposals [Karpoff et al., 1996], targeted companies have larger size and poorer long-term performance in terms of book-to-market ratio and past stock returns. Not surprisingly, companies with higher percentage of politically connected directors are more likely to be targeted. Targets also exhibit relatively higher institutional ownership, which makes it easier for activist shareholders to acquire stakes and coordinate with other stakeholders [Agarwal, 2007; Brav et al., 2016].

Conditional on activist investors' target decision, we find the likelihood of successful engagement depends on activist types. Consistent with institutional investors are superior in accumulating shares and coordinating with other investors, we find that institutional investors are more likely to succeed. We further document that, engagements by SRI funds, among different types of institutional investors, are most likely to be successful. This is consistent with SRI funds, due to their expertise in areas related to social aspects of firms, are more able to provide relevant guidance to targeted firms. As the stated objectives of SRI funds involve delivering social benefits to stakeholders apart from financial benefits to their investors, SRI funds might also be more aggressive in achieving social objectives than other types of active investors in order to attract more investment. In line with labor unions suffering conflict of interest with company management [Agrawal, 2012], we find that labor unions are less likely to achieve progress in their engagements than other institutional investors.

Turning to ex-post implications, we first provide evidences that successful shareholder engagements lead to bigger improvement in political transparency. We rely on CPA-Zicklin index to measure political transparency level, which significantly shrank the sample in this part of analysis due to its limited coverage. We still find that successfully engaged companies experience a bigger improvement in political transparency at the event year than unsuccessfully engaged companies. This finding reassures that CPT-related shareholder engagements can indeed bring in changes to targeted companies.

We next examine the impact of political transparency based on short-term stock market reactions to shareholder engagement outcomes. Our approach has several advantages. First, the stock market is able to aggregate and process the information in a timely manner and impound the information in stock prices. Second, we use the public announcement date and therefore ensures that stock market participants are aware of the outcome. Third, the outcome of shareholder engagement is unlikely to be fully anticipated by the market participants before the announcement date. The biggest challenge in the analysis is lack of archival data on the public outcome announcement date. To solve this problem, we hand collect outcome announcement dates of both successful engagements and unsuccessful engagements from various sources. We find that stock market responds favorably to successful engagements in politically active companies. The cumulative abnormal return (CAAR) during the (-1,10) announcement window is 3.16%. Comparing successful engagements and unsuccessful engagements reveals that the market reaction to successful engagements is statistically more positive. However, the effect is not present in politically inactive companies.

We next investigate the channels through which political transparency affects firm value. Market reaction is more favourable to successful engagements in high political uncertainty environment. This finding suggests that corporate political transparency is more valuable when hidden political risk is higher. Consistent with the disciplinary effect of corporate political transparency, we also find that successful shareholder engagements result in slower growth of PAC expenditure in politically active companies. In asset pricing sense, these findings suggest that increased corporate political transparency reduces firms' cost of capital (discount rate) by lowering associated risk premium and thus raises firms' stock prices. Positive market reactions to successful engagements in politically active companies are more likely to be attributed to decreased cost of capital rather than revised cash flow projections.

Lastly, we examine the institutional investors' behavior in the medium to long-term. We find that successfully engaged companies, relative to unsuccessfully engaged companies, experience an increase in institutional ownership following the outcome announcement date. The effect persists more than one quarter after outcome announcement date. This finding supports institutional investors' preference for sustainability and corporate social responsibility [Hartzmark and Sussman, 2018; Gibson and Krueger, 2018].

Overall, we find that shareholder engagements help shape corporate political transparency. Our market-based tests provide empirical support for corporate political transparency. The evidences lend support to the petition requesting that SEC develop rules on the transparency of corporate political spending [e.g. Bebchuk and Jackson Jr, 2012].

Our paper is closely related to growing literature on political uncertainty. Political uncertainty is shown to increase volatility, risk premia, and correlations among stocks [Pastor and Veronesi, 2012; Pástor and Veronesi, 2013; Boutchkova et al., 2011; Brogaard and Detzel, 2015]. Political uncertainty also affects corporate real decisions, such as investment [Durnev, 2010; Julio and Yook, 2012; Gulen and Ion, 2015; Jens, 2017]. Overall, existing literature focuses exclusively on "external" political uncertainty from firms' point of view. We contribute to the literature by examining the effect of "internal" political uncertainty from shareholders' perspective.

Our paper is also closely related to the literature on corporate political connection. Prior literature has established the value implications of corporate political connection. Faccio [2006] finds that overlap between controlling shareholders or managers and politicians provides significant benefits to the firm although connected firms under-perform their peers on an ex–ante basis. Faccio and Parsley [2009] finds the negative market response around sudden death of connected politicians. Cooper et al. [2010] documents that companies' PAC contributions are positively related to their long-term stock returns. Using different events and international data, other studies also find the value effect of political connection [e.g. Borisov et al., 2015; Lee et al., 2013; Acemoglu et al., 2016, 2017; Aggarwal et al., 2012; Unsal et al., 2016]. These findings provide the foundation for shareholders' concern about corporate political transparency.

Another related area is the burgeoning literature on active ownership. Prior research has documented the active role of investors in firms' decisions and management, such as capital structure, business strategy, merger and acquisition, and general corporate governance. [Karpoff et al., 1996; Smith, 1996; Brav et al., 2008; Klein and Zur, 2009; Wahal, 1996; Carleton et al., 1998; Del Guercio and Hawkins, 1999; Gillan and Starks, 2000; Appel et al., 2016; Dimson et al., 2015]. However, researches examining the impact of shareholder activism on corporate political transparency are very limited.[6] This is surprising given the importance of corporate political connection for firm value and heavy media coverage on the issue. Our paper intends to bridge this gap.

Last but not the least, we contribute to the literature on information asymmetry between shareholders and management. Previous literature, especially theoretical literature, assumes that to some extent managers are able to take undesired action from shareholders' standpoint without notifying shareholders. Our paper

[6]Bebchuk and Jackson Jr [2012] provides only summary statistics on the CPT-related shareholder proposals. A contemporaneous working paper by Baloria et al. [2017] uses shareholder engagements on company political activities but their main focus is on the determinants of shareholder activism, especially activist types. We focus exclusively on CPT-related shareholder proposals since we recognize that the effect of transparency and prohibition could be dramatically different. Most importantly, we place more emphasis on the ex-post implication of shareholder engagements which is crucial for policy makers.

adds to the literature by documenting that significant information asymmetry exists in corporate political engagement. Increasing corporate political transparency helps reduce information asymmetry and align both parties' interests.

The rest of paper proceeds as follows. Section 2 outlines institutional background. Section 3 develops research hypotheses. Section 4 describes data and provides summary statistics. Section 5 presents empirical findings. Section 6 concludes.

3.2 Institutional Background

In this section, we explain corporate political transparency and show that it is historically low in U.S. public companies. According to the definition by *Center for Political Accountability*, corporate political transparency comprises of three components, namely disclosure, policy and oversight.

Lack of disclosure is reflected in two aspects. First, some corporate political spending has no public records. Companies can channel political spending through third parties that do not have the legal obligation to disclose their donors. Some non-profit organizations, primarily trade associations or business associations, often act as intermediaries through which corporations anonymously influence politics.[7] This type of corporate political spending started long time ago. Citizens United v.s. Federal Election Commission in 2010 makes this type of political spending even more convenient by permitting corporations, including some non-profit organizations, to spend unlimited amounts of money on advertisements and other political tools as long as they are not coordinated or prearranged with a candidate or a campaign. Bebchuk and Jackson Jr [2012] provides some statistics on the overall magnitude of this type of spending. Total political spending of eight active non-profit organizations, such as US Chamber of Commerce, Pharmaceutical Research and Manufacturers Association, American Petroleum Institute, America's Health Insurance Plans, Financial Services Roundtable and etc., reaches $1,559.6 million between 2005 and

[7] Those organizations are mainly formed under sections 501(c)(4) and 501(c)(6) of the tax code.

2010.[8] Further, companies' state lobbying expenses, i.e., expenses that are incurred to influence state legislators, are not disclosed on a mandatory basis in half of U.S. states. Meanwhile, companies also influence politics via indirect lobbying (sometimes called grassroot lobbying) where companies try to influence the legislators via general public. Investors can only speculate this type of corporate political spending at best. Second, even for those spending that does have public records, it is difficult and time-consuming for investors to assemble those information. According to existing election-law, companies may have to report some of their political spending, such as spending of political action committees, key executives, to federal election commission (FEC). But these information is generally distributed throughout separate filings in various formats. Assembling those information together is not straight-forward and would incur significant amount of costs. Some investors argue that companies should include these information on its website to reduce their costs.

Historically, most of public companies do not have and disclose internal policies governing the companies' political contributions and expenditures and the set of people who are accountable for the decisions. Lack of oversight is reflected by the fact that most of companies do not have supervisory board committee for corporate political spending in early 2000s.

Political opacity exposes investors to significant political risk. Not only could the revelation of hidden political engagement result in reputation damage and public mistrust, companies' political connection could expose themselves to unexpected regulatory change. In recent decade, a group of shareholder activists started filing shareholder proposals requesting corporate political transparency.

[8]Bebchuk and Jackson Jr [2012] extracts those eight non-profit organizations' lobbying and political expenditures from their Internal Revenue Service (IRS) filings.

3.3 Hypotheses Development

3.3.1 Development of Hypothesis 1

The first hypothesis concerns how activist shareholders select their target companies for improving corporate political transparency. Since the purpose of engagements is to bring transparency to corporate political spending, it is reasonable to expect that they would target companies with higher political spending and lower past transparency level. Prior literature and media reports have repeatedly emphasized the importance of Political Action Committee (PAC) in influencing the perception of general public [e.g. Sorauf, 1984; Burris, 2010]. Taken together, we put forward the following hypothesis.

Hypothesis H3.1 *Shareholders target companies with Political Action Committee (PAC) and lower political transparency level.*

3.3.2 Development of Hypothesis 2

The second hypothesis concerns what affects the likelihood of shareholder engagements being successful. Institutional investors, due to their superior ability to accumulate shares and coordinate with other investors, are more likely to achieve their goals [Barber and Odean, 2000; Jones and Lipson, 1999; Brav et al., 2016]. This is especially true for SRI funds. SRI funds specialize in influencing environmental, social, and governance (ESG) aspects of firms and thus are in a better position to provide relevant guidance and support for targeted firms. Further, the stated objectives of SRI fund typically involve achieving positive social impact in addition to financial gain.[9] Thus SRI funds might be more aggressive than other types of active investors in their engagements to attract potential investment.[10] Putting together,

[9]For example, in the homepage of Domini Social Investments (https://www.domini.com/), the fund's objectives include "engaging with issuers, civil society organizations, and policymakers to create financial, environmental, and societal value" and "encouraging corporate responsibility".

[10]For instance, Domini Social Investments identifies its potential investor as those "committed to the Fund's social and environmental investment standards".

we propose the following hypothesis.

Hypothesis H3.2 *Institutional activist investors, especially SRI funds, are more likely to succeed in their engagements.*

3.3.3 Development of Hypothesis 3

The third hypothesis is on how overall stock market reacts to outcomes of CPT-related shareholder engagements in the short term.

On one hand, investors might react more positively to successful shareholder engagements since information asymmetry and agency costs are reduced after successful shareholder intervention. On the other hand, increasing political transparency would impose additional costs on companies. Explicit costs include compilation costs, publication costs, costs to set up special supervisory committees and costs to set up and implement related policies, etc. Implicit costs include potential loss of competitive advantage due to the revelation of political engagement strategy to competitors. Taken together, investors would evaluate the benefits and costs and react accordingly. Based on above arguments, we propose two competing hypotheses on overall stock market reactions.

Hypothesis $\mathbf{H3.3_n}$ *Stock market reacts more positively to successful engagements than unsuccessful engagements.*

Hypothesis $\mathbf{H3.3_a}$ *Stock market reacts more negatively to successful engagements than unsuccessful engagements.*[11]

3.3.4 Development of Hypothesis 4

The fourth hypothesis is on how institutional investors, as an important category of investors emphasized by previous literature on corporate governance, react to

[11] The ideology of shareholder activists might be different from that of the broad investor base [e.g. Bolton et al., 2018]. Therefore even if broad investor base views corporate political transparency negatively, shareholder activists might still have the incentive to launch these campaigns.

outcomes of CPT-related shareholder engagements in the medium to long term. Following the same reasoning as in hypothesis 3, we propose two competing hypotheses on institutional investors' holding behaviour.

Hypothesis $\mathbf{H3.4_n}$ *Institutional investors increase their holdings after successful shareholder engagements.*

Hypothesis $\mathbf{H3.4_a}$ *Institutional investors decrease their holdings after successful shareholder engagements.*

3.3.5 Development of Hypothesis 5

This last hypothesis is on how companies' PAC expenditure change in reaction to outcomes of shareholder engagements.

As shareholder activists typically request more oversight, responsibility and business rationale for corporate political spending, company management will have significantly less discretion over political spending. For example, in a 2010 shareholder proposal to Waste Management Inc., the activist (International Brotherhood of Teamsters) requests disclosure of policies and procedures for political contributions and expenditures, identification of the person or persons in the company who is responsible for making the decisions to make the political contribution or expenditure, internal guidelines governing the company's political contributions and expenditures, and presentation to relevant oversight committee in the board. Therefore, we expect corporate political spending to decrease (or increase less fast) after successful shareholder engagements.

Hypothesis H3.5 *PAC expenditure decreases (or increases less fast) after successful shareholder engagements.*

3.4 Data and Summary Statistics

3.4.1 Data

The main data we use is shareholder proposals on corporate political transparency. The shareholder proposal data is from Institutional Shareholder Services (ISS) database. ISS covers shareholder proposals for Russell 3000 companies from 2006. We first screen out shareholder proposals on corporate political transparency.[12] We supplemented the data by a few additional proposals which are obtained through internet searches and are not in the ISS database. The outcomes of shareholder proposals could be classified into successful shareholder engagement and unsuccessful shareholder engagement. Successful shareholder engagement includes proposals that passed in the shareholder meeting and proposals that are withdrawn after shareholders reached agreement with company management to increase political transparency. Unsuccessful shareholder engagement includes proposals that failed in the shareholder meeting and proposals omitted by the company management after approval from Securities and Exchange Commission (SEC).[13]

Since we want to examine the market reaction, outcome announcement dates are needed. We manually collect outcome announcement dates from several sources. For proposals that passed or failed in the shareholder meeting, we collect announcement dates of shareholder meeting results in 8K filings from SEC Edgar database if possible.[14] If announcement dates are not available in 8K filings, especially before requirements on reporting enhancement in 2010, we use shareholder meeting

[12] The proposals are labelled as "Political Contributions Disclosure" or "Political Lobbying Disclosure" in ISS shareholder proposal resolutions.

[13] Omission of shareholder proposals provides a way for company management to fight against shareholders. Matsusaka et al. [2018] provides some explanations and analysis of omitted shareholder proposals.

[14] Company management are generally against CPT related shareholder proposals in proxy statement. The only exception is in Amgen Inc. 2006 shareholder meeting where company management voiced support for the shareholder proposal. In this case the final outcome is almost surely determined before shareholder meeting. Therefore we use the filing date of proxy statement as the outcome announcement date since it is the earliest date when management publicly announced support for the shareholder proposal.

dates as outcome announcement dates.[15] For proposals that are withdrawn after shareholder-management agreement, we collect announcement dates of agreement using extensive web searches, mostly from filing shareholders' press releases and centre for political accountability's joint press releases. Figure 3.9 presents a snapshot of announcement of the agreements. Not in all cases do shareholders publicly announce the agreement. Since testing market reaction requires the outcome to be public knowledge, we rely on withdrawn proposals for which public announcement dates of agreements can be identified for ex-post analyses. For omitted proposals, we obtain SEC approval dates as the outcome announcement dates from SEC Division of Corporation Finance website.

To remove confounding effects, in ex-post analysis we drop unsuccessful engagements if there are preceding successful engagements for the same company in the same election cycle.[16] The final sample contains 636 events from 2005 through 2016.

Consistent with the argument in Bebchuk and Jackson Jr [2012], we use sample companies' PAC expenditure to measure corporate political activism. There are two reasons for this measure. First, PAC expenditure is most direct measure shareholders could observe. Media frequently cites a company's PAC expenditure to indicate its political activism. It proxies for the market's perception of corporate political activism. Second, PAC expenditure is correlated with companies' hidden political spending through intermediaries. Bebchuk and Jackson Jr [2012] collects some data on corporations' political spending through intermediaries after disclosure and provides some examples. We then cross check these example companies' political spending through intermediaries with their PAC expenditure. For example, in 2011 Prudential Financial spent $570,000 through U.S. Chamber of Commerce while EMC corp. with similar size spent nothing. Correspondingly, Prudential Fi-

[15] During this procedure, we corrected several mistaken dates and outcomes in ISS database.

[16] The election cycle is two year as the Senate and the House of Representatives both hold election every two years. This definition is consistent with politics literature and practice. The results are similar if we include those unsuccessful engagements.

nancial PAC spent \$911,371 in 2012 election cycle while EMC corp. PAC only spent \$87,642. The PAC expenditure data is obtained from Federal Election Commission (FEC).[17]

Index on corporate political transparency is also used in part of this study. The index is also called CPA-Zicklin index since it is produced by Center for Political Accountability (CPA) in conjunction with the Zicklin Center for Business Ethics Research at The Wharton School at the University of Pennsylvania. The index measures corporate political transparency from three dimensions (disclosure, policy and oversight) on an annual basis. Detailed description of the index components can be found in appendix 3.C.B. The index becomes available in 2011 and gradually increases its coverage.[18] Since its horizon and coverage are limited, our sample size reduces significantly when we analyse the change in political transparency around shareholder engagements. The data I use in this study is from 2011 to 2016.

Data on Russell 3000 index constituents is obtained from Blommberg. We use index constituents at the end of each year. Stock price and market capitalization is obtained from CRSP. Accounting data is from Compustat. Analyst coverage is extracted from I/B/E/S. We use BoardEx to get information on companies' board of directors. Institutional ownership is obtained from 13F data.

3.4.2 Summary Statistics

Table 3.1 lists the top ten shareholder activists in terms of filing frequency in our sample. New York State Common Retirement Fund is the most active investor in this area. In Panel A of Figure 3.1, we provide statistics on activist types. Pubic pension fund, socially responsible investment (SRI) fund, labor union, religious group are the most common activist types. In Panel B of Figure 1, we find that financial and energy industry are most likely to be targeted by activists perhaps due

[17] The PAC names in FEC data are matched with company names in our sample first through a computerized fuzzy matching algorithm based on probabilistic record linkage. Then we manually inspect the matches to ensure accuracy.

[18] Please refer to Figure 3.7 for index coverage.

to their close nature with politics.

[Place Table 3.1 about here]

[Place Figure 3.1 about here]

Figure 3.2 presents the distribution of sample events used in ex-post analysis. The sample starts from 2005 and ends in 2016. Note that number of events is small in 2005 relative to other years. This is due to the fact that ISS shareholder proposal data starts from 2006 and we supplement the data by a few additional proposals obtained through web searches which leads to a few cases in 2005. There is a general increasing trend in the incidences of CPT-related shareholder engagements.

Observe that there are non-negligible amount of successful shareholder engagements, mostly in the form of settlement agreements between activist shareholders and management. This contrasts the argument in previous studies [e.g. Bebchuk and Jackson Jr, 2012; Cohn et al., 2016; Copland and O'Keefe, 2016] that CPT-related shareholder proposals rarely succeed and the sudden disclosure of political spending by companies is on a "voluntary" basis. The reason is previous literature focuses exclusively on the proposals that went to the final stage of shareholder meeting. However, by further investigation we find that in those cases activists and company management reached agreement before the meeting and subsequently pull back their proposals in exchange for improved corporate political transparency. This is in line with McCahery et al. [2016] where they find that behind-the-door discussions between shareholder and management are prevalent and effective. Note that the percentage of successful shareholder proposal is on a decline in recent years. However, this is not necessarily an evidence of companies' increasing objection to corporate political transparency since it is perhaps due to company management and shareholders already reaching agreement before shareholder proposals were filed.

[Place Figure 3.2 about here]

Russell 3000 sample from 2005 to 2015 is used in ex-ante analysis because from 2006 to 2016 we can collect complete shareholder proposal data in Russell 3000 universe from ISS. In ex-ante analysis we do not remove events without outcome announcement dates or events that could potentially result in confounding ex-post effects. The summary statistics of variables of Russell 3000 Sample are provided in Panel A of Table 3.2. In addition, summary statistics of variables of the sample used in ex-post analysis are provided in Panel B of Table 3.2.

[Place Table 3.2 about here]

3.5 Empirical Findings

3.5.1 Ex-ante Analysis

Target Selection

In this section I test which companies are more likely to be targeted by shareholder activists for improving corporate political transparency. Using Russell 3000 panel from 2005 to 2015, I run the following multivariate probit regression

$$\begin{aligned}\mathbf{P}(Target_{i,t}) =&\Phi(\beta_0 + \beta_1 PAC\ Existence_{i,t} + \beta_2 Transparency_{i,t-1} \\ &+ \beta_3 Targeted\ in\ the\ past_{i,t} + \beta_4 Size_{i,t-1} + \beta_5 BM_{i,t-1} \\ &+ \beta_6 Ret12M_{i,t-1} + \beta_7 Analyst\ Coverage_{i,t-1} + \beta_8 BoardSize_{i,t-1} \\ &+ \beta_9 CEO\text{-}Chairman\ Duality_{i,t-1} + \beta_{10}\%Outside\_Directors_{i,t-1} \\ &+ \beta_{11} Director\_Tenure_{i,t-1} + \beta_{12}\%Connected\_Directors_{i,t-1} \\ &+ \beta_{13} Institutional\ Onwership_{i,t-1} + \epsilon_{i,t})\end{aligned} \tag{3.1}$$

where *Target* is a dummy variable that takes value one if shareholder activists file a proposal for the company in the subsequent year and zero otherwise.

We consider a large set of explanatory variables. *PAC Existence* is a dummy variable that equals one if the company has a Political Action Committee(PAC) and zero otherwise. *Transparency* corresponds to the company' pre-target political transparency level measured by CPA-Zicklin index. *Targeted in the past* is a dummy variable equal to one if the company was previously targted by shareholder activists and zero otherwise. *Size* is the natural logrithm of market capitalization of the company. *BM* is the book value of equity divided by market value of equity. *Ret12M* is the stock return in past 12 months. *Analyst Coverage* is the number of analysts that make annual earnings forecasts for the company in previous twelve months. *BoardSize* is the total number of directors on the board. *CEOChairman Duality* is a dummy variable that equals one if the CEO is also the chairman of the board, and zero otherwise. *%Outside_Directors* is the percentage of outside (independent) directors on the board. *Director_Tenure* is the average tenure of all directors sitting on the board. *%Connected_Directors* is the percentage of government-connected directors on the board. *Institutional Onwership* is the percentage of outstanding shares held by institutional investors.

Since *Transparency*, measured by CPA-Zicklin index, is only available for a small number of firms within a short period of time (2011 - 2016), including *Transparency* in the regression would significantly shrink sample size. Based on above considerations, we run both regressions, with and without adding *Transparency* as explanatory variables. Regression results and marginal effects at the mean are reported in Table 3.3.

Results are generally consistent in all regressions. Shareholders are significantly more likely to target companies with political action committee (PAC). This shows that PAC activities are important in influencing shareholders' perception of corporate political activism. Consistent with the purpose of shareholder engagements, activist investors are more likely to target companies with lower political transparency level.

We also find the evidence of repeated engagements. Being targeted in the past increases the target probability by about 1.1%. Consistent with companies that receive governance-related shareholder proposals have larger size and poorer long-term performance [Karpoff et al., 1996], companies with larger size, lower stock return and higher book-to-market ratio are more likely to be targeted by shareholder activists. Analyst coverage, however, is unrelated to activists' target decision.

Coefficients on characteristics associated with board monitoring are generally insignificant. Consistent with board of directors' political connection and corporate political spending are two complementary ways of political investment[19], companies with a larger fraction of politically connected directors are more likely to attract shareholder activists' attention. Lastly, targeted companies exhibit higher institutional ownership. This is consistent with institutional ownership is positively related to sophistication of shareholder base [Brav et al., 2008]. Thus high institutional ownership makes it easier for activist shareholders to gain support and understanding from fellow shareholders.

Taken together, the set of explanatory variables are quite successful in explaining activists' target selection, yielding a Pseudo R^2 of 44.1%.

[Place Table 3.3 about here]

Likelihood of Successful Engagement

In this section we test which types of activist investors are more likely to succeed in their engagements. Using the sample of final events from 2005 to 2016, we run the following multivariate probit regression

$$\mathbf{P}(Success_{i,t}) = \Phi(\beta_0 + \beta_1 Sponsor\ Type_{i,t} + \gamma Controls + \epsilon_{i,t}) \tag{3.2}$$

[19]This is also confirmed using our sample as the correlation between percentage of connected directors and PAC expenditure is significantly positive.

where *Success* is a dummy variable that takes value one if the shareholder engagement is successful and zero otherwise.

Sponsor Type represents a set of dummy variables with respect to activist types. The first variable considered *Sponsor is an institutional investor* is a dummy variable equal to 1 if the sponsor of the proposal is an institutional investor (SRI fund/public pension/religious group/labor union). Then we further break down the variable into four dummy variables (*Sponsor is a SRI fund/public pension/religious group/labor union*) and include them in a horse race type regression. *Controls* represents a set of control variables, including PAC Existence, firm size, book-to-market ratio, past one-year return, analyst coverage, board characteristics, and institutional ownership. Regression results and marginal effects at the mean are reported in Table 3.4.

First we find that institutional investors are more likely to succeed in their engagements. The probability of successful engagement is about 11% higher for institutional activist investors than for other investors. This is consistent with institutional investors, due to expertise and scale advantage, possess superior ability to accumulate shares and coordinate with other investors [Agarwal, 2007; Brav et al., 2016]. Next, we compare different types of investors within the institutional investor domain by running the horse race type regression with four sponsor type dummies. We find that SRI funds are most likely to achieve progress in their engagements. This finding supports the view that SRI funds, as having more expertise in areas related to social aspects of firms, are more able to work with targeted companies by offering appropriate guidance and support. It is also consistent with SRI funds are more aggressive in their engagements to achieve their advocated objectives and attract more investment. Among institutional activist investors, labor unions are found to be less successful. This finding supports the view that labor unions suffer more conflict of interest with company management [Agrawal, 2012].

Most control variables, such as PAC existence, size, book-to-market ratio, past one-year return, analyst coverage, and institutional ownership, do not show significant explanatory power over engagement outcomes. The only exception is that larger board size contributes positively to the likelihood of successful engagement.

[Place Table 3.4 about here]

3.5.2 Ex-post Analysis

Change in Corporate Political Transparency around Events

This section examines change in corporate political transparency around events. This also acts as a validation test so that we are sure successful shareholder engagements would result in better corporate political transparency.

All events with available outcome dates are merged with CPA-Zicklin index which is an annual measure of corporate political transparency. In order to compare changes, we require the final sample to have CPA-Zicklin index from one year prior to event year until one year after event year. As the coverage and length of CPA-Zicklin index is limited, we am able to obtain 10 successful engagements and 176 unsuccessful engagements with available CPA-Zicklin index. The sample size is consistent with the fact that CPA-Zicklin index starts coverage from 2011 and the percentage of successful shareholder engagements is on a decline since 2010.

In Figure 3.3, we plot the average CPA-Zicklin index from one year prior to event year ($t-1$) until one year after event year ($t+1$), both for successful shareholder engagements and unsuccessful shareholder engagements. All indices, including disclosure, policy, oversight, and grand total, feature a significant jump in year t for successful engagements relative to unsuccessful engagements. The trend becomes parallel in year $t+1$.

[Place Figure 3.3 about here]

Table 3.5 provides some statistical tests. In most panels, $t-1$ to t political transparency change is statistically higher in successful engagements. Consistent with the parallel trend, t to $t+1$ political transparency change is statistically indifferent between successful engagements and unsuccessful engagements.

[Place Table 3.5 about here]

This finding shows that successful shareholder engagements would lead to concrete positive changes in corporate political transparency.

Stock Market Reaction

In this section we examine short-term stock market reactions to different shareholder engagement outcomes. We use event study methodology to perform the analysis. A brief review of event study methodology is provided first and then results are reported.

Event Study Methodology Event study methodology is used to estimate abnormal return attributed to corporate event. The abnormal return is defined as the actual return of the stock over the event window minus the normal return of the stock over the same window. The normal return is defined as the expected return without the event taking place.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|I_t) \tag{3.3}$$

where $AR_{i,t}$ represents the abnormal return, $R_{i,t}$ is the actual return and I_t represents the conditioning information. Here we use Carhart four-factor model to compute the normal return.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i1}(R_{m,t} - R_{f,t}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}MOM_t + \epsilon_{i,t} \tag{3.4}$$

where $R_{i,t}$ is the return of stock i on day t, $R_{m,t}$ and $R_{f,t}$ are the market return and risk-free rate on day t respectively, SMB_t is the size factor which is computed as the return difference between portfolios of small cap stocks and large cap stocks, HML_t is the value factor which is computed as the return difference between portfolios of high book-to-market stocks and low book-to-market stocks, MOM_t is the momentum factor which is computed as the return difference between portfolios of high performing stocks and low performing stocks.

To get the average effect of events, abnormal returns are aggregated over the specified event window and then taken average over all events.

$$CAAR = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=t_1}^{t_2} AR_{i,t} \tag{3.5}$$

where CAR is cumulative abnormal return over event window $[t_1, t_2]$, N is total number of events.

Event Study Results Based on reasoning provided before, shareholders could potentially react differently to engagement outcomes in companies with different level of political activism. Therefore we partition the sample into two groups based on PAC expenditure. A company is classified as being politically active if its PAC expenditure is higher than or equal to sample median PAC expenditure in the two-year election cycle of the event.[20] Further, we consider four event windows: $[-1, 5]$, $[-1, 10]$, $[-1, 15]$, and $[-1, 20]$. Unlike financial information (e.g. earnings announce-

[20]Average PAC expenditure of politically active companies is about \$1.85 million. By contrast, average PAC expenditure of politically inactive companies is about \$0.24 million.

ment), shareholders may not immediately gather, process and interpret this type of non-financial information and thus we use relatively longer event windows.

Table 3.6 provides event study results. The results for politically active companies are displayed in Panel A. Successful engagements lead to positive abnormal returns in politically active companies. The cumulative abnormal return is 3.16% within 12 days. Unsuccessful engagements are decomposed into three categories: omission of shareholder proposal, fail in shareholder meeting but with high support (i.e. "For" votes $>=$ 30%), fail in shareholder meeting and with low support (i.e. "For" votes $<$ 30%). Engagements that fail in shareholder meeting but with high support result in negative stock market reaction with a cumulative abnormal return of -1.14% from -1 to 10. The stock market reaction to omission of shareholder proposal and engagements that fail in shareholder meeting and with low support is statistically indifferent from zero. Taken together, the results suggest that stock market investors value political transparency in politically active companies. In other words, the benefit of corporate political transparency to shareholders outweighs the cost borne by shareholders in politically active companies. Panel A of Figure 3.4 depicts the short-term abnormal return for politically active companies.

Panel B shows the results for politically inactive companies. Short-term stock market reactions are statistically indifferent from zero in all categories. This suggests that in politically inactive companies, the benefit of corporate political transparency to shareholders is mitigated by the cost borne by shareholders. Panel B of Figure 3.4 depicts the short-term abnormal return for politically inactive companies.

[Place Table 3.6 about here]

[Place Figure 3.4 about here]

In order to further remove noise and control for other explanatory variables, we compare market reactions to successful engagements with that to unsuccessful engagements in a multivariate regression framework. The comparison is important because if there is some unobservable common trend influencing all firms targeted by activists, then the effect of unobservable common trend can be mitigated by the comparison. The following regression is estimated for both politically active and inactive companies.

$$CAAR_{i,t} = \alpha + \gamma Success_{i,t} + \beta Controls + \epsilon_{i,t} \tag{3.6}$$

where *CAAR* is cumulative abnormal return in event window $[-1, 10]$. *Success* is a dummy variable that takes value one if shareholder engagement is successful and zero otherwise. *Controls* represents a set of control variables, including firm size, book-to-market ratio, past one-year return, analyst coverage, board size, CEO-chairman duality, percentage of independent directors, director tenure and institutional ownership.

Table 3.7 presents the estimation results. In politically active companies, the difference between market reactions to successful engagements and those to unsuccessful engagements is 3.48% as displayed in column one. The difference remains statistically significant and becomes stronger after controlling for other explanatory variables. In politically inactive companies, the difference is statistically insignificant.

[Place Table 3.7 about here]

Political Uncertainty and Market Reactions

In the previous section we find that stock market reacts positively to successful engagements in politically active companies. The explanation could be that information asymmetry and hidden risk to shareholders are alleviated after successful intervention. To further test this explanation, we re-estimate regression 3.6 in two regimes separately: high political uncertainty regime and low political uncertainty regime. The intuition is that hidden risk associated with corporate political opacity is higher when political uncertainty is high. Using policy uncertainty index developed by Baker et al. [2016], we partition the sample into two groups. An event is classified as in high policy uncertainty regime if the index is above sample median. We use both overall index and news-based index.

Table 3.8 displays the regression results. In politically active companies (Panel A), the difference between market reactions to successful engagement and those to unsuccessful engagement is more positive when policy uncertainty is high. By contrast, in politically inactive companies (Panel B), the coefficients on *Success* dummy are not much different between two regimes.

[Place Table 3.8 about here]

Change in Political Spending

Increased transparency is associated with more effective monitoring and discipline [Wang, 2010; Downar et al., 2017; De Franco et al., 2013; Berger and Hann, 2003]. This could offer another explanation for the stock market reactions to shareholder engagements. We use change in companies' PAC expenditure to test the disciplinary effect. The intuition is that if successful shareholder engagements result in better monitoring of company management, management would have less discretion over the political spending. Thus political spending of successfully engaged companies would increase less fast (or decrease) relative to that of unsuccessfully engaged companies.

We require the company to have PAC expenditure information from two election cycles before shareholder engagements to two election cycles after shareholder engagements. The events in or after 2013 are excluded since PAC expenditure information are not available up to two election cycles after shareholder engagements.

To remove confounding effects, we remove unsuccessful engagements that are subsequently targeted and end up being engaged successfully within the next two election cycles. Figure 3.5 depicts the PAC expenditure of both successfully engaged companies and unsuccessfully engaged companies. In politically active companies (Panel A), successful engagements indeed result in a smaller increase in PAC expenditure relative to unsuccessful engagements. We also plot the differences in PAC expenditure between successfully engaged companies and unsuccessfully engaged companies. The pattern shows that the difference becomes more negative after shareholder intervention, supporting the previous statement. In politically inactive companies (Panel B), successful engagements result in a larger increase in PAC expenditure relative to unsuccessful engagements. The difference plot also confirms this statement.

[**Place Figure 3.5 about here**]

To formally test the above discipline effect, we adopt the following difference-in-differences framework.

$$PAC\_EXP_{i,t} = \alpha Success_i + \beta \sum_{j=0}^{2} Post_j + \gamma \sum_{j=0}^{2} Success_i * Post_j + \theta Controls + \epsilon_{i,t} \tag{3.7}$$

where $PAC\_EXP_{i,t}$ is the company's PAC expenditure. $Success_i$ is a dummy variable that takes value one if shareholder intervention is successful and zero otherwise. $Post_j$ is a dummy variable that takes value one if shareholder engagement takes place in election cycle $t - j$ and zero otherwise. *Controls* represents a set of control variables. The regression is estimated both with and without industry fixed effects. Standard errors are clustered at firm level to account for within-firm correlation.

Regression Results are presented in column 1 and 2 of Table 3.9. Consistent with the graphical results, the interaction term is significantly negative at time 0.

The interaction term at time 1 and 2 is also negative although statistical significance is dampened. The coefficient on $Success * Post_0$ in column 2 means that change in PAC expenditure of successfully intervened companies is \$82,120 less than that of unsuccessfully intervened companies at time 0 (election cycle of shareholder engagement). Graphically, the effect is mainly from politically active companies. In order to test it, we perform the following triple difference regression.

$$\begin{aligned} PAC\_EXP_{i,t} =& \alpha Success_i + \xi Active_i + \delta Success_i * Active_i + \beta \sum_{j=0}^{2} Post_j \\ & + \gamma \sum_{j=0}^{2} Success_i * Post_j + \eta \sum_{j=0}^{2} Active_i * Post_j \\ & + \nu \sum_{j=0}^{2} Success_i * Active_i * Post_j + \theta Controls + \epsilon_{i,t} \end{aligned} \tag{3.8}$$

where $Active_i$ is a dummy variable that equals one if the company is politically active and zero otherwise. Other variables are the same as in previous regression. The regression is estimated both with and without industry fixed effects. Standard errors are clustered at firm level to account for within-firm correlation.

Regression results are presented in column 3 and 4 of Table 3.9. Consistent with the discipline effect is more significant in politically active companies, the triple interaction term $Success_i * Active_i * Post_j$ is negative at time 0, 1, 2 though insignificant. The magnitude of coefficients is economically significant.

[**Place Table 3.9 about here**]

Taken together, the results suggest that shareholder engagements have disciplinary effect on corporate political spending, mostly in politically active companies.

Change in Institutional Ownership

In this section we investigate institutional investors' behavior in response to engagement outcomes. This analysis complements previous studies on the role of institutional investors in general corporate governance and sustainability by probing deeper into one specific area in ESG: corporate political transparency. We use quarterly holdings of institutional investors to perform the analysis. Therefore we focus on institutional investors' behaviour in medium to long-term.

The engaged companies need to have information on institutional ownership from four quarters before shareholder engagements to four quarters after shareholder engagements. The events in 2016 are excluded since information on institutional ownership are not available up to four quarters after shareholder engagements. Figure 3.6 depicts the institutional ownership of both successfully engaged companies and unsuccessfully engaged companies. Successfully engaged companies experience an increase in institutional holdings. By contrast, unsuccessfully engaged companies experience an decrease in institutional holdings. The effect persists more than one quarter after shareholder engagements. The difference between institutional ownership of successfully engaged companies and that of unsuccessfully engaged companies turns more positive after shareholder engagements, echoing the previous finding.

[Place Figure 3.6 about here]

To formally test the above effect, we estimate the following difference-in-differences regression.

$$IO_{i,t} = \alpha Success_i + \beta \sum_{j=0}^{4} Post_j + \gamma \sum_{j=0}^{4} Success_i * Post_j + \theta Controls + \epsilon_{i,t} \quad (3.9)$$

where $IO_{i,t}$ is the company's institutional ownership. Other variables have the same definitions as in previous regressions. The regression is estimated both with and without industry fixed effects. Standard errors are clustered at firm level to account for within-firm correlation.

Table 3.10 provides the estimation results. The interaction term is significantly positive at time 0, 1. The coefficient on interaction term is 2% at time 0 and 5% at time 1, which is economically large. This means that institutional ownership of successfully engaged companies increased by 2%(5%) more than that of unsuccessfully engaged companies at time 0(1). Echoing previous literature that documents the positive role of institutional investors in general ESG area [Appel et al., 2016; He et al., 2017; Dimson et al., 2015], our finding provides support for the view that institutional investors have a preference for political transparency of their portfolio companies.

[Place Table 3.10 about here]

3.6 Concluding Remarks

With ever growing corporate political spending and recent regulatory changes on political spending, it is crucial to understand the drivers and implications of corporate political transparency. This paper seeks to provide some insights by studying corporate political transparency through the lens of shareholder engagements.

We begin by documenting that there are many more successful shareholder engagements than previous literature have recognized. They are mostly in the form of settlement agreements between activist shareholders and management. Therefore shareholder engagements help shape corporate political transparency.

We then examine factors that drive activist investors' target decision. Activist investors tend to target companies with political action committee and lower political transparency level. We also find evidence of repeated engagements. Next, we study which types of activist investors are more likely to succeed in their engagements. Consistent with institutional investors' superior ability to accumulate shares and coordinate with other investors, we find engagements launched by institutional investors are more likely to be successful. Among the domain of institutional activist investors, we find that SRI funds are best performers and labor unions are worst performers.

On the implication side, we find that successful shareholder engagements indeed lead to much bigger improvement in corporate political transparency, measured by CPA-Zicklin index, compared to unsuccessful engagements. We provide market-based tests on how market participants view corporate political transparency. Stock market responses are significantly positive to successful engagements and negative to a subset of unsuccessful engagements in politically active companies. We do not find such responses in politically inactive companies. This suggests that the benefit of corporate political transparency to shareholders outweighs the cost borne by shareholders in politically active companies.

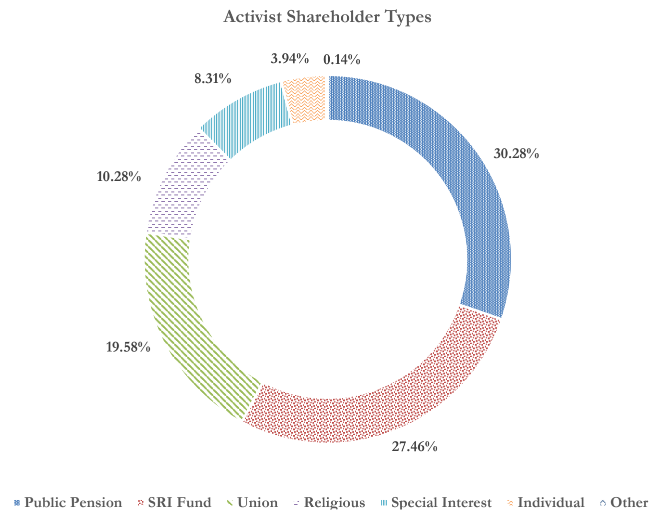
We then analyse the channels through which political transparency affects firm value. Consistent with corporate political transparency lowering hidden risk to investors, the market reactions are stronger when political uncertainty is high. Consistent with the disciplinary effect of corporate political transparency, successful shareholder interventions result in a slower growth of PAC expenditure than unsuccessful interventions in politically active companies. Lastly, we also provide evidences that institutional investors have a preference for corporate political transparency. Institutional ownership of successfully engaged companies experience an increase whilst that of unsuccessfully engaged companies experience a decrease in medium to long-term.

Overall, our market-based tests provide support for corporate political transparency. It would be interesting to examine whether corporate political transparency would disadvantage companies by revealing their business-related information. We leave this question for future research.

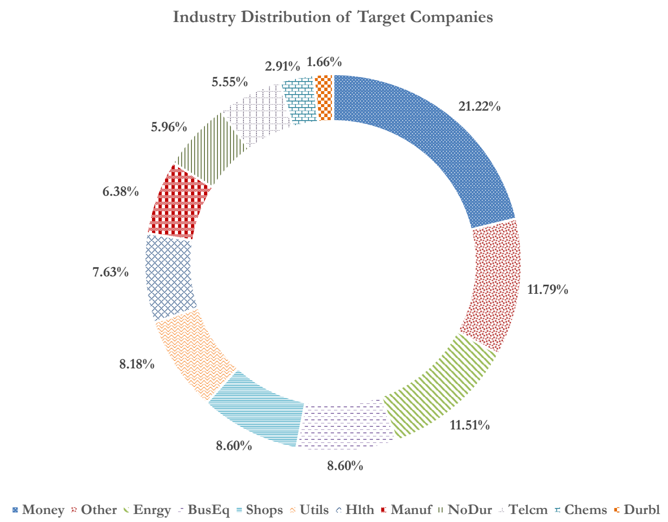
Appendix 3.A Figures

Figure 3.1: Activist Shareholder Type and Industry Distribution of Target Companies

This figure represents activist shareholder types (Panel (a)) and industry distribution of target companies (Panel (b)). We use collected shareholder engagements on corporate political transparency from 2005 to 2016.



(a)



(b)

Figure 3.2: CPT-related Shareholder Engagements from 2005 to 2016

This figure plots the number of shareholder engagements from 2005 to 2016 that are used in ex-post analysis. Successful shareholder engagements include proposals that passed in the shareholder meeting and proposals that are withdrawn after shareholders reached agreement with company management to increase political transparency. Unsuccessful shareholder engagements include proposals that failed in the shareholder meeting and proposals omitted by the company management after approval from SEC.

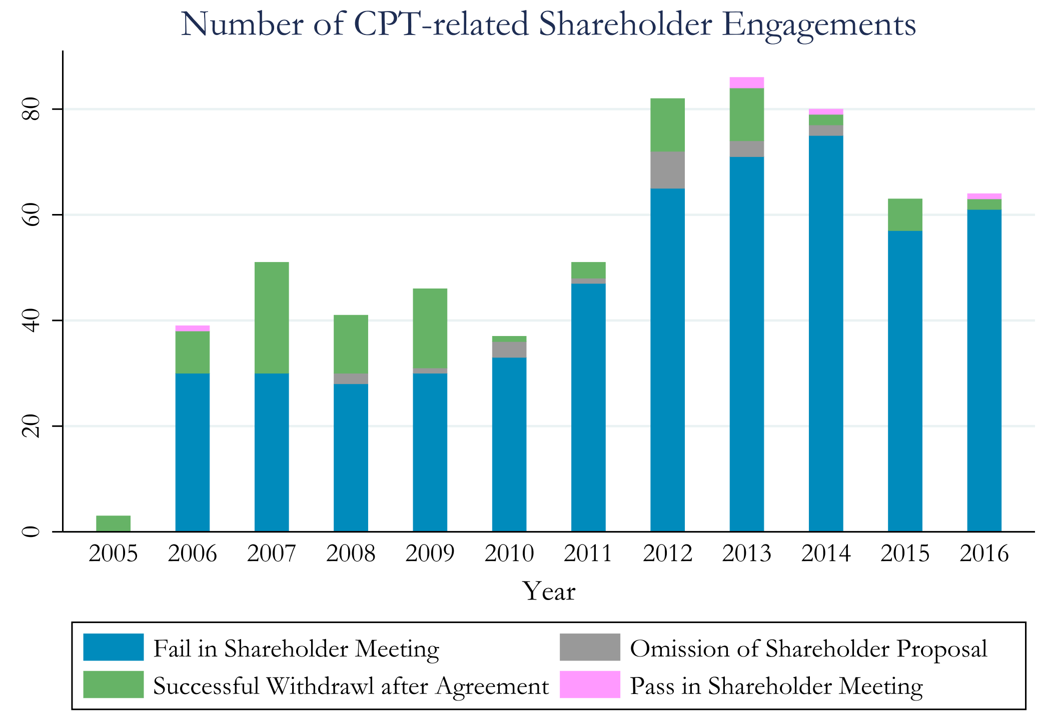


Figure 3.3: Change in Corporate Political Transparency around Events

This figure represents the change in corporate political transparency measured by CPA-Zicklin index around shareholder engagements. All indices are in annual frequency. *Grand_Total* is the company's overall CPA-Zicklin index. *Disclosure*, *Policy*, *Oversight* are individual components of CPA-Zicklin index with detailed definitions in Table 3.11. $t-1$, t, $t+1$ correspond to one year before outcome announcement, the year of outcome announcement, and one year after outcome announcement, respectively.

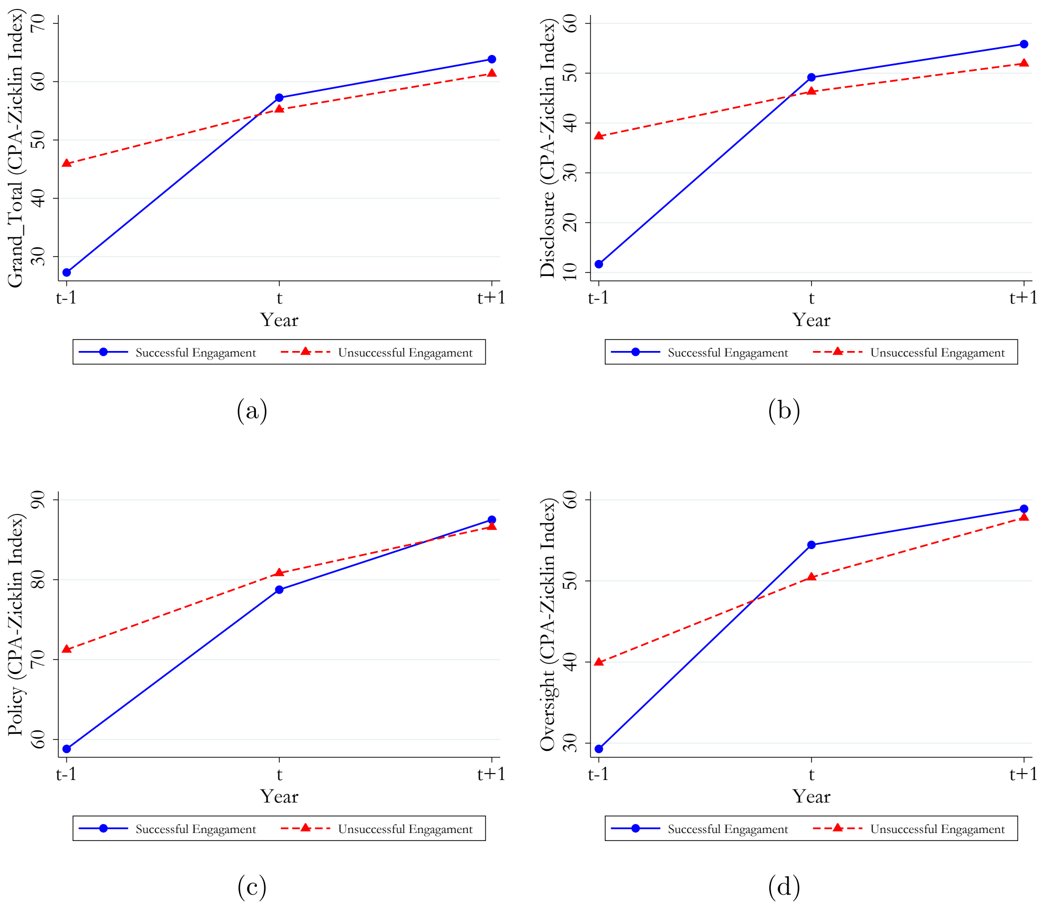
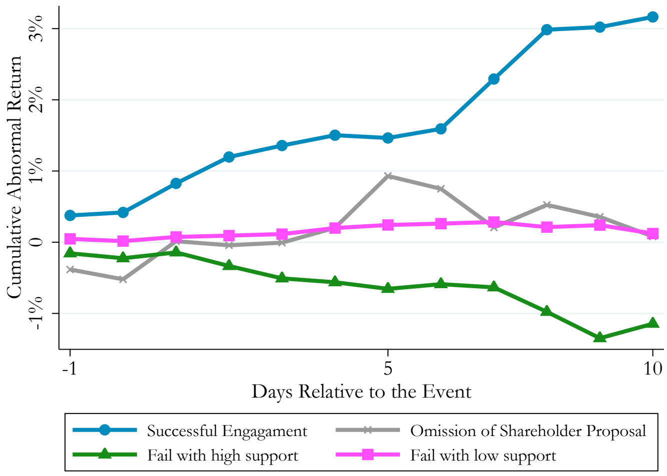
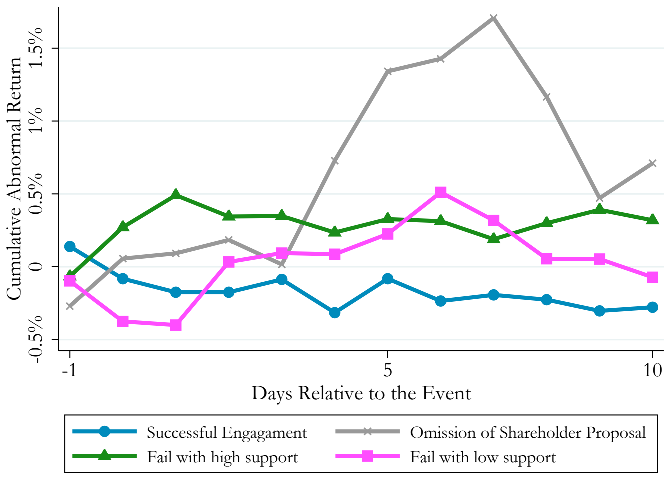


Figure 3.4: Stock Market Reactions to Engagement Outcomes

This figure represents stock market reactions to different shareholder engagement outcomes in politically active companies (Panel (a)) and politically inactive companies (Panel (b)). The engagement outcomes are classfied into two categories: *Successful Engagement* and *Unsuccessful Engagement*. *Unsuccessful Engagement* is further decomposed into three sub-categories: *Omission of Shareholder Proposal*, *Fail in shareholder meeting with high support*, and *Fail in shareholder meeting with low support*. We consider a window from 1 days before to 10 days after the outcome announcement date (Day 0). Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model.



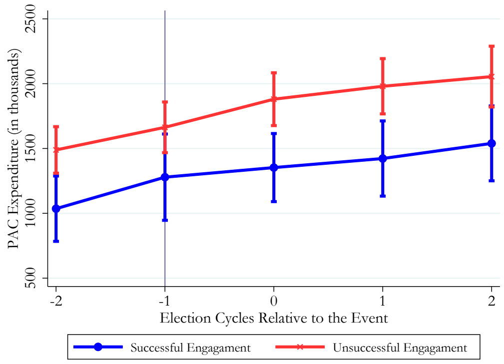
(a) Politically Active Companies



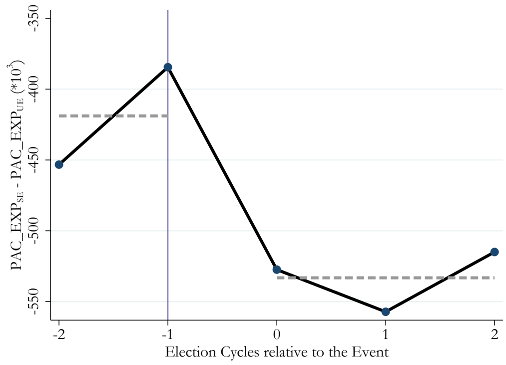
(b) Politically Inactive Companies

Figure 3.5: Change in PAC expenditure

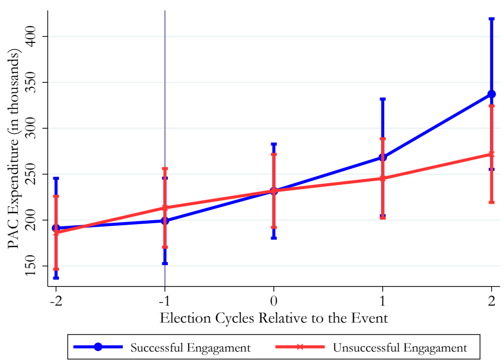
This figure represents changes in PAC expenditure around shareholder engagements. Top panels (Panel (a) and (b)) represent politically active companies. Bottom panels (Panel (c) and (d)) represent politically inactive companies. Figures on the left (Panel (a) and (c)) represent the average PAC expenditure and 95% confidence intervals. Figures on the right (Panel (b) and (d)) represent the difference in PAC expenditure between successfully engaged companies (PAC_EXP_{SE}) and unsuccessfully engaged companies(PAC_EXP_{UE}).



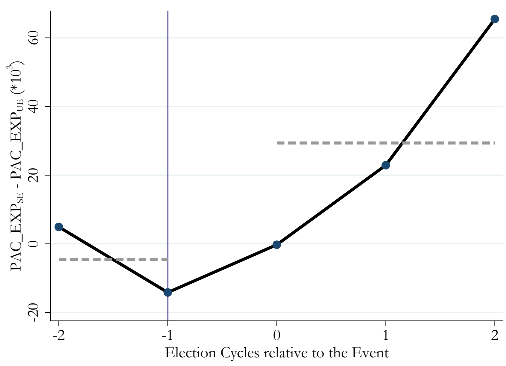
(a) Politically Active Companies



(b) Politically Active Companies



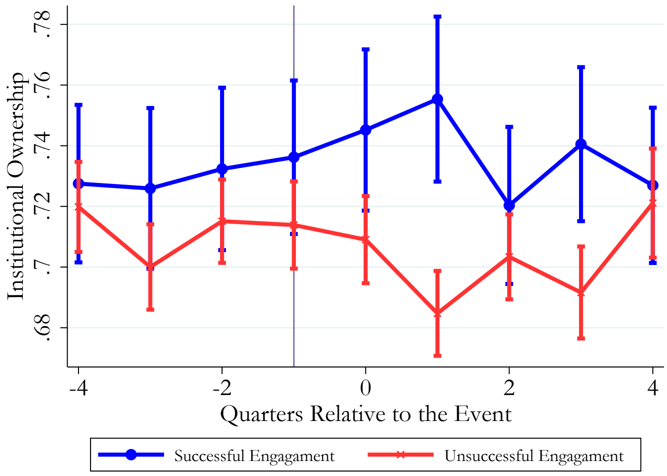
(c) Politically Inactive Companies



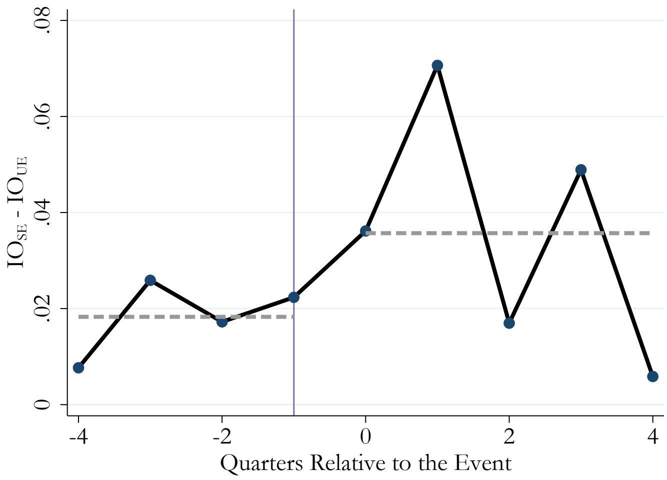
(d) Politically Inactive Companies

Figure 3.6: Change in Institutional Ownership

This figure represents changes in institutional ownership around shareholder engagements. Panel (a) represents the average institutional ownership and 95% confidence intervals. Panel (b) represents the difference in institutional ownership between successfully engaged companies (IO_{SE}) and unsuccessfully engaged companies(IO_{UE}).



(a)



(b)

Appendix 3.B Tables

Table 3.1: Most Frequent Shareholder Activists

This table shows the top ten shareholder activists that have filed corporate political tranprency (CPT) related proposals in terms of frequency.

Top Ten Shareholder Activists		
Rank	Sponsor Name	Frequency
1	New York State Common Retirement Fund	89
2	New York City Pension Funds	84
3	AFL-CIO	55
4	Trillium Asset Management	38
5	Walden Asset Management	36
6	Sisters of Mercy	25
7	Nathan Cummings Foundation	24
8	Domini Social Investments	24
9	Green Century Capital Management	23
10	International Brotherhood of Teamsters	21

Table 3.2: Summary Statistics

This table shows the summary statistics of each variable for Russell 3000 sample (Panel A) that is mainly used in ex-ante analysis and event study sample (Panel B) that is mainly used in ex-post analysis. *Size* is the natural logrithm of market capitalization of the company. *B/M* is the book value of equity divided by market value of equity. *Past 12M Return* is the past stock return for the previous twelve months. *Analyst Coverage* is the number of analysts that make annual earnings forecasts for the company in previous twelve months. *Board Size* is the total number of directors on the board. *CEO-Chairman Duality* is a dummy variable that equals one if the CEO is also the chairman of the board, and zero otherwise. *%Outside Directors* is the percentage of outside (independent) directors on the board. *Director Tenure* is the the average tenure of all directors sitting on the board. *PAC Expenditure* is expenditure of the company's political action committee (PAC) in a two-year election cycle. *Institutional Ownership* is the percentage of outstanding shares held by institutional investors.

Panel A: Summary Statistics of Russell 3000 Sample

	Obs	Mean	25%	50%	75%	Std.Dev
Size	32634	7.12	5.95	6.93	8.07	1.56
B/M	32353	0.5870	0.2821	0.5044	0.8114	2.1846
Past 12M Return	32021	0.1375	-0.1568	0.0773	0.3193	0.8400
Analyst Coverage	31162	11.6338	5.0000	9.0000	16.0000	8.9282
Board Size	31634	8.9143	7.0000	9.0000	10.0000	2.4495
CEO-Chairman Duality	31634	0.4601	0.0000	0.0000	1.0000	0.4984
%Outside Directors	31634	0.8083	0.7500	0.8333	0.8889	0.1039
Director Tenure	31634	7.8387	4.7571	7.4769	10.4000	4.3859
PAC Expenditure (in thousands)	32749	75.27	0.00	0.00	0.00	342.85
Institutional Ownership	32604	0.6939	0.5424	0.7485	0.8901	0.2472

Panel B: Summary Statistics of Event Study Sample

	Obs	Mean	25%	50%	75%	Std.Dev
Size	636	10.29	9.51	10.31	11.20	1.34
B/M	627	0.5988	0.2822	0.5034	0.8227	0.6654
Past 12M Return	636	0.1225	-0.0515	0.1174	0.2668	0.3551
Analyst Coverage	636	26.1824	20.0000	26.0000	32.0000	10.1074
Board Size	635	11.5969	10.0000	12.0000	13.0000	2.2616
CEO-Chairman Duality	635	0.6472	0.0000	1.0000	1.0000	0.4782
%Outside Directors	635	0.8789	0.8571	0.9000	0.9167	0.0645
Director Tenure	635	7.9899	6.1700	7.7500	9.2500	2.7461
PAC Expenditure (in thousands)	636	1059.12	210.93	634.51	1478.13	1246.44
Institutional Ownership	636	0.7273	0.6342	0.7271	0.8434	0.1861

Table 3.3: Target Selection

This table examines the determinants of activists' target selection using Russell 3000 sample from 2005 to 2015. The dependent variable *Target* is a dummy variable that equals one if shareholder activists file a proposal for the company in the subsequent year and zero otherwise. *PAC Existence* is a dummy variable that equals one if the company has a Political Action Committee(PAC) and zero otherwise. *Grand_Total* is the company's overall CPA-Zicklin index on corporate political transparency. *Disclosure, Policy, Oversight* are individual components of CPA-Zicklin index with detailed definitions in Table 3.11. *Targeted in the Past* is a dummy variable equal to one if the company was previously targted by shareholder activists and zero otherwise. *Size* is the natural logrithm of market capitalization of the company. *B/M* is the book value of equity divided by market value of equity. *Ret12M* is the past stock return for the previous twelve months. *Coverage* is the number of analysts that make annual earnings forecasts for the company in previous twelve months. *BoardSize* is the total number of directors on the board. *Duality* is a dummy variable that equals one if the CEO is also the chairman of the board, and zero otherwise. *%Outside_Directors* is the percentage of outside (independent) directors on the board. *Tenure* is the average tenure of all directors sitting on the board. *%Connected_Directors* is the percentage of government-connected directors on the board. *IO* is the percentage of outstanding shares held by institutional investors. In each column, we report coefficient estimates, their heteroscedasticity-robust t-statistics and the corresponding marginal probability change induced by a one-unit change in the value of a specific covariate from its sample average. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Target	Mfx	Target	Mfx	Target	Mfx	Target	Mfx	Target	Mfx
PAC Existence	0.74782***	0.00881***	0.45629***	0.09689***	0.42002***	0.08977***	0.49940***	0.10960***	0.49432***	0.10680***
	[12.50]	[6.81]	[3.06]	[3.45]	[2.82]	[3.14]	[3.48]	[3.99]	[3.39]	[3.87]
Grand_Total			-0.01686***	-0.00396***						
			[-8.49]	[-8.82]						
Disclosure					-0.01539***	-0.00361***				
					[-8.84]	[-9.11]				
Policy							-0.00956***	-0.00233***		
							[-5.22]	[-5.41]		
Oversight									-0.01206***	-0.00290***
									[-7.11]	[-7.07]
Targeted in the Past	0.69492***	0.01074***	0.95671***	0.21200***	0.90160***	0.20010***	0.79612***	0.18506***	0.81681***	0.18673***
	[11.17]	[3.95]	[6.72]	[7.14]	[6.57]	[6.91]	[5.76]	[6.15]	[6.22]	[6.48]
Size	0.33626***	0.00196***	0.32330***	0.07587***	0.30202***	0.07078***	0.25549***	0.06236***	0.29943***	0.07195***
	[12.65]	[7.27]	[4.76]	[4.72]	[4.47]	[4.42]	[3.91]	[3.89]	[4.34]	[4.32]
B/M	0.12149***	0.00071***	0.24450**	0.05737**	0.23928**	0.05607**	0.24902**	0.06078**	0.25556**	0.06141**
	[5.12]	[4.43]	[2.39]	[2.39]	[2.29]	[2.29]	[2.44]	[2.44]	[2.49]	[2.49]
Ret12M	-0.14669**	-0.00086**	-0.16043	-0.03765	-0.14609	-0.03424	-0.13604	-0.03320	-0.14271	-0.03429
	[-2.36]	[-2.29]	[-0.85]	[-0.85]	[-0.77]	[-0.77]	[-0.75]	[-0.75]	[-0.75]	[-0.75]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Target	Mfx	Target	Mfx	Target	Mfx	Target	Mfx	Target	Mfx
Coverage	0.00213	0.00001	0.00424	0.00099	0.00547	0.00128	0.00431	0.00105	0.00407	0.00098
	[0.77]	[0.77]	[0.81]	[0.81]	[1.05]	[1.05]	[0.84]	[0.84]	[0.78]	[0.78]
BoardSize	-0.00295	-0.00002	-0.04936**	-0.01158**	-0.04627*	-0.01084*	-0.05283**	-0.01289**	-0.04532*	-0.01089*
	[-0.27]	[-0.27]	[-2.07]	[-2.08]	[-1.94]	[-1.94]	[-2.26]	[-2.27]	[-1.94]	[-1.95]
Duality	0.04182	0.00025	0.18933*	0.04394**	0.20413**	0.04727**	0.11772	0.02854	0.12958	0.03091
	[0.87]	[0.84]	[1.96]	[1.99]	[2.09]	[2.13]	[1.25]	[1.26]	[1.36]	[1.37]
%Outside_Directors	0.37567	0.00219	0.51649	0.12120	0.27090	0.06348	0.54960	0.13414	0.50965	0.12247
	[0.98]	[1.01]	[0.68]	[0.69]	[0.36]	[0.36]	[0.76]	[0.76]	[0.70]	[0.70]
Tenure	0.00077	0.00000	-0.02500	-0.00587	-0.02223	-0.00521	-0.01985	-0.00484	-0.02252	-0.00541
	[0.13]	[0.13]	[-1.37]	[-1.37]	[-1.22]	[-1.22]	[-1.12]	[-1.12]	[-1.24]	[-1.24]
%Connected_Directors	0.56169***	0.00328***	1.44287***	0.33859***	1.49948***	0.35138***	1.33946***	0.32692***	1.23925***	0.29780***
	[3.97]	[3.53]	[4.63]	[4.68]	[4.75]	[4.80]	[4.51]	[4.56]	[4.11]	[4.11]
IO	0.28790**	0.00168**	0.32051	0.07521	0.33367	0.07819	0.24783	0.06049	0.28106	0.06754
	[2.25]	[2.37]	[1.03]	[1.03]	[1.06]	[1.05]	[0.84]	[0.83]	[0.93]	[0.93]
Observations	29648	29648	1225	1225	1225	1225	1225	1225	1225	1225
Pseudo R^2	0.441	0.441	0.214	0.214	0.223	0.223	0.176	0.176	0.194	0.194

Table 3.4: Likelihood of Successful Engagement

This table examines the determinants of activists' engagement outcomes using event study sample from 2005 to 2016. The dependent variable *Success* is a dummy variable that equals one if shareholder engagement is successful and zero otherwise. *Sponsor is a SRI fund/public pension/religious group/labor union* is a dummy variable equal to 1 if the sponsor of the proposal is a SRI fund/public pension/religious group/labor union. *Sponsor is an institutional investor* is a dummy variable equal to 1 if the sponsor of the proposal is an institutional investor (SRI fund/public pension/religious group/labor union). *PAC Existence* is a dummy variable that equals one if the company has a Political Action Committee(PAC) and zero otherwise. *Size* is the natural logrithm of market capitalization of the company. *B/M* is the book value of equity divided by market value of equity. *Ret12M* is the past stock return for the previous twelve months. *Coverage* is the number of analysts that make annual earnings forecasts for the company in previous twelve months. *BoardSize* is the total number of directors on the board. *Duality* is a dummy variable that equals one if the CEO is also the chairman of the board, and zero otherwise. *%Outside_Directors* is the percentage of outside (independent) directors on the board. *Tenure* is the average tenure of all directors sitting on the board. *%Connected_Directors* is the percentage of government-connected directors on the board. *IO* is the percentage of outstanding shares held by institutional investors. In each column, we report coefficient estimates, their heteroscedasticity-robust t-statistics and the corresponding marginal probability change induced by a one-unit change in the value of a specific covariate from its sample average. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Success	Mfx	Success	Mfx
Sponsor is an institutional investor	0.66538***	0.11237***		
	[3.11]	[4.30]		
Sponsor is a SRI fund			1.12276***	0.30494***
			[4.67]	[4.11]
Sponsor is a public pension			0.60641***	0.14401**
			[2.58]	[2.33]
Sponsor is a religious group			0.47758	0.12146
			[1.62]	[1.38]
Sponsor is a labor union			0.20176	0.04505
			[0.73]	[0.69]
PAC Existence	0.25197	0.04865	0.34802	0.06047
	[0.86]	[0.99]	[1.11]	[1.37]
Size	-0.08440	-0.01847	-0.12219*	-0.02545*
	[-1.32]	[-1.31]	[-1.79]	[-1.78]
B/M	-0.13419	-0.02937	-0.08069	-0.01681
	[-1.16]	[-1.17]	[-0.81]	[-0.81]
Ret12M	-0.23862	-0.05222	-0.20644	-0.04300
	[-0.83]	[-0.84]	[-0.71]	[-0.72]
Coverage	-0.00787	-0.00172	-0.01112	-0.00232
	[-0.99]	[-1.00]	[-1.32]	[-1.32]
BoardSize	0.05168*	0.01131*	0.06380**	0.01329**
	[1.73]	[1.72]	[1.99]	[1.99]
Duality	0.15525	0.03314	0.13549	0.02760
	[1.07]	[1.11]	[0.90]	[0.93]
%Outside_Directors	0.35115	0.07684	0.00382	0.00080
	[0.31]	[0.31]	[0.00]	[0.00]
Tenure	0.02712	0.00593	0.02037	0.00424
	[1.12]	[1.13]	[0.82]	[0.83]
%Connected_Directors	-0.52469	-0.11482	-0.62679	-0.13055*
	[-1.40]	[-1.41]	[-1.63]	[-1.66]
IO	0.15161	0.03318	0.25799	0.05374
	[0.46]	[0.46]	[0.74]	[0.74]
Observations	626	626	626	626
Pseudo R^2	0.048	0.048	0.092	0.092

Table 3.5: Change in Corporate Political Transparency around Events

This table shows the change in corporate political transparency measured by CPA-Zicklin index around shareholder engagements. All indices are in annual frequency. *Grand_Total* is the company's overall CPA-Zicklin index. *Disclosure, Policy, Oversight* are individual components of CPA-Zicklin index with detailed definitions in Table 3.11. $t-1$, t, $t+1$ correspond to one year before outcome announcement, the year of outcome announcement, and one year after outcome announcement, respectively. We also report $t-1$ to t changes, t to $t+1$ changes, and their associated t-statistics. Differences between *Successful Engagement* and *Unsuccessful Engagement* are computed in the last row. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Grand_Total

	Obs	t-1	t	t+1	$\text{Change}_{\text{t-1}\to\text{t}}$	t-stat	$\text{Change}_{\text{t}\to\text{t+1}}$	t-stat
Successful Engagement	10	27.28	57.26	63.86	29.98**	2.64	6.6	0.51
Unsuccessful Engagement	176	45.93	55.22	61.37	9.30***	3.38	6.15**	2.36
Difference	186	-18.65	2.03	2.49	20.68***	3.75	0.45	0.11

Panel B: Disclosure

	Obs	t-1	t	t+1	$\text{Change}_{\text{t-1}\to\text{t}}$	t-stat	$\text{Change}_{\text{t}\to\text{t+1}}$	t-stat
Successful Engagement	10	11.67	49.17	55.83	37.50***	3.22	6.67	0.44
Unsuccessful Engagement	176	37.33	46.31	51.94	8.98***	2.78	5.63*	1.75
Difference	186	-25.66	2.86	3.89	28.52***	4.45	1.03	0.2

Panel C: Policy

	Obs	t-1	t	t+1	$\text{Change}_{\text{t-1}\to\text{t}}$	t-stat	$\text{Change}_{\text{t}\to\text{t+1}}$	t-stat
Successful Engagement	10	58.82	78.75	87.50	19.93	1.47	8.75	0.79
Unsuccessful Engagement	176	71.24	80.82	86.61	9.58***	3.57	5.79**	2.56
Difference	186	-12.42	-2.07	0.89	10.35	1.52	2.96	0.67

Panel D: Oversight

	Obs	t-1	t	t+1	$\text{Change}_{\text{t-1}\to\text{t}}$	t-stat	$\text{Change}_{\text{t}\to\text{t+1}}$	t-stat
Successful Engagement	10	29.29	54.44	58.89	25.15*	1.91	4.44	0.33
Unsuccessful Engagement	176	39.94	50.45	57.80	10.51***	3.46	7.35**	2.45
Difference	186	-10.64	4.00	1.09	14.64**	2.31	-2.91	-0.57

Table 3.6: Stock Market Reactions to Engagement Outcomes

This table shows stock market reactions to different shareholder engagement outcomes in politically active companies (Panel A) and politically inactive companies (Panel B). The engagement outcomes are classfied into two categories: *Successful Engagement* and *Unsuccessful Engagement*. *Unsuccessful Engagement* is further decomposed into three sub-categories: *Omission of Shareholder Proposal*, *Fail in shareholder meeting with high support*, and *Fail in shareholder meeting with low support*. We consider four different windows surrounding the outcome annoucement date (Day 0). Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Politically Active Companies

	N	CAAR[-1,5]	CAAR[-1,10]	CAAR[-1,15]	CAAR[-1,20]
Successful Engagement	33	1.46%**	3.16%**	3.80%**	3.88%*
		[2.14]	[2.57]	[2.27]	[1.77]
Unsuccessful Engagement					
Omission of Shareholder Proposal	12	0.93%	0.08%	1.71%	0.97%
		[0.98]	[0.06]	[0.99]	[0.51]
Fail in shareholder meeting with high support	100	-0.66%**	-1.14%***	-1.25%**	-1.20%**
		[-2.29]	[-2.64]	[-2.43]	[-1.99]
Fail in shareholder meeting with low support	178	0.24%	0.12%	0.13%	0.20%
		[1.22]	[0.45]	[0.39]	[0.49]

Panel B: Politically Inactive Companies

	N	CAAR[-1,5]	CAAR[-1,10]	CAAR[-1,15]	CAAR[-1,20]
Successful Engagement	63	-0.08%	-0.28%	0.19%	0.10%
		[-0.16]	[-0.47]	[0.24]	[0.11]
Unsuccessful Engagement					
Omission of Shareholder Proposal	7	1.34%	0.71%	0.38%	-0.64%
		[1.63]	[0.5]	[0.24]	[-0.31]
Fail in shareholder meeting with high support	111	0.33%	0.32%	0.27%	-0.08%
		[0.80]	[0.54]	[0.42]	[-0.12]
Fail in shareholder meeting with low support	132	0.23%	-0.07%	-0.20%	0.39%
		[0.56]	[-0.14]	[-0.36]	[0.61]

Table 3.7: Regression on Short Term Abnormal Return

This table examines the difference in stock market responses between successful engagements and unsuccessful engagements in a regression framework. The dependent variable *CAAR[-1,10]* is the cumulative average abnormal return (CAAR) within wndow [-1,10]. *Success* is a dummy variable that equals one if shareholder engagement is successful and zero otherwise. *Size* is the natural logrithm of market capitalization of the company. *B/M* is the book value of equity divided by market value of equity. *Ret12M* is the past stock return for the previous twelve months. *Coverage* is the number of analysts that make annual earnings forecasts for the company in previous twelve months. *BoardSize* is the total number of directors on the board. *Duality* is a dummy variable that equals one if the CEO is also the chairman of the board, and zero otherwise. *%Outside_Directors* is the percentage of outside (independent) directors on the board. *Tenure* is the average tenure of all directors sitting on the board. *IO* is the percentage of outstanding shares held by institutional investors. Column 1 and 2 reports the results for politically active companies. Column 3 and 4 reports the results for politically inactive companies. In each column, we report coefficient estimates and their heteroscedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Politically Active Companies		Politically Inactive Companies	
	CAAR[-1,10]			
Success	0.0348***	0.0359***	-0.0040	-0.0056
	[2.81]	[2.83]	[-0.57]	[-0.77]
Size		0.0029		0.0020
		[0.95]		[0.52]
B/M		-0.0056		0.0005
		[-0.52]		[0.08]
Ret12M		-0.0020		-0.0090
		[-0.28]		[-0.76]
Coverage		-0.0000		0.0003
		[-0.07]		[0.83]
BoardSize		-0.0024		0.0005
		[-1.57]		[0.32]
Duality		0.0025		-0.0075
		[0.45]		[-1.07]
%ODirectors		0.0736		0.0889
		[1.47]		[1.51]
Tenure		0.0017		0.0022*
		[1.51]		[1.90]
IO		-0.0108		-0.0135
		[-0.78]		[-0.64]
Observations	323	321	313	305
R^2	0.056	0.089	0.001	0.038

Table 3.8: Political Uncertainty and Stock Market Reaction

This table examines the effect of political uncertainty on stock market responses in both politically active companies (Panel A) and politically inactive companies (Panel B). Sample events are classfied as in either high policy uncertainty environment or low policy uncertainty environment based on index developed by Baker et al. [2016]. We use both overall index and news-based index. Depedent variable and independent variables are the same as in Table 3.7. In each column, we report coefficient estimates and their heteroscedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Politically Active Companies

	(1)	(2)	(3)	(4)
	Overall Index		News-based Index	
	High Policy Uncertainty	Low Policy Uncertainty	High Policy Uncertainty	Low Policy Uncertainty
	CAAR[-1,10]			
Success	0.0595**	0.0188*	0.0770***	0.0188*
	[2.55]	[1.91]	[2.67]	[1.95]
Size	-0.0034	0.0080**	-0.0017	0.0078**
	[-0.85]	[2.57]	[-0.42]	[2.36]
B/M	-0.0170**	0.0107	-0.0168**	0.0086
	[-2.16]	[1.13]	[-2.12]	[1.00]
Ret12M	-0.0108	0.0134**	-0.0101	0.0152**
	[-1.28]	[1.98]	[-1.19]	[2.18]
Coverage	-0.0002	-0.0001	-0.0001	-0.0002
	[-0.41]	[-0.24]	[-0.22]	[-0.42]
BoardSize	-0.0063***	0.0006	-0.0055**	0.0014
	[-2.81]	[0.31]	[-2.57]	[0.80]
Duality	-0.0018	-0.0018	-0.0029	0.0015
	[-0.23]	[-0.27]	[-0.37]	[0.23]
%ODirectors	0.1168	-0.0016	0.1119	0.0278
	[1.44]	[-0.03]	[1.27]	[0.49]
Tenure	-0.0003	0.0020	-0.0003	0.0026**
	[-0.20]	[1.59]	[-0.19]	[1.99]
IO	-0.0057	-0.0124	-0.0181	0.0017
	[-0.22]	[-0.92]	[-0.79]	[0.12]
Observations	170	151	168	153
R^2	0.247	0.135	0.250	0.117

Panel B: Politically Inactive Companies

	(1)	(2)	(3)	(4)
	Overall Index		News-based Index	
	High Policy Uncertainty	Low Policy Uncertainty	High Policy Uncertainty	Low Policy Uncertainty
	CAAR[-1,10]			
Success	-0.0081	-0.0051	-0.0065	-0.0108
	[-0.82]	[-0.48]	[-0.58]	[-1.11]
Size	-0.0044	0.0091	0.0030	-0.0006
	[-1.01]	[1.36]	[0.57]	[-0.11]
B/M	-0.0029	0.0013	-0.0014	0.0161
	[-0.48]	[0.08]	[-0.24]	[1.19]
Ret12M	0.0013	-0.0179	-0.0165	-0.0037
	[0.08]	[-0.95]	[-0.95]	[-0.25]
Coverage	0.0010**	-0.0008	0.0008**	-0.0005
	[2.51]	[-1.56]	[2.02]	[-1.01]
BoardSize	0.0013	-0.0007	0.0012	0.0011
	[0.59]	[-0.29]	[0.55]	[0.46]
Duality	-0.0116	-0.0100	-0.0062	-0.0071
	[-1.39]	[-0.76]	[-0.70]	[-0.64]
%ODirectors	0.0612	0.1215	-0.0353	0.1996***
	[0.70]	[1.40]	[-0.41]	[2.67]
Tenure	0.0027*	0.0010	0.0019	0.0018
	[1.85]	[0.55]	[1.36]	[1.00]
IO	-0.0259	0.0048	-0.0093	-0.0213
	[-0.96]	[0.15]	[-0.34]	[-0.70]
Observations	166	139	152	153
R^2	0.077	0.054	0.096	0.077

Table 3.9: Change in PAC expenditure

This table examines changes in PAC expenditure around shareholder engagements. Column 1 and 2 estimate the following regression:

$$PAC\_EXP_{i,t} = \alpha Success_i + \beta \sum_{j=0}^{2} Post_j + \gamma \sum_{j=0}^{2} Success_i * Post_j + \theta Controls + \epsilon_{i,t}$$

Column 3 and 4 estimate the following regression:

$$\begin{aligned} PAC\_EXP_{i,t} =& \alpha Success_i + \xi Active_i + +\delta Success_i * Active_i + \beta \sum_{j=0}^{2} Post_j \\ &+\gamma \sum_{j=0}^{2} Success_i * Post_j + \eta \sum_{j=0}^{2} Active_i * Post_j \\ &+\nu \sum_{j=0}^{2} Success_i * Active_i * Post_j + \theta Controls + \epsilon_{i,t} \end{aligned}$$

The dependent variable *PAC_EXP* is the company's PAC expenditure in a two-year election cycle. *Success* is a dummy variable that equals one if shareholder engagement is successful and zero otherwise. $Post_j$ is a dummy variable that takes value one if shareholder engagement takes place in election cycle $t-j$ and zero otherwise. $Active_i$ is a dummy variable that equals one if the company is politically active and zero otherwise. Other variables have same definitions as in Table 3.7. Industry fixed effects based on Fama-French 12 industry classification are included in columns 2 and 4. Standard errors are clustered at the firm level. In each column, we report coefficient estimates and their t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	PAC_EXP			
Success	-362.76***	-221.70*	-60.35	-22.62
	[-2.78]	[-1.90]	[-0.82]	[-0.27]
Active			1182.91***	1089.99***
			[7.74]	[7.44]
Success*Active			-292.48	-201.38
			[-1.54]	[-1.15]
$Post_0$	181.28***	181.28***	32.05**	32.05**
	[5.21]	[5.19]	[2.40]	[2.39]
Success*$Post_0$	-82.12*	-82.12*	4.35	4.35
	[-1.92]	[-1.91]	[0.22]	[0.22]
$Post_0$*Active			272.06***	272.06***
			[4.65]	[4.63]
Success*$Post_0$*Active			-112.90	-112.90
			[-1.35]	[-1.35]
$Post_1$	241.99***	241.99***	45.57**	45.57**
	[4.87]	[4.85]	[2.17]	[2.16]
Success*$Post_1$	-93.09	-93.09	27.52	27.52
	[-1.56]	[-1.55]	[0.90]	[0.90]
$Post_1$*Active			358.09***	358.09***
			[4.30]	[4.28]
Success*$Post_1$*Active			-165.86	-165.86
			[-1.41]	[-1.40]

	(1)	(2)	(3)	(4)
		PAC_EXP		
$Post_2$	294.78***	294.78***	72.00**	72.00**
	[4.47]	[4.45]	[2.43]	[2.42]
$Success*Post_2$	-58.06	-58.06	70.10	70.10
	[-0.78]	[-0.78]	[1.55]	[1.54]
$Post_2*Active$			406.14***	406.14***
			[3.63]	[3.61]
$Success*Post_2*Active$			-166.21	-166.21
			[-1.18]	[-1.18]
Size	229.38***	328.47***	52.91	126.51**
	[3.23]	[4.82]	[0.90]	[2.33]
B/M	54.38	113.70*	-58.29	-6.26
	[0.73]	[1.66]	[-1.05]	[-0.14]
Ret12M	-46.60	-91.00	83.89	58.73
	[-0.30]	[-0.64]	[0.83]	[0.62]
Coverage	15.27	13.60	14.51*	11.05*
	[1.44]	[1.57]	[1.79]	[1.76]
BoardSize	66.36*	14.31	4.22	-11.52
	[1.77]	[0.44]	[0.16]	[-0.51]
Duality	182.48	169.87	92.28	73.46
	[1.17]	[1.30]	[0.71]	[0.69]
%Outside_Directors	-114.20	-501.59	31.43	-144.17
	[-0.14]	[-0.57]	[0.05]	[-0.23]
Tenure	-22.24	-35.68*	-15.91	-19.18
	[-0.98]	[-1.73]	[-0.87]	[-1.04]
IO	-221.27	-186.35	-429.87	-414.03
	[-0.31]	[-0.29]	[-0.80]	[-0.90]
Industry Fixed Effects	No	Yes	No	Yes
Observations	1540	1540	1540	1540
R^2	0.258	0.405	0.513	0.600

Table 3.10: Change in Institutional Ownership

This table examines changes in institutional ownership around shareholder engagements. The following regression is estimated:

$$IO_{i,t} = \alpha Success_i + \beta \sum_{j=0}^{4} Post_j + \gamma \sum_{j=0}^{4} Success_i * Post_j + \theta Controls + \epsilon_{i,t}$$

The dependent variable *IO* is the percentage of outstanding shares held by institutional investors. *Success* is a dummy variable that equals one if shareholder engagement is successful and zero otherwise. $Post_j$ is a dummy variable that takes value one if shareholder engagement takes place in quarter $t-j$ and zero otherwise. Other variables have same definitions as in table 7. Industry fixed effects based on Fama-French 12 industry classification are included in columns 2. Standard errors are clustered at the firm level. In each column, we report coefficient estimates and their t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	IO	
Success	0.01	0.01
	[0.47]	[0.92]
$Post_0$	-0.00	-0.00
	[-1.01]	[-1.01]
Success*$Post_0$	0.02**	0.02**
	[2.50]	[2.50]
$Post_1$	-0.03***	-0.03***
	[-6.58]	[-6.57]
Success*$Post_1$	0.05***	0.05***
	[5.17]	[5.17]
$Post_2$	-0.01**	-0.01**
	[-2.31]	[-2.30]
Success*$Post_2$	-0.00	-0.00
	[-0.13]	[-0.13]
$Post_3$	-0.02***	-0.02***
	[-4.68]	[-4.68]
Success*$Post_3$	0.03***	0.03***
	[4.06]	[4.06]
$Post_4$	0.01	0.01
	[1.05]	[1.05]
Success*$Post_4$	-0.01	-0.01
	[-1.05]	[-1.05]

	(1)	(2)
	IO	
Size	-0.04***	-0.04***
	[-4.32]	[-3.89]
B/M	-0.05***	-0.05***
	[-3.83]	[-4.02]
Ret12M	0.02	0.02*
	[1.60]	[1.65]
Coverage	0.00**	0.00
	[2.02]	[1.07]
BoardSize	-0.01	-0.01
	[-1.58]	[-1.54]
Duality	0.00	0.00
	[0.24]	[0.24]
%Outside_Directors	0.29**	0.27**
	[2.00]	[2.08]
Tenure	0.00	0.00
	[1.35]	[1.44]
Industry Fixed Effects	No	Yes
Observations	4977	4977
R^2	0.184	0.249

Appendix 3.C Additional Material

A. Introduction

This part contains 1) description of CPA-Zicklin index used in the paper, 2) examples of media report on corporate political transparency, 3) examples of public announcements of successful shareholder engagements, 4) placebo test for event study results, 5) tests of parallel trend assumption in difference-in-differences analysis.

B. Description of CPA-Zicklin Index

CPA-Zicklin Index, which measures the level of corporate political transparency, is produced by Center for Political Accountability, a non-profit organisation, in conjunction with the Zicklin Center for Business Ethics Research at The Wharton School at the University of Pennsylvania. Data on corporate political transparency is collected from company websites twice a year. The compilation of CPA-Zicklin index starts from 2011 with only 99 of S&P 500 companies. The coverage has been gradually expanded to S&P 500 companies. Figure 3.7 displays the coverage of CPA-Zicklin Index from 2011 to 2016.

CPA-Zicklin index has three major components: disclosure, policy and oversight. The detailed breakdown of scoring criteria is presented in Table 3.11.[21]

C. Examples of Media Report on Corporate Political Transparency

Corporate political transparency has been widely reported and discussed by media in recent decade. To show importance of the topic, we provide some snapshots of media coverage on this issue in Figure 3.8.

D. Examples of Public Announcements of Successful Shareholder Engagements

In this section, we provide some snapshots of public announcements of successful shareholder engagements from which we collected announcement dates.

[21] We use 2016 scoring criteria as an example since the criteria in other years are very similar.

Table 3.11: Scoring Criteria of CPA-Zicklin Index

Category	#	Criteria	Max Score
Disclosure	1	Does the company publicly disclose corporate contributions to political candidates, parties and committees, including recipient names and amounts given?	4
	2	Does the company publicly disclose payments to 527 groups, such as governors associations and super PACs, including recipient names and amounts given?	4
	3	Does the company publicly disclose independent political expenditures made in direct support of or opposition to a campaign, including recipient names and amounts given?	4
	4	Does the company publicly disclose payments to trade associations that the recipient organization may use for political purposes?	6
	5	Does the company publicly disclose payments to other tax-exempt organizations, such as 501(c)(4)s, that the recipient may use for political purposes?	6
	6	Does the company publicly disclose a list of the amounts and recipients of payments made by trade associations or other tax exempt organizations of which the company is either a member or donor?	2
	7	Does the company publicly disclose payments made to influence the outcome of ballot measures, including recipient names and amounts given?	4
	8	Does the company publicly disclose the company's senior managers (by position/title of the individuals involved) who have final authority over the company's political spending decisions?	2
	9	Does the company publicly disclose an archive of each political expenditure report, including all direct and indirect contributions, for each year since the company began disclosing the information (or at least for the past five years)?	4
Policy	10	Does the company disclose a detailed policy governing its political expenditures from corporate funds?	6
	11	Does the company have a publicly available policy permitting political contributions only through voluntary employee-funded PAC contributions?	Yes/No
	12	Does the company have a publicly available policy stating that all of its contributions will promote the interests of the company and will be made without regard for the private political preferences of executives?	2
	13	Does the company publicly describe the types of entities considered to be proper recipients of the company's political spending?	2
	14	Does the company publicly describe its public policy positions that become the basis for its spending decisions with corporate funds?	2
	15	Does the company have a public policy requiring senior managers to oversee and have final authority over all of the company's political spending?	2
	16	Does the company have a publicly available policy that the board of directors regularly oversees the company's corporate political activity?	2
Oversight	17	Does the company have a specified board committee that reviews the company's policy on political expenditures?	2
	18	Does the company have a specified board committee that reviews the company's political expenditures made with corporate funds?	2
	19	Does the company have a specified board committee that reviews the company's payments to trade associations and other tax-exempt organizations that may be used for political purposes?	2
	20	Does the company have a specified board committee that approves political expenditures from corporate funds?	2
	21	Does the company have a specified board committee, composed entirely of outside directors, that oversees its political activity?	2
	22	Does the company post on its website a detailed report of its political spending with corporate funds semiannually?	4
	23	Does the company make available a dedicated political disclosure web page found through search or accessible within three mouse-clicks from homepage?	2
	24	Does the company disclose an internal process for or an affirmative statement on ensuring compliance with its political spending policy?	2

Figure 3.7: Number of S&P 500 Companies Covered by CPA-Zicklin Index

This figure represents number of S&P 500 companies covered by CPA-Zicklin index from 2011 to 2016.

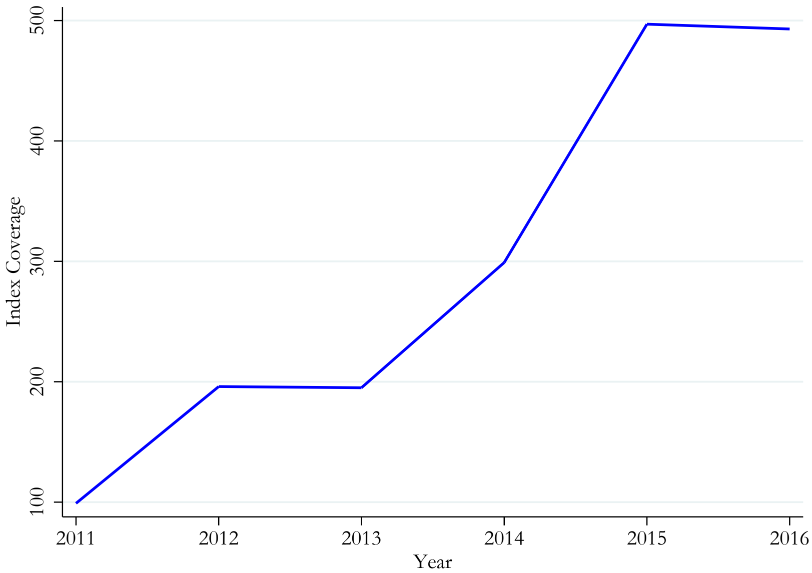


Figure 3.8: Media Coverage on Corporate Political Transparency

This figure represents examples of media coverage on corporate political transparency.

More shareholders call on companies to disclose their political spending

A national campaign has led a dozen companies to announce they will not renew their membership in the American Legislative Exchange Council (ALEC). Wal-Mart, the giant retailer under fire for allegedly bribing Mexican officials, encountered another wave of vitriol when it was reported that the company also was a member of ALEC. (Edgard Garrido/Reuters)

(a) Washington Post

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Investors Push for Fuller Picture of Corporate Political Contributions

Donations to trade groups, candidates and political-action committees attract more scrutiny

ILLUSTRATION: ERIC PALMA

By Mara Lemos Stein and Maxwell Murphy

April 4, 2016 9:38 p.m. ET

1 COMMENTS

(b) Wall Street Journal

Figure 3.9: Public Announcements of Successful Shareholder Engagements

NEWS
From the Office of the New York State Comptroller
Thomas P. DiNapoli

March 23, 2015, Contact: Press Office (518) 474-4015

U. S. Steel and DiNapoli Agree on Enhanced Disclosure of Corporate Political Contributions

New York State Comptroller Thomas P. DiNapoli today announced that United States Steel Corporation has agreed to the New York State Common Retirement Fund's request that it publicly report its corporate political spending. As a result of the agreement, the Fund withdrew a shareholder proposal it had filed for consideration at the Fortune 500 company's annual meeting. The Fund holds approximately 907,577 shares of U. S. Steel with an estimated value of $20 million.

(a)

CENTER FOR POLITICAL ACCOUNTABILITY

For Immediate Release
December 14, 2009

Press Contacts:
Bruce F. Freed, Center for Political Accountability, 301-233-3621
Bruce Herbert or Larry Dohrs, Newground Social Investment, 206-522-1944

New companies bring political disclosure to nearly half of trend-setting S&P 100

Washington DC - Four new companies have agreed to adopt disclosure and board oversight of political spending with corporate funds, the Center for Political Accountability (CPA) and Newground Social Investment announced today.

With these agreements, 48 public companies in the trend-setting S&P 100--an index of the largest and most influential members of the corporate community--have agreed to adopt the CPA's framework for political disclosure. Overall, 70 companies have embraced this corporate governance standard.

Three of the new companies adopting the framework belong to the S&P 100. They are Microsoft (NYSE: MFST), Time Warner (NYSE: TWX), and Campbell Soup (NYSE: CPB). The other company, Wisconsin Energy (NYSE: WEC), is in the S&P 500, a listing of the large cap companies actively traded in the United States. Newground Social Investment engaged Microsoft.

(b)

E. Placebo Test for Event Study Results

In this section we conduct robustness check of event study results in the form of placebo tests. We examine the abnormal return when day 0 is two months before the actual outcome announcement date. Table 3.12 presents the results.

Table 3.12: Placebo Test for Event Study Results

This table computes the abnormal return using the same classification and methodology as Table 3.6 except that we assume day 0 is two months before the actual outcome announcement date. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Politically Active Companies

	N	CAAR[-1,10]	CAAR[-1,20]
Successful Engagement	33	0.06%	-1.35%
		[-0.04]	[-0.79]
Unsuccessful Engagement			
Omission of Shareholder Proposal	12	0.24%	0.08%
		[0.22]	[-0.06]
Fail in shareholder meeting with high support	100	0.22%	-0.41%
		[0.43]	[-0.63]
Fail in shareholder meeting with low support	178	0.21%	0.10%
		[0.49]	[0.18]

Panel B: Politically Inactive Companies

	N	CAAR[-1,10]	CAAR[-1,20]
Successful Engagement	63	-2.42%***	-2.37%**
		[-2.77]	[-2.01]
Unsuccessful Engagement			
Omission of Shareholder Proposal	7	-1.34%	-1.91%
		[-0.63]	[-0.44]
Fail in shareholder meeting with high support	111	-0.55%	-0.06%
		[-0.94]	[-0.08]
Fail in shareholder meeting with low support	132	0.57%	-0.38%
		[1.28]	[-0.62]

Abnormal returns are statistically indifferent from zero in politically active companies, including reactions to successful engagements and unsuccessful engagements that obtained relatively high support. Abnormal returns are also statistically insignificant in politically inactive companies, except for successful engagements. Taken together, this evidence supports our event study methodology.

F. Tests of Parallel Pre-treatment Trend in Difference-in-differences Analysis

In this section we test the parallel trend assumption for the variables of interest used in difference-in-differences analysis. We first review the methodology to test parallel pre-treatment trend and then present the results.

Methodology

The commonly used method to test parallel pre-treatment trend is to add interaction terms with lag dummy variables. If the interaction terms with lag dummy variables are jointly insignificant, then we can conclude that parallel trend assumption holds. For the difference-in-differences analysis with companies' PAC expenditure, we adopt the following regression specification to test parallel trend assumption.

$$\begin{aligned} PAC\_EXP_{i,t} = {} & \alpha Success_i + \xi Pre_{-1} + \beta \sum_{j=0}^{2} Post_j + \underbrace{\delta}_{\text{Pre-trend}} Success_i * Pre_{-1} \\ & + \underbrace{\gamma}_{\text{Treatment Effect}} \sum_{j=0}^{2} Success_i * Post_j + \theta Controls + \epsilon_{i,t} \end{aligned} \tag{3.10}$$

where Pre_{-1} is a dummy variable that takes value one if shareholder engagement takes place in election cycle $t+1$ and zero otherwise. Other variables are the same as in regression 3.7. The regression is estimated both with and without industry fixed effects. Standard errors are clustered at firm level to account for within-firm correlation. δ measures the pre-treatment trend and thus insignificant δ would indicate non-existence of pre-treatment trend. We only include one lag dummy variable since we have only two periods before the announcement.

Similarly, for the difference-in-differences analysis with companies' institutional ownership, we adopt the following regression specification to test parallel trend assumption.

$$IO_{i,t} = \alpha Success_i + \xi \sum_{k=-2}^{-1} Pre_k + \beta \sum_{j=0}^{4} Post_j + \underbrace{\delta}_{\text{Pre-trend}} \sum_{k=-2}^{-1} Success_i * Pre_k$$
$$+ \underbrace{\gamma}_{\text{Treatment Effect}} \sum_{j=0}^{4} Success_i * Post_j + \theta Controls + \epsilon_{i,t} \quad (3.11)$$

where Pre_k is a dummy variable that takes value one if shareholder engagement takes place in election cycle $t-k$ and zero otherwise. Other variables are the same as in regression 3.9. The regression is estimated both with and without industry fixed effects. Standard errors are clustered at firm level to account for within-firm correlation. δ measures the pre-treatment trend and thus jointly insignificant δ would indicate non-existence of pre-treatment trend.

Results

Table 3.13 presents the estimation results. In both Panel A and B, the interaction terms associated with pre-treatment trend are insignificantly different from zero. F-test also indicates that the pre-trend interaction terms are jointly insignificant. Therefore the evidences suggest that parallel trend assumptions hold for the variables of interest in the period before announcement of engagement outcomes. The effects presented in the paper are likely to be causal assuming the trends would have remained parallel in the absence of shareholder engagement.

Table 3.13: Parallel Pre-treatment Trend Test for Difference-in-differences Analysis

This table shows the estimates of regression 3.10 (Panel A) and 3.11 (Panel B), respectively. Industry fixed effects based on Fama-French 12 industry classification are included in columns 2. Standard errors are clustered at the firm level. In each column, we report coefficient estimates and their t-statistics. We also report F-statistics and associated p-value for testing joint significance of pre-trend interaction terms. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: PAC Expenditure

	(1)	(2)
	PAC_EXP	
Success	-359.20***	-218.14*
	[-2.94]	[-1.94]
Pre_{-1}	107.79***	107.79***
	[3.32]	[3.30]
Success*Pre_{-1}	-7.12	-7.12
	[-0.14]	[-0.14]
F-stat for Pre-trend interaction terms	0.02	0.02
P-value for F-stat	0.89	0.89
Treatment Effect Terms	Yes	Yes
Control Variables	Yes	Yes
Industry Fixed Effects	No	Yes
Observations	1540	1540
R^2	0.259	0.406

Panel B: Institutional Ownership

	(1)	(2)
	IO	
Success	0.00	0.01
	[0.35]	[0.78]
Pre_{-2}	0.01*	0.01*
	[1.78]	[1.77]
Success*Pre_{-2}	0.00	0.00
	[0.06]	[0.06]
Pre_{-1}	0.00	0.00
	[1.27]	[1.27]
Success*Pre_{-1}	0.01	0.01
	[0.77]	[0.77]
F-stat for Pre-trend interaction terms	0.41	0.41
P-value for F-stat	0.66	0.66
Treatment Effect Terms	Yes	Yes
Control Variables	Yes	Yes
Industry Fixed Effects	No	Yes
Observations	4977	4977
R^2	0.184	0.249

G. Joint Target-Outcome Dynamics

In this section we conduct the analysis in Table 3, 4, and 7 in a joint framework. In equilibrium, the activists' target selection and outcomes are likely to be endogenously determined. One one hand, activists may selectively pick companies in which they are more likely to win the battle, especially given the substantial costs incurred [Gantchev, 2013]. On the other hand, market reactions might be correlated with activists' target decisions, to the extent that target decisions potentially indicate negative governance concerns or positive monitoring effort by activist shareholders.

We thus employ a empirical specification in the spirit of Heckman [1979] to capture the joint target-outcome dynamics [e.g. Renneboog and Szilagyi, 2011; Cziraki et al., 2010]. The model is as follows:

$$y^*_{1i,t} = X'_{1i,t}\beta_1 + \epsilon_{1i,t} \tag{3.12}$$

$$y_{1i,t} = \begin{cases} 1 & \text{if } y^*_{1i,t} > 0 \\ 0 & \text{if } y^*_{1i,t} \leq 0 \end{cases}$$

$$y^*_{2i,t} = X'_{2i,t}\beta_2 + \epsilon_{2i,t} \tag{3.13}$$

$$y_{2i,t} = y^*_{2i,t} \quad \text{iff } y^*_{1i,t} > 0$$

where $\epsilon_{1i,t}, \epsilon_{2i,t}$ are drawn from a multivariate normal distribution with zero mean, variance σ_1^2 and σ_2^2, and correlation $\rho_{1,2}$. The model contains two parts: selection equations 3.12 and outcome equations 3.13. The variable $y_{1i,t}$ is a dummy variable indicating whether firm i is targeted in year t, while the variable $y_{2i,t}$ is the outcome of interest (i.e. engagement outcomes and market reactions to engagement outcomes at the proposal level). Importantly, the model assumes that target decision $y_{1i,t}$ is observed while the outcome of interest $y_{2i,t}$ is only observed when the firm is targeted by an activist, i.e. $y_{1i,t} = 1$. This is consistent with our data feature. The variables $X_{1i,t}$ and $X_{2i,t}$ are explanatory variables for target selection and outcomes of interest. They do differ but are not mutually exclusive. The compostion of $X_{1i,t}$ and $X_{2i,t}$ can be found in Table 3, 4, and 7. β_1 and β_2 correspond to cofficients of interest.

The simultaneous nature of the model stems from the fact that the correlation $\rho_{1,2}$ between two error terms in selection equation and outcome equation are potentially nonzero. Intuitively, we hypothesize that the correlation between error terms in target selection and likehood of successful engagement are likely to be positive since unobserved factors that make the engagement more likely to be successful should be taken into account by activist investors in making their target decisions. However, we cannot unamiguously hypothesize the existence and the sign of correlation between error terms in target selection and market reactions due to the lack of direct link.

The model is estimated using Heckman [1979] two-step methodology. In the first step, we estimate the selection equation and compute the inverse Mills ratio as

$$InvMill_{i,t} = \frac{\phi(X'_{1i,t}\hat{\beta}_1)}{\Phi(X'_{1i,t}\hat{\beta}_1)} \tag{3.14}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density function and distribution function of normal distribution, respectively. In the second step, we include the inverse Mills ratio in the outcome equation. Thus the outcome equation estimated becomes

$$y_{2i,t} = X'_{2i,t}\beta_2 + \lambda\, InvMill_{i,t} + \epsilon_{2i,t} \tag{3.15}$$

It could be shown that λ has the same sign as the correlation $\rho_{1,2}$.

Table IA.4 presents the estimation results. The selection equations, shown in Panel A, are configured identically in Panel A and Table 3. The outcome equations analysing the likelihood of successful engagement are provided in Panel B. The conclusion in section A.2. that institutional activist investors, especially SRI funds, are more likely to achieve success in ther engagements, continues to hold. The likelihood of successful engagement is around 9% (26%) higher for institutional activist investors (SRI funds) than for other investors. Coefficients of some control variables differ from those in Table 4 after taking engodoneous target decision into account. The existence of PAC committee, firm size, percentage of outside and politically connected directors, average director tenure, and institutional onwership, all contribute positively to the probability of successful shareholder engagement. The significantly positive coefficient on inverse Mills ratio confirms our hypothesis that activists tend to target companies in which they are more likely to win the battle. The model's explanatory power measured by R^2 also increases from 9% in Table 4 to 24%.

Panel C shows the outcome equations analysing stock market reactions. The conclusions in section B.2. that in politically active companies, the stock market reacts more positively to successful engagements than to unsuccessful engagements, remains valid. The spread in market reactions remains statistically insignificant in politically inactive companies. Consistent with Cziraki et al. [2010] and Renneboog and Szilagyi [2011], we find no evidence that market reactions are endogenous to activists' target decisions, as shown by insignificant coefficients on inverse Mills ratio.

Table 3.14: Joint Target-Outcome Dynamics

This table shows the estimates of self-selection model presented in section G. Panel A presents the results of selection equations. Panel B and C presents the results of outcome equations (likelihood of successful engagement and market reactions). The dependent variable in the selection equations (Panel A), *Target*, equals one if a firm is targeted by a shareholder activist, and zero otherwise. The first dependent variable in outcome equations (Panel B), *Success*, equals one if shareholder engagement is successful, and zero otherwise. The second dependent variable in outcome equations (Panel C), *CAAR[-1,10]*, is the cumulative average abnormal return (CAAR) within wndow [-1,10] around the public announcement of engagement outcomes. All independent variables in selection equations and outcome equations are as defined in Table 3, 4, and 7. In Panel B and C, inverse Mills ratio, *InvMill*, estimated from selection equations, is included as an independent variable. In each column, we report coefficient estimates, their heteroscedasticity-robust t-statistics, and when applicable, the corresponding marginal probability change induced by a one-unit change in the value of a specific covariate from its sample average. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Target Selection

	(1)	(2)
	Target	Mfx
PAC Existence	0.74782***	0.00881***
	[12.50]	[6.81]
Targeted in the Past	0.69492***	0.01074***
	[11.17]	[3.95]
Size	0.33626***	0.00196***
	[12.65]	[7.27]
B/M	0.12149***	0.00071***
	[5.12]	[4.43]
Ret12M	-0.14669**	-0.00086**
	[-2.36]	[-2.29]
Coverage	0.00213	0.00001
	[0.77]	[0.77]
BoardSize	-0.00295	-0.00002
	[-0.27]	[-0.27]
Duality	0.04182	0.00025
	[0.87]	[0.84]
%Outside_Directors	0.37567	0.00219
	[0.98]	[1.01]
Tenure	0.00077	0.00000
	[0.13]	[0.13]
%Connected_Directors	0.56169***	0.00328***
	[3.97]	[3.53]
IO	0.28790**	0.00168**
	[2.25]	[2.37]
Observations	29648	29648
Pseudo R^2	0.441	0.441

Panel B: Likelihood of Successful Engagement

	(1)	(2)	(3)	(4)
	Success	Mfx	Success	Mfx
Sponsor is an institutional investor	0.72006***	0.09232***		
	[3.19]	[4.41]		
Sponsor is a SRI fund			1.15852***	0.26387***
			[4.52]	[3.67]
Sponsor is a public pension			0.81857***	0.16282***
			[3.23]	[2.68]
Sponsor is a religious group			0.47139	0.09598
			[1.52]	[1.26]
Sponsor is a labor union			0.09870	0.01645
			[0.34]	[0.33]
PAC Existence	2.16660***	0.12614***	2.25583***	0.11323***
	[5.68]	[8.05]	[5.96]	[7.41]
Size	0.62603***	0.10994***	0.64369***	0.10292***
	[5.60]	[5.77]	[5.41]	[5.30]
B/M	0.16009	0.02811	0.19959*	0.03191*
	[1.37]	[1.34]	[1.88]	[1.83]
Ret12M	-0.46212	-0.08116	-0.46581	-0.07448
	[-1.25]	[-1.29]	[-1.26]	[-1.29]
Coverage	0.00363	0.00064	-0.00041	-0.00007
	[0.43]	[0.43]	[-0.05]	[-0.05]
BoardSize	0.03591	0.00631	0.04737	0.00757
	[1.17]	[1.17]	[1.41]	[1.41]
Duality	0.05181	0.00901	0.03560	0.00565
	[0.34]	[0.34]	[0.22]	[0.22]
%Outside_Directors	3.29829***	0.57924***	2.93237**	0.46885**
	[2.59]	[2.59]	[2.15]	[2.16]
Tenure	0.06928***	0.01217***	0.06069**	0.00970**
	[2.71]	[2.73]	[2.28]	[2.32]
%Connected_Directors	1.05703**	0.18563**	1.09367**	0.17486**
	[2.48]	[2.45]	[2.46]	[2.39]
IO	0.67940*	0.11931*	0.79197**	0.12663**
	[1.84]	[1.83]	[2.02]	[2.00]
InvMill	2.41991***	0.42498***	2.55076***	0.40784***
	[8.43]	[8.38]	[8.68]	[8.00]
Observations	626	626	626	626
Pseudo R^2	0.197	0.197	0.243	0.243

Panel C: Market Reactions

	(1)	(2)
	Politically Active Companies	Politically Inactive Companies
	CAAR[-1,10]	
Success	0.0349***	-0.0074
	[2.87]	[-0.98]
Size	0.0041	0.0049
	[0.84]	[1.16]
B/M	-0.0051	0.0016
	[-0.46]	[0.26]
Ret12M	-0.0022	-0.0108
	[-0.30]	[-0.92]
Coverage	-0.0000	0.0003
	[-0.03]	[1.00]
BoardSize	-0.0024	0.0004
	[-1.56]	[0.28]
Duality	0.0026	-0.0075
	[0.46]	[-1.06]
%ODirectors	0.0784	0.1006*
	[1.45]	[1.66]
Tenure	0.0018	0.0022*
	[1.53]	[1.87]
IO	-0.0102	-0.0100
	[-0.73]	[-0.48]
InvMill	0.0041	0.0095
	[0.35]	[1.02]
Observations	321	305
R^2	0.090	0.041

Chapter 4

The Spillover effect of Corporate Fraud: Evidence from Firm-Level Supply Chain Data

4.1 Introduction

Corporate fraud revelation is detrimental to accused firms themselves [Karpoff et al., 2008b,a]. In an interlinked economy, however, the impact of such revelation is not restricted to accused firms themselves. On the contrary, direct costs imposed on fraudulent firms may only constitute a small portion of overall economic impact of corporate fraud.

In this paper, we analyse the implication of corporate fraud revelation for a particular type of stakeholders: economically linked firms through supply chain relationship. This is important from the social welfare perspective since it points to an indirect cost of corporate fraud largely overlooked in the literature.

Our analysis, built on a large sample of 693 corporate fraud revelations with supplier-customer links, aims to uncover the implication of fraud revelation for suppliers and customer from a market perspective. Meanwhile, we also analyse which factors contribute to the market reactions of suppliers and customers. This analysis sheds light on the main channel of propagation of shocks.

Our corporate fraud events are mainly financial misreporting. Built on this sample, we first document that on average fraudulent firms have 10.33 links, including suppliers and customers.[1] This shows the widespread connection between firms in the economy.

We then demonstrate that suppliers and customers experience significantly negative market reactions around fraud revelation. For example, three-day cumulative abnormal return is -0.49% for suppliers and -0.30% for customers. The magnitude is small relative to the market reaction of fraudulent firms. However, it is still economically and statistically significant.

Since corporate fraud revelations are likely to occur during economic downturn or in poorly-performing industries [Povel et al., 2007; Rosner, 2003], one might wonder to what extent our results are driven by industry trend or business cycle. To alleviate those concerns, we construct a sample of matched suppliers (customers) in the same industry and year as the suppliers (customers) of fraudulent firms. Matched suppliers (customers) and their linked firms, however, have not been exposed to corporate fraud revelations. We find that the three-day abnormal returns of event suppliers (customers) around fraud revelations are still significantly more negative than those of matched suppliers (customers). This confirms our previous finding that fraud revelations are viewed negatively by stock market investors for the linked suppliers (customers).

We also examine whether the negative impact depends on the reporting party of supplier-customer links with fraudulent firms. We find that both suppliers (cus-

[1] We restrict our analysis to suppliers and customers that are disclosed and in CRSP universe. The implication can be generalized to some extent.

tomers) with links reported by themselves and suppliers (customers) with links not reported by themselves are negatively impacted within 10 days of fraud revelation. The negative market reactions immediately materialize for suppliers (customers) whose links are self-reported. By contrast, the negative market reactions gradually materialize for suppliers (customers) whose links are not self-reported. This findings supports the view that, due to limited attention and information processing constraints, investors of suppliers and customers are slower in recognizing the link with fraudulent firms and consequential spillover effect if suppliers and customers do not self-report the links.

To understand the channel of propagation of shocks, we analyse the cross-section of abnormal returns of affected suppliers (customers). We find that fraud severity, as measured by the market reactions of fraudulent firms, is positively related to the market responses of linked suppliers (customers). In stark contrast with previous literature on the network effects of production shocks [e.g. Barrot and Sauvagnat, 2016], we do not find the significant relationship between product market conditions of fraudulent firms and market responses of linked suppliers (customers). Instead, we find that information environment and corporate reputation are two important determinants of the suppliers' (customers') market reactions to fraud revelations. Robustness checks, such as removal of repeated events and utilization of clustered standard error, also confirm our results.

Taken together, our market-based tests suggest that corporate fraud revelation, especially financial fraud, negatively impacts linked firms mainly through reputation and information shock channel. Our results provide empirical support for enhanced corporate disclosure and social capital accumulation.

Our paper is closely related to the literature on implications of corporate fraud. Prior literature has documented the effect of corporate fraud on accused firms, industry peers, and household stock market participation. Karpoff et al. [2008b] find that on average firms lose 38% of their market values when financial misconduct is revealed. Fraudsters appear to produce less innovation than non-fraudsters [Wang and Li, 2014]. Giannetti and Wang [2016] demonstrate that after the revelation of corporate fraud in a state, the equity holdings of households in that state decrease significantly. Goldman et al. [2012] show that fraud revelation benefits industry rivals in less competitive industries whilst it hurts industry rivals in competitive industries. Since the nature of supplier-customer relationship is vastly different from other parties, such as industry rival and householder, we contribute to the literature by analysing the effect of fraud revelation on these important yet under-explored stakeholders.

Our paper is also related to the literature on shock spillover along corporate supply chain network. Prior literature has documented the effect of bankruptcy filings, financial distress, and production shocks on linked firms along the supply chain [Hertzel et al., 2008; Hortaçsu et al., 2013; Barrot and Sauvagnat, 2016; Wu, 2016]. The shocks they identify all significantly affect firms' operation. Therefore they find the suppliers and customers are affected through operation channel. However, the financial fraud we analyse has a less direct effect on accused firms' operation. Accordingly, we find the channels through which suppliers and customers are affected by fraud revelation are different from production shocks in the literature.

Another related area is literature on corporate disclosure and information environment. Previous literature argue that enhanced disclosure has benefits and costs [e.g. Diamond, 1985; Frankel et al., 1995; Wang, 2007; He and Tian, 2013]. Our research contributes to the debate by showing that enhanced information environment can help alleviate the negative shock to suppliers (customers) brought by corporate fraud revelation.

Last but not the least, we contribute to the literature on the implication of corporate social responsibility (CSR). Edmans [2011, 2012] and Edmans et al. [2017] all document the positive effect of CSR on firm market valuation. Lins et al. [2017] find that firms with high social capital performs better during the 2008-2009 financial crisis. Our research adds to the literature by showing that high social capital can also mitigate the negative reputation shocks of fraud revelation.

The rest of paper proceeds as follows. Section 2 develops research hypotheses. Section 3 describes data and provides summary statistics. Section 4 presents empirical findings. Section 5 concludes.

4.2 Hypotheses Development

We hypothesize the public revelation of corporate fraud can potentially affect the stock price of suppliers and customers though two channels. First, corporate fraud might negatively impact the stock prices of suppliers and customers by directly affecting their operations. Second, corporate fraud might result in the reputation concerns of suppliers and customers since investors might worry about fraud in firms that deal with fraudulent firms as well. Both mechanisms point to the following hypothesis:

Hypothesis H4.1 *The stocks of fraudulent firms' suppliers and customers react negatively to the fraud revelation.*

When fraudulent firms are in less competitive industries, suppliers (customers) are in weaker bargaining positions of production network. In other word, it is more difficult for suppliers (customers) to opt out of their contracting relationships with fraudulent firms in less competitive industries. Under operation channel, the operations and stock prices of suppliers and customers are expected to be impacted more negatively in less competitive industries. However, under reputation channel, the level of competition should have no bearing on the stock prices of suppliers and customers. Based on the above argument, we put forward the following hypotheses:

Hypothesis $\mathbf{H4.2_n}$ *The abnormal returns of suppliers (customers) are more negative when fraudulent firms are in less competitive industries.*

Hypothesis H4.2$_\mathbf{a}$ *The abnormal returns of suppliers (customers) are unaffected by the level of industry competition of fraudulent firms.*

Corporate social responsibility (CSR) are associated with corporate social capital [e.g. Lins et al., 2017].[2] Under reputation channel, higher CSR performance of suppliers (customers) help restore public trust and therefore mitigate the reputation concerns of investors. By contrast, under operation channel, companies' CSR performance should have no bearing on the stock prices of suppliers and customers. Based on the above argument, we put forward the following hypotheses:

Hypothesis H4.3$_\mathbf{n}$ *The abnormal returns of suppliers (customers) are less negative when they have a higher CSR score.*

Hypothesis H4.3$_\mathbf{a}$ *The abnormal returns of suppliers (customers) are unaffected by their CSR performances.*

The information generated by the fraud revelation will be used by the stock market investors to update their belief about the firm valuation. The more opaque the information environment of suppliers (customers) is, the more weight the market will put on the new negative information shock.[3] This reasoning leads to the following hypothesis:

Hypothesis H4.4 *The greater opacity in suppliers (customers) is associated with more negative abnormal returns.*

[2]This is supported by both academic studies and industry practitioners. For example, Sacconi and Antoni [2010] relates the definition of CSR to many aspects of social capital and shows that firms can accumulate social capital through CSR investments. CEO surveys conducted by PricewaterhouseCoopers in 2013 and 2014 also relate firms' CSR investments to trust and social capital. We refer to Lins et al. [2017] for a more detailed discussion of using CSR as a proxy for corporate social capital.

[3]Detailed explanations are given in appendix 4.A.

4.3 Data and Summary Statistics

4.3.1 Data

The data we use in our analysis are drawn from several sources. Data on corporate fraud is from Audit Analytics Litigation database. Audit Analytics Litigation database provides detailed data on all federal securities class action claims and SEC related litigation action against SEC registrants. Using this data has two advantages. First, all cases are material legal proceedings which will have non-negligible impact on accused firms. Second, the class period end date in legal proceedings enables us to accurately identify when corporate fraud is publicly revealed.[4] The coverage of litigation data starts from 2000 to 2015.

We require the legal cases to have non-missing company identifier information and the class period end date.[5] The companies have to be defendant in each legal proceeding. Based on the case information provided by the database and the level of aggregation suggested by previous literature, we further classify each legal case into the following 8 categories: 1) financial reporting, 2) breach of contracts, 3) patent and copyright related, 4) product & service liability, 5) social responsibility related, 6) antitrust violation, 7) operational malpractice, 8) others. Since the focus of our paper is on corporate fraud, we exclude legal cases on "social responsibility related", "antitrust violation", and "others".[6] We then exclude fraud in financial

[4]In securities class action lawsuit, class period end date is typically defined as the date when wrongdoing becomes public knowledge.

[5]Audit Analytics Litigation database uses Central Index Key (CIK) code as the company identifier.

[6]"social responsibility related" lawsuits include cases related to civil rights, disability law, employment law, environmental law, etc. "operational malpractice" lawsuits include cases related to racketeering, corruption, and tax evasion. Broadly speaking, corporate fraud involves companies' misrepresentation of accounting reports, contractual terms, intellectual property possession, product quality, and key employees' misconduct. "Antitrust violation", on the other hand, mainly includes corporate abusive behavior in product market instead of misrepresentation behavior. Similarly, "social responsibility related" lawsuits include corporate exploitation behavior rather than misrepresentation. Since "Antitrust violation" and "social responsibility related" lawsuits are different in nature from items under corporate fraud, we exclude them from our corporate fraud sample. Further, if we adopt the "stricter" definition of corporate fraud and include only cases related to "financial reporting", results remain qualitatively similar. This is expected as our current sample consists predominately of "financial reporting" legal cases.

firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900-4999), and government entities (SIC codes of 9000 or above). As indicated in Panel A of Table 4.1, this filtering process yields 2,580 corporate fraud events in 2,010 unique firms. On average, there are 1.28 fraud events per firm.

Corporate supplier-customer link data is from Factset Revere database. Factset Revere contains companies' relationship information from primary public sources such as SEC 10-K annual filings, 10-Q quarterly filings, investor presentations, press releases, corporate announcements, and company websites. The coverage of supplier-customer link data starts from 2003. Two features of the dataset make it appealing to our study. First, the data contains the start date and end date for each relationship. This allows us to unambiguously identify the fraudulent firms' suppliers and customers at the exact date of public revelation. Second, the data coverage is comprehensive as compared to alternative data sources. Alternative data sources for supplier-customer links, such as Compustat segment data, contains only a subset of the most important customers of each firm on an annual basis.[7]

To get the most complete picture of companies' suppliers and customers, we capitalize on the information disclosed by both suppliers and customers. For instance, an earnings statement from Mattel (NASDAQ: MAT) discloses Walmart (NYSE: WMT) as its customer. The Factset relationship data would therefore identify Walmart as Mattel's customer under 'customer' type. We invert the relationship to label Mattel as the suppliers of Walmart even if Walmart did not disclose Mattel as its supplier.[8]

We merge corporate fraud event sample with supplier-customer link data. We also exclude financial firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900-4999), and government entities (SIC codes of 9000 or above) from suppliers and customers of fraudulent firms. After matching with supplier-

[7] This data is used in Cohen and Frazzini [2008] and other studies.

[8] This is a standard procedure in literature on supply chain. For instance, Gofman et al. [2018], Wu [2016], Kolay et al. [2016] all adopt such procedure in forming supplier-customer links.

customer link data, we have 693 fraud events with 7,156 supplier-customer links. The sample period is from 2003 to 2015.

The stock price information is obtained from Center for Research on Security Prices (CRSP) database. Accounting information is extracted from Compustat. Analyst data comes from I/B/E/S database. Data on CSR is from the Kinder, Lydenberg, Domini, & Co. (KLD) database. Following Cheng et al. [2013] and Hong et al. [2012], we focus on five categories of CSR performance: community activities, diversity, employee relations, environmental policies, and the social benefits of their products.[9] Each firm' CSR score is then computed as the sum of the number of CSR strengths across those five categories minus the sum of the number of CSR concerns across those five categories.[10]

[9]KLD ratings consist of the following categories: community activities, diversity, employee relations, environmental policies, human rights, social benefits of firms' products, involvement in controversial industries (e.g. alcohol, gaming, gambling, etc.), and corporate governance. We do not classify corporate governance as part of corporate social responsibility for two reasons. First, as argued by Servaes and Tamayo [2013] and Shleifer and Vishny [1997], corporate governance refers to channels through which shareholders could effectively motivate company management to work in their best interest. By contrast, corporate social responsibility refers to the positive externalities companies impose on other stakeholders, such as community, employee, etc. The relationship entities are very different. Second, corporate governance might be correlated with corporate fraud which is the main subject in our study. This might affect our tests of the effect of CSR on spillover effect of corporate fraud. The coverage of human rights score is very limited and inconsistent. For instance, one subcategory "Positive Record in S. Africa" contains only ratings from 1994 to 1995. Another subcategory "Labor Rights Strength" starts from 2002 and discontinues after 2009. Thus to avoid inconsistency and discontinuity in our measure, we exclude human rights category from our CSR measure. Lastly, as there is virtually nothing firms can do to change its industry affiliation, the involvement in controversial industries is not effective in capturing companies' CSR dynamics. Therefore we also do not use this item in generating our CSR measure.The representativeness of our CSR scores in measuring corporate social responsibility is supported by literature, practice and some anecdotal examples. First, a large number of studies have pointed out that the KLD ratings are "the largest multidimensional CSR databases publicly available" and "the de facto research standard in CSR" [e.g. Deckop et al., 2006; Waddock and Graves, 1997; Cheng et al., 2013; Hong et al., 2012; Servaes and Tamayo, 2013; Lins et al., 2017]. Chatterji et al. [2009] cross checks the KLD environmental ratings with U.S. EPA environmental data and finds evidences that support the effectiveness of KLD ratings in measuring firms' environmental performance. Second, KLD ratings are utilized by a number of asset management companies, especially SRI funds, in evaluating companies' CSR performance and forming their portfolios accordingly. Last but not the least, Cheng et al. [2013] also gives some anecdotal examples on the effectiveness of CSR scores. We cross checked those examples with our CSR scores and find that our CSR scores are able to capture the CSR dynamics. For example, after Steve Jobs took over Apple's CEO role in 1996 and aggregatively cut Apple's CSR programs, Apple's CSR score featured a negative jump from 4 in 1995 to 0 in 2000. Google's CSR score rose steadily from 2 in 2004 to 6 in 2010 after it announced the famous "1% profit-for-social responsibility program".

[10]The equal weighting scheme employed by us in computing overall CSR scores is consistent with the methodology used in literature [e.g. Chatterji et al., 2009; Cheng et al., 2013; Hong et al., 2012;

We use the industry concentration and product similarity data from Hoberg-Phillips Data Library to measure market power and structure.[11] The industry concentration and product similarity is computed based on Text-based Network Industry Classifications (TNIC) developed in a series of papers by Prof. Hoberg and Prof. Phillips [e.g. Hoberg and Phillips, 2016].[12]

4.3.2 Summary Statistics

Table 4.1 gives summary statistics on corporate fraud events in our sample. As described in the data section, the final sample contains 693 fraud events. Panel B reports the distribution of fraud types. Most of our fraud events are related to financial reporting (96.97%). Panel C reports the top five industries of fraudulent firms in our final sample.[13] Corporate fraud occurs most frequently in pharmaceutical products (16.31%), business services (13.42%), electronic equipment (9.38%) industry. Figure 4.1 presents the distribution of fraud events in our final sample across different years. Note in 2003 the number of fraud events is relatively small since the database just started coverage at that time.

[Place Table 4.1 about here]

[Place Figure 4.1 about here]

Table 4.2 presents summary statistics on the supplier-customer links in our final sample. The sample fraudulent firms have in total 7,156 links, in which 4,175 are suppliers and 2,981 are customers. Each firm has, on average, 10.33 supplier-customer links. Average number of suppliers each firm (7.88) is slightly higher than

Servaes and Tamayo, 2013; Lins et al., 2017].

[11] http://hobergphillips.usc.edu/

[12] Hoberg and Phillips [2016] describes and tests the superiority of their measures over measures based on traditional industry classification, such as Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS).

[13] We use Fama-French 48 industry classifications.

average number of customers each firm (5.83). This shows the widespread inter-firm connection in the economy. Panel B and C report the top five industries of fraudulent firms' suppliers and customers respectively. Suppliers of fraudulent firms are mainly in business services (24.89%), electronic equipment (16.26%), and pharmaceutical products (8.62%) industry. Customers of fraudulent firms are mainly in retail (17.04%), business services (14.06%), and wholesale (10.16%) industry.

[Place Table 4.2 about here]

Table 4.3 presents summary statistics on the company characteristics of suppliers and customers.

[Place Table 4.3 about here]

4.4 Empirical Findings

4.4.1 Short Term Stock Market Reactions

In this section we examine suppliers' and customers' short-term stock market reactions to corporate fraud revelation. We use event study methodology to perform the analysis. A brief review of event study methodology is provided and then results are reported.

Event Study Methodology

Event study methodology is used to estimate abnormal return attributed to corporate event.[14] The abnormal return is defined as the actual return of the stock over the event window minus the normal return of the stock over the same window. The normal return is defined as the expected return without the event taking place.

[14]See MacKinlay [1997] for a comprehensive review of event study methodology and applications in economics and finance.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|I_t) \tag{4.1}$$

where $AR_{i,t}$ represents the abnormal return, $R_{i,t}$ is the actual return and I_t represents the conditioning information. In this study we use Carhart four-factor model to compute the normal return.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i1}(R_{m,t} - R_{f,t}) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}MOM_t + \epsilon_{i,t} \tag{4.2}$$

where $R_{i,t}$ is the return of stock i on day t, $R_{m,t}$ and $R_{f,t}$ are the market return and risk-free rate on day t respectively, SMB_t is the size factor which is computed as the return difference between portfolios of small cap stocks and large cap stocks, HML_t is the value factor which is computed as the return difference between portfolios of high book-to-market stocks and low book-to-market stocks, MOM_t is the momentum factor which is computed as the return difference between portfolios of high performing stocks and low performing stocks.

To get the average effect of events, abnormal returns are aggregated over the specified event window and then taken average over all events.

$$CAAR = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=t_1}^{t_2} AR_{i,t} \tag{4.3}$$

where CAR is cumulative abnormal return over event window $[t_1, t_2]$, N is total number of events.

Event Study Results

Table 4.4 provides the event study results for four different event windows, 3 (-1 to 1), 4 (-1 to 2), 2 (-1 to 0), 4 (-2 to 1), with day 0 being the date of fraud revelation. Panel A presents the cumulative abnormal returns (CAAR) of fraudulent firms. Panel B and C present cumulative abnormal returns (CAAR) of fraudulent firms' suppliers and customers respectively.

Consistent with Karpoff et al. [2008b], corporate fraud results in a highly negative stock market reactions. The three-day abnormal return is -17.40% for fraudulent firms on average. As displayed in Panel B and C, fraud revelations result in significantly negative abnormal return for both suppliers and customers. For example, on average the three-day abnormal return is -0.49% (-0.30%) for suppliers (customers). This confirms our previous hypothesis on the negative externalities of corporate fraud revelation. Notice customers' market reactions are smaller in magnitude than suppliers' market reactions. Panel A (Panel B) of Figure 4.2 depicts the short-term abnormal return of fraudulent firms' suppliers (customers) around fraud revelation.

[Place Table 4.4 about here]

[Place Figure 4.2 about here]

4.4.2 Robustness

In this section we conduct three robustness checks on the negative externalities of corporate fraud revelation.

Repeated Events within a Firm

To ensure our results are not driven by a particular company and are not clustered in time, we re-run event study on corporate fraud events that are not preceded by another event in the same company within two-year window prior to the date of fraud revelation. We are then left with 603 fraud events.

Table 4.5 reports the event study results. All results remain similar in magnitude and statistical significance. The abnormal returns of fraudulent firms and their suppliers, in fact, become slightly larger. This is consistent with abnormal returns do not fully reflect the extent of market reactions if there are prior events since investors have already formed some expectations from previous events.

[Place Table 4.5 about here]

Comparison with Matched Firms

Previous literature argue that fraud revelation is more likely to take place during economic downturn or in poorly-performing industries [Povel et al., 2007; Rosner, 2003]. One might argue that the negative market reactions of suppliers (customers) are due to business cycle or industry trend.

To address these concerns, we construct a set of matched suppliers (customers). We require matched suppliers (customers) to be in the same Fama-French 48 industry and year as event suppliers (customers). Further, we require the matched suppliers (customers) and their linked firms, have not been exposed to corporate fraud revelation within -2 year to 2 year window.[15] To make sure the firm characteristics of matched suppliers (customers) are as close to treated suppliers (customers) as possible, we employ mahalanobis distance matching based on five dimensions: log(Assets), book-to-market ratio, return on asset (ROA), book leverage, and past 12-month return.[16] Lastly, if multiple treated events are matched to the same con-

[15] We take a conservative approach to ensure our matched firms are clean. When we construct the sample of matched suppliers (customers), we also remove those firms that have supply or purchase from fraudulent firms within -1 year to 1 year surrounding the date of fraud revelation. Again, this conservative approach is to make sure that the undisclosed suppliers (customers) of fraudulent firms are not in the control sample.

[16] Mahalanobis distance matching minimizes the mahalanobis distance between two datasets. The mahalanobis distance between two data matrix X_i and X_j is computed as $M(X_i, X_j) =$

trol event, we only keep one control event in our event study analysis to avoid double counting. After applying the above procedure, we obtain 2,875 untreated suppliers for 3,977 treated suppliers and 1,873 untreated customers for 2,801 treated customers.

The event study results are presented in Table 4.6. In Panel A (Panel C), we compare the abnormal returns between treated suppliers (customers) and untreated suppliers (customers) before the date of fraud revelation. Specifically, we consider event window -10 to -5. This serves as a placebo test. We find no significant difference between abnormal returns of treated suppliers (customers) and untreated suppliers (customers) before the date of fraud revelation. Panel B (Panel D) presents the abnormal returns of treated suppliers (customers) and untreated suppliers (customers) within four event windows. The abnormal returns of treated suppliers are statistically more negative than those of untreated suppliers surrounding the date of fraud revelation. For example, the average three-day abnormal return of treated suppliers is -0.51% whilst that of untreated suppliers is 0.01%, with the difference being about -0.51%. The abnormal returns of treated customers are also more negative than those of untreated customers during event windows although the difference is statistically significant only in window -2 to 1.

[Place Table 4.6 about here]

Taken together, the above tests ensure that the negative externalities of corporate fraud revelation on suppliers and customers are not driven by business cycle or industry trend.

$\sqrt{(X_i - X_j)' S^{-1} (X_i - X_j)}$, where S is the sample covariance matrix of X_i and X_j. The usage of mahalanobis distance matching is supported by previous researches [e.g. King and Nielsen, 2016]. It adjusts for covariance in the data.

Reporting Party and Market Reactions

There are two types of links used in our analysis: links that are reported by suppliers (customers) and links that are not reported by suppliers (customers) but are reported by fraudulent firms. In this section, we investigate whether the reporting party of those links affects the market reactions to fraud revelation. We separately conduct event study for above two types of linked suppliers (customers).

The composition of supplier-customer links in terms of link reporting party are presented in Panel A and C of Table 4.7. A large fraction (85.58%) of supplier links are reported by supplier themselves. Meanwhile, customer links are divided more evenly between those reported by customer themselves (42.41%) and those reported by fraudulent firms (57.59%).

Column 2 and 3 of Table 4.7's Panel B (D) present market reactions of suppliers (customers) within window [-1,1] and [-1,2], respectively. Even though both are negative, market reactions of suppliers (customers) with links reported by themselves are significantly more negative than those of suppliers (customers) with links not reported by themselves but reported by fraudulent firms, within a very short period of time ([-1,1] and [-1,2]). The difference in *CAAR[-1,1]* between these two types of suppliers (customers) is -0.49% (-0.32%). There are two potential explanations for this finding. First, links with fraudulent firms might carry more weight for suppliers (customers) who self-report these links. Therefore the negative shock (either through operation or reputation channel) would be greater for suppliers (customers) who self-report these links. Second, it might take more time for investors of suppliers (customers) to gather information and infer links with fraudulent firms if links are not self-reported by suppliers (customers). This is consistent with investor limited attention in Cohen and Frazzini [2008] and information processing constraints of investors. Indeed, as links are scattered in various sources of fraudulent firms' disclosure, it might be difficult for investors of suppliers (customers) to immediately notice and gather these information if those investors do not specialize in analyzing corporate supply chain information. Under this explanation market reactions of suppliers (customers) who do not self-report these links would be smaller in magnitude compared to those of suppliers (customers) who self-report these links within a very short period of time.

To test which of these explanations are valid in our sample, we examine stock market reactions in a relatively longer event window. The intuition is that if the second explanation is valid, then investors' limited attention and information processing constraints would lead to slower market reactions for suppliers (customers) with links not reported by themselves. We would thus expect the stock market to gradually adjust prices of suppliers (customers) that do not self-report the link with fraudulent firms. Meanwhile, if the second explanation does not hold and first explanation holds, the stock market would immediately impound the shock into prices and there would be no further adjustment.

Column 4 of Table 4.7's Panel B (D) presents market reactions of suppliers (customers) within window [-1,10]. Figure 4.3 graphically displays the market reactions of suppliers (customers) over time. Both types of suppliers (customers) have a negative CAAR within ten days of fraud revelation. However, suppliers (customers) with links reported by themselves feature a sharp drop in CAAR while suppliers (customers) with links not reported by themselves feature a steady decrease in CAAR. After ten days of fraud revelation, CAAR of these two types of suppliers (customers) gradually converge to a comparable level. The difference in *CAAR[-1,10]* between these two types of suppliers (customers) is insignificant. This finding provides strong support for the explanation that investors of suppliers (customers) are slower in recognizing the link with fraudulent firms and potential spillover effect if suppliers (customers) do not self-report these links.

[Place Table 4.7 about here]

[Place Figure 4.3 about here]

4.4.3 Cross-Sectional Determinants of Market Reactions

In this section we explore the cross sectional determinants of stock market responses. This help shed light on the main channel of propagation of shocks.

Cross-sectional Regressions

To test hypothesis H4.2 to H4.4 and separate between two explanations (operation channel and reputation channel) of negative stock market reactions, we estimate the regression:

$$CAAR_{i,j,t} = \alpha + \gamma X_{i,j,t-1} + \beta Controls + \epsilon_{i,j,t} \tag{4.4}$$

where $CAAR_{i,j,t}$ is three-day cumulative abnormal return of fraudulent firm j's supplier i or customer i in event window $[-1, 1]$.[17] $X_{i,j,t-1}$ is a set of explanatory variables that can be categorized into four categories.

The first category is fraud severity. We use the fraudulent firms' three-day cumulative abnormal return as the measure. This measure has two advantage. First, alternative measures are almost imperfect. For instance, using settlement amount as a measure will lead to significant data loss and bias since a non-negligible fraction of cases are not settled and even for those settled cases, settlement amount only reflects the direct costs while the indirect costs might be much larger in magnitude and more significant in terms of impact. Second, the stock market is able to aggregate and process the information in a timely manner and impound the information in stock prices. In this sense the stock market reactions of fraudulent firms sever as a good proxy for the overall fraud severity.

The second category is fraudulent firms' product market conditions. As explained in the data section, we use two measures developed by Hoberg and Phillips

[17]We also use CAAR[-1,10] as a robustness check. The results are qualitatively similar.

[2016]: TNIC-based industry concentration (Herfindahl-Hirschman index) and product similarity. TNIC is a dynamic and firm-specific industry classification. It is formed by examining the closeness of business descriptions between two firms. The number of firms in each industry is calibrated to match three-digit SIC industries. Both Herfindahl-Hirschman index and product similarity are real numbers in the interval [0,1]. Higher Herfindahl-Hirschman index represents higher industry concentration and less competition. Higher product similarity translates to more overlap between the firm's product and their competitors' product.

The third category is suppliers' (customers') information environment. We employ three distinct measures following the literature. The first measure we consider is analyst coverage. Lang and Lundholm [1996] show that analyst coverage is positively associated with information disclosure practice. Other studies have also used it as a proxy for information asymmetry [e.g. Hong et al., 2000; Zhang, 2006]. For each year, we count the number of analysts following the firms in I/B/E/S. Then we transform the raw analyst coverage into decile ranks to remove the effect of outliers. The second measure is analyst forecast dispersion. It is widely supported in previous literature [Barron et al., 1998; Barron and Stuerke, 1998; Diether et al., 2002; Imhoff Jr and Lobo, 1992; Lang and Lundholm, 1996; Zhang, 2006] that high analyst forecast dispersion is associated with severe information asymmetry. Consistent with Zhang [2006], we compute the forecast dispersion as standard deviation of analyst earnings forecasts scaled by prior year-end stock price.[18] Thus a firm has to be followed by at least two analysts to enter the computation. We then transform the raw analyst forecast dispersion into vigintile ranks to remove the effect of outliers.[19] The third measure is stock return volatility. It is recognized by numerous prior literature [Zhang, 2006; Van Ness et al., 2001; Wang, 1993] that

[18] For each analyst, we retrieve the latest forecast in the fiscal year. We exclude stale or look-back analyst forecasts in our computation, i.e. forecast horizon needs to be within 1 to 6 months prior to forecast period end date.

[19] We choose vigintile ranks instead of decile ranks to capture more variation. The results are robust to using decile ranks.

higher stock return volatility is associated with more information asymmetry. We use the standard deviation of monthly returns in past one year to compute stock return volatility.

The fourth and last category is corporate reputation or social capital of suppliers (customers). We use firm-level CSR scores computed using data from KLD database. As explained in previous hypothesis development, using CSR performance to measure corporate social capital is supported by various academic literature and industry practitioners [e.g. Lins et al., 2017; Sacconi and Antoni, 2010; World Business Council for Sustainable Development, 2004]. *Controls* represents a set of control variables, including suppliers' (customers') book leverage, fraudulent firms' book leverage and book-to-market ratio.

Regression results are presented in Table 4.8. Panel A (Panel B) reports the results on cross-sectional determinants of suppliers' (customers') market responses. In all models, we find a positive relationship between fraudulent firms' market reactions and suppliers' market reactions. In column 1, the coefficient is 0.0259, which means on average a 1% decrease in fraudulent firms' abnormal return results in about 0.026% decrease in suppliers' abnormal return. This suggests that market reactions increase with fraud severity. However, customers' market responses do not exhibit significant relationship with fraudulent firms' market responses.

In model 2 and 3, the coefficients on variables associated with product market conditions (TNIC_HHI, TNIC_Simmilarity) are not statistically significant, both for suppliers and customers. This suggests that the negative market reactions are not attributed to operation channel. This finding is in contrast to previous literature on the network effects of production shocks [e.g. Barrot and Sauvagnat, 2016; Wu, 2016] where the spillover effect is more significant when shocked firms are in less competitive industries. Unlike previous studies, the focus of our study is the revelation of corporate fraud, especially financial misreporting, which has no direct effect on firm production and operation. This could potentially explain these results.

In model 4, 5 and 6, we demonstrate that better information environment help reduce the negative shocks of fraud revelation along supply chain. For instance, higher analyst coverage corresponds to more positive (less negative) abnormal returns of fraud revelation. Both earnings forecast dispersion and stock return volatility are negatively related to abnormal returns of fraud revelation. These findings are consistent with more opaque information environment of suppliers (customers) will result in the more weight the market puts on the new negative information shock in updating their beliefs of suppliers' (customers') firm valuation.

In model 7, we find that suppliers' and customers' CSR performance are positively related to their abnormal returns of fraud revelation. Suppliers' (Customers') enhanced CSR performance help mitigate the negative impact of fraud revelation on their investor trust and subsequently market reactions. This finding supports previous hypothesis that the revelation of corporate fraud mainly affects the reputation and trust of investors in the economically linked firms. To our knowledge the positive role of CSR investment on firms' ability to restore public trust facing adverse shocks has rarely been empirically documented in previous literature.[20]

[Place Table 4.8 about here]

Overall, we find that the negative market reactions of suppliers' (customers') stock to corporate fraud revelation are mainly attributed to reputation and information shock channel. Our results also highlight the importance of distinguishing shock types in determining the main channels of shock propagation.

In asset pricing sense, the findings reflect that the revelation of corporate fraud mainly raises suppliers' and customers' cost of capital (discount rate) due to potential representational risk and therefore lowers suppliers' and customers' stock prices. The negative market reactions of linked firms are more likely to be attributed to increased cost of capital instead of revised cash flow projections.

[20]The only exception is Lins et al. [2017] where they document the positive effect of CSR on firms' stock market performance during the 2008-2009 financial crisis.

Clustering by Firm-Year

As a robustness check, in this section we re-estimate model 4.4 while clustering the standard error at the firm-year level.[21] This is to take into account the potential correlation of returns within each firm-year.

Table 4.9 presents the estimation results. Significance levels of all variables remain unchanged after clustering the standard error at the firm-year level. Thus conclusions drawn are same as those in Table 4.8. For instance, consistent with fraud severity negatively impacts the market reactions of suppliers in Table 4.8, we find a significantly positive coefficient on fraudulent firms' abnormal returns. The insignificant coefficients on variables associated with fraudulent firms' market power are consistent with results in Table 4.8. Variables related to the information environment of suppliers (customers) are shown to have the mitigating effect on the suppliers' (customers') negative reactions to fraud revelation, as in Table 4.8. Lastly, consistent with previous results, CSR scores of suppliers (customers), which are utilized to measure corporate reputation or social capital, are found to be positively related to the abnormal returns of suppliers (customers).

[Place Table 4.9 about here]

Repeated Events within a Firm

For same reasons described in section 4.4.2, in the cross-sectional analysis we also remove corporate fraud events that are preceded by another event in the same company within two-year window prior to the date of fraud revelation. We then re-run the multivariate regressions in 4.4.

Regression results are presented in Table 4.10. Results are found to be similar to Table 4.8. Thus, we conclude that our findings are not driven by a particular company at a specific period of time.

[21] We also cluster the standard error at the industry-year level. The results are qualitatively similar.

[Place Table 4.10 about here]

4.5 Concluding Remarks

With ever growing corporate production network[22], it is vital to understand how the revelation of corporate misconduct affects economically linked firms along the supply chain. Using a large sample of corporate fraud events and corporate relationship data, this paper seeks to answer this question.

We use a market-based approach to examine its impact since the stock market is able to aggregate and process the information timely and incorporates the information in stock prices. We show empirically that the revelation of corporate misconduct results in negative short-term market reactions for the stocks of suppliers and customers. We show that the effect is not driven by a particular firm at a specific period of time, industry trend, or business cycle. The reporting party of supplier-customer links, i.e. whether the links are self-reported by suppliers (customers) or not, affects how quickly the negative market reactions fully materialize.

We then analyse the determinants of suppliers' and customers' abnormal returns to uncover channels through which corporate fraud influences upstream and downstream firms. In contrast to previous literature on production shocks, we do not find evidence in support of operation channel. We provide evidences in line with reputation channel. In addition, we also find the negative shock is amplified by low-quality information environment. Our results highlight the importance of distinguishing shock types in determining the main channels of shock propagation.

Overall, our market-based tests provide support for the spillover effect of corporate fraud revelation on upstream and downstream firms. Our results also provide support for improving corporate disclosure and social capital accumulation when facing negative reputation shocks in linked firms. Our paper extends the

[22]See Figure 1 in Wu [2016] for a visual comparison of supply chain network between 2002 and 2015.

previous literature on the broader costs of corporate misconduct [Giannetti and Wang, 2016; Goldman et al., 2012]. It would be interesting to analyse the effect of corporate misconduct on other key stakeholders. We leave this question for future research.

Appendix 4.A Conceptual Framework of Information Environment on Shock Spillover

To support our empirical findings, in this section we present a simple conceptual framework explaining the effect of information environment on shock spillover. Let x denote the suppliers' (customers') capital that can only be observed by market investors with noise. Suppose before the arrival of new information shock the market investors can only observe u, expressed as

$$u = x + \epsilon_u \tag{4.5}$$

where $\epsilon_u \sim N(0, \frac{1}{p_u})$ and independent of u. In this sense p_u measures the firms' information environment. High p_u corresponds to low variance of the noise term and thus more informative of u on x.

Let v be the new information shock on suppliers' (customers') capital received by market investors which also contains noise (e.g. fraud revelation of linked firms). v is expressed as

$$v = x + \epsilon_v \tag{4.6}$$

where $\epsilon_v \sim N(0, \frac{1}{p_v})$ and independent of x and ϵ_u. The market investors then use information shock v to update their estimate of x. Bayes updating implies

$$E(x|u, v) = w_v v + w_u u \tag{4.7}$$

where w_v and w_u are weights assigned to new information shock and prior consensus respectively. The expression of w_v is

$$w_v = \frac{p_v}{p_u + p_v} \tag{4.8}$$

Therefore we observe that the weights assigned to new information shock w_v decreases with quality of firms' information environment p_u, i.e.

$$\frac{\partial w_v}{\partial p_u} = -\frac{p_v}{(p_u + p_v)^2} < 0 \tag{4.9}$$

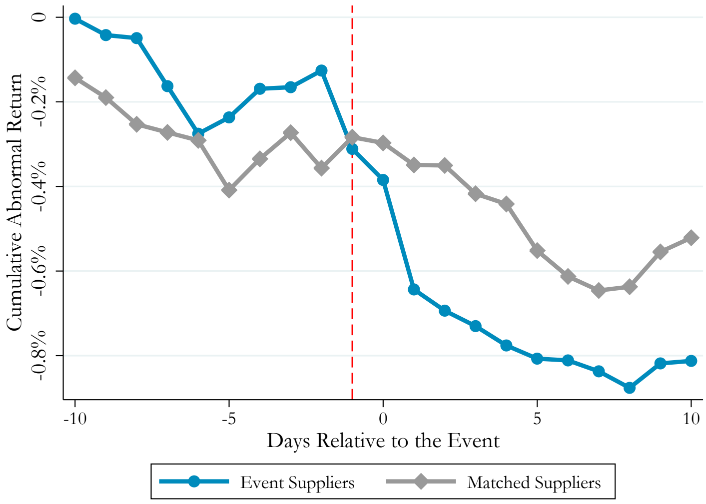
Appendix 4.B Figures

Figure 4.1: Corporate Fraud Events from 2003 to 2015

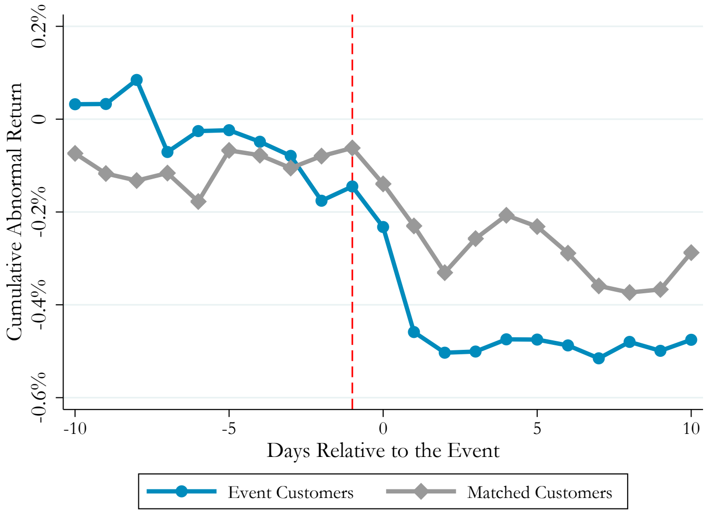
This figure plots the number of corporate fraud events from 2003 to 2015 in our final sample.

Figure 4.2: Market Reactions of Suppliers and Customers to Fraud Revelation

This figure presents cumulative average abnormal returns (CAAR) of suppliers (Panel(a)) and customers (Panel (b)) around the date of fraud revelation. Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. We consider a window of from 10 days before to 10 days after the date of fraud revelation (Day 0). For comparison purpose, we also plot the cumulative average abnormal returns (CAAR) of matched suppliers (Panel(a)) and matched customers (Panel (b)).



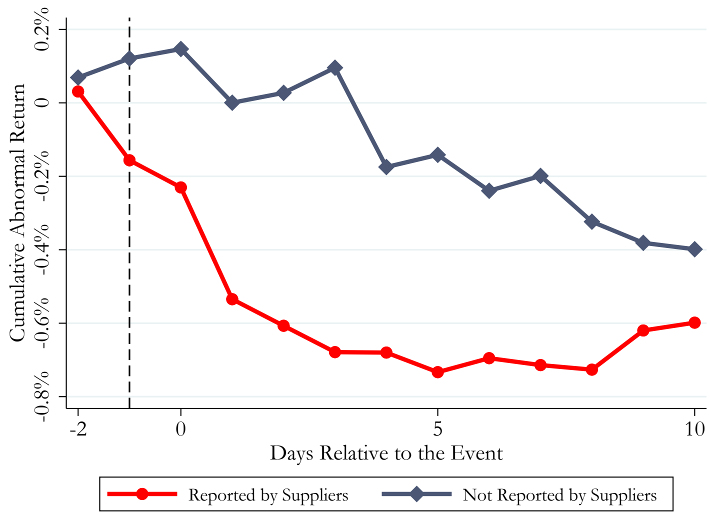
(a) Suppliers



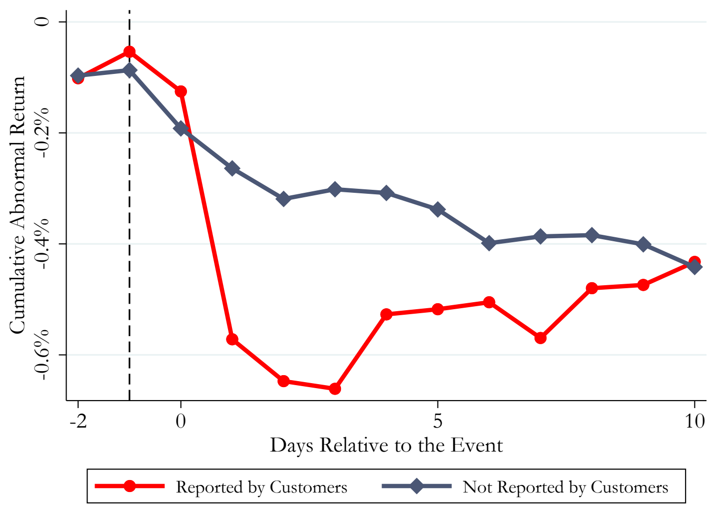
(b) Customers

Figure 4.3: Reporting Party and Market Reactions

This figure presents cumulative average abnormal returns (CAAR) of suppliers (Panel(a)) and customers (Panel (b)) around the date of fraud revelation. The red line plots the CAAR of suppliers (customers) with links reported by themselves. The navy line plots the CAAR of suppliers (customers) with links not reported by themselves but reported by fraudulent firms. Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. We use a window of from 2 days before to 10 days after the date of fraud revelation (Day 0).



(a) Suppliers



(b) Customers

Appendix 4.C Tables

Table 4.1: Summary Statistics on Sample Corporate Fraud Events

This table presents summary statistics on sample corporate fraud events from 2003 to 2015. Panel A reports sample sizes and number of firms. Panel B reports the breakdown of corporate fraud types. Panel C reports the top five industries of fraudulent firms in the final sample.

Panel A: Fraud Statistics		
Total Number	2,580	
Total no. of unique firms	2,010	
Avg no. of fraud events per firm	1.28	
No. of fraud events matched to supplier-customer link data	693	
Panel B: Distribution of Fraud Types in the Final Sample		
Types of Corporate Fraud	*# of Events*	*Percentage*
Financial Reporting	672	96.97%
Breach of Contracts	14	2.02%
Product & Service Liability	5	0.72%
Patent and Copyright Related	1	0.14%
Operational Malpractice	1	0.14%
Total	693	100.00%
Panel C: Top Five Industries of Fraudulent Firms in the Final Sample		
Industry	*# of Events*	*Percentage*
Pharmaceutical Products	113	16.31%
Business Services	93	13.42%
Electronic Equipment	65	9.38%
Retail	64	9.24%
Computers	44	6.35%

Table 4.2: Summary Statistics on Supplier-Customer Links of Fraudulent Firms

This table presents summary statistics on supplier-customer links of fraudulent firms. Panel A reports summary statistics on linkages. Panel B reports top five industries of suppliers in the final sample. Panel C reports top five industries of customers in the final sample.

Panel A: Average Link Statistics		
Total no. of Links	7,156	
Total no. of Suppliers	4,175	
Total no. of Customers	2,981	
Avg no. of Links per firm	10.33	
Avg no. of Suppliers per firm	7.88	
Avg no. of Customers per firm	5.83	
Panel B: Top Five Industries of Suppliers in the Final Sample		
Industry	*# of Suppliers*	*Percentage*
Business Services	1039	24.89%
Electronic Equipment	679	16.26%
Pharmaceutical Products	360	8.62%
Computers	343	8.22%
Communication	167	4.00%
Panel C: Top Five Industries of Customers in the Final Sample		
Industry	*# of Customers*	*Percentage*
Retail	508	17.04%
Business Services	419	14.06%
Wholesale	303	10.16%
Communication	293	9.83%
Computers	291	9.76%

Table 4.3: Summary Statistics on Firm Characteristics of Fraudulent Firms' Suppliers and Customers

This table presents summary statistics on firm characteristics of fraudulent firms' suppliers and customers. *Total assets* is firms' total assets in millions of dollars. *B/M* is the book value of equity divided by market value of equity. *ROA* is defined as operating income before depreciation scaled by total assets. *Book Leverage* is defined as the sum of current liabilities and long-term debt divided by total assets. *Analyst Coverage Rank* is the decile rank of the number of analysts following the firm. *Forecast Dispersion Rank* is the vigintile rank of the firm's earnings forecast dispersion (standard deviation of analyst earnings forecasts scaled by prior year-end stock price). *Stock Return Volatility* is the standard deviation of the firm's monthly returns in past one year. *CSR* is the firms's CSR score computed as the sum of the number of CSR strengths minus the sum of the number of CSR concerns.

Panel A: Suppliers

	Obs	Mean	25%	50%	75%	Std.Dev
Total Assets (in millions)	4175	2815.21	172.216	762.36	4586.211	3625.994
B/M	4095	0.50	0.25	0.42	0.67	0.42
ROA	4172	0.07	0.05	0.11	0.16	0.16
Book Leverage	4131	0.40	0.24	0.38	0.53	0.22
Analyst Coverage Rank (in decile)	3694	5.85	4.00	6.00	8.00	2.78
Forecast Dispersion Rank (in vigintile)	3315	8.66	4.00	8.00	13.00	5.56
Stock Return Volatility	4090	0.12	0.07	0.11	0.15	0.08
CSR	2631	1.05	-1.00	0.00	2.00	3.52

Panel B: Customers

	Obs	Mean	25%	50%	75%	Std.Dev
Total Assets (in millions)	2979	5678.03	887.64	7663.00	9629.73	4151.44
B/M	2940	0.48	0.23	0.39	0.65	0.39
ROA	2977	0.11	0.08	0.13	0.17	0.14
Book Leverage	2876	0.46	0.31	0.44	0.59	0.21
Analyst Coverage Rank (in decile)	2780	7.21	6.00	8.00	9.00	2.50
Forecast Dispersion Rank (in vigintile)	2612	7.57	3.00	7.00	12.00	5.43
Stock Return Volatility	2947	0.10	0.06	0.08	0.12	0.10
CSR	2183	1.76	-1.00	1.00	4.00	3.81

Table 4.4: Stock Market Reactions to Fraud Revelation

This table presents the cumulative average abnormal returns (CAAR) of fraudulent firms (Panel A), suppliers (Panel B), and customers (Panel C) around the date of fraud revelation. We consider four different windows surrounding the date of fraud revelaton (Day 0). Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. We also report the associated test statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fraudulent Firms			
Window	N	CAAR	t-statistics
[-1,1]	678	-17.40%***	-24.30
[-1,2]	678	-17.70%***	-24.13
[-1,0]	678	-5.38%***	-10.30
[-2,1]	678	-17.80%***	-23.66
Panel B: Suppliers			
Window	N	CAAR	t-statistics
[-1,1]	4099	-0.49%***	-5.99
[-1,2]	4099	-0.55%***	-6.00
[-1,0]	4099	-0.21%***	-3.16
[-2,1]	4099	-0.45%***	-4.79
Panel C: Customers			
Window	N	CAAR	t-statistics
[-1,1]	2946	-0.30%***	-3.16
[-1,2]	2946	-0.36%***	-3.53
[-1,0]	2946	-0.07%	-0.91
[-2,1]	2946	-0.39%***	-3.83

Table 4.5: Stock Market Reactions after Elimination of Clustered Company Events

This table presents the cumulative average abnormal returns (CAAR) of fraudulent firms (Panel A), suppliers (Panel B), and customers (Panel C) around the date of fraud revelation after eliminating events that are preceded by another event in the same company within two-year window prior to the event date. We consider four different windows surrounding the date of fraud revelaton (Day 0). Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. We also report the associated test statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fraudulent Firms			
Window	N	CAAR	t-statistics
[-1,1]	603	-18.20%***	-23.91
[-1,2]	603	-18.60%***	-23.71
[-1,0]	603	-5.32%***	-9.59
[-2,1]	603	-18.70%***	-23.33
Panel B: Suppliers			
Window	N	CAAR	t-statistics
[-1,1]	3391	-0.56%***	-6.09
[-1,2]	3391	-0.68%***	-6.66
[-1,0]	3391	-0.25%***	-3.31
[-2,1]	3391	-0.53%***	-5.10
Panel C: Customers			
Window	N	CAAR	t-statistics
[-1,1]	2603	-0.24%**	-2.29
[-1,2]	2603	-0.31%***	-2.76
[-1,0]	2603	-0.02%	-0.28
[-2,1]	2603	-0.32%***	-2.83

Table 4.6: Comparison with Matched Suppliers (Customers)

This table presents the comparison of suppliers' (Panel A and B) and customers' (Panel C and D) CAAR against matched suppliers' and customers' CAAR. Matched suppliers and customers are in same industry and year as event suppliers and customers. Panel A (Panel C) reports the comparison of pre-event abnormal returns between suppliers (customers) and matched suppliers (customers). Panel B (Panel D) reports the comparison of event abnormal returns between suppliers (customers) and matched suppliers (customers). We report levels, differences, and their associated test statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Comparison of pre-event abnormal return between suppliers and matched firms

Variables	Suppliers (1)	Matched Firms (2)	Difference (1) - (2)
CAAR[-10,-5]	-0.24%**	-0.41%***	0.17%
	[-2.03]	[-3.04]	[0.96]

Panel B: Comparison of event abnormal return between suppliers and matched firms

Variables	Suppliers (1)	Matched Firms (2)	Difference (1) - (2)
CAAR[-1,1]	-0.51%***	0.01%	-0.51%***
	[-6.08]	[0.07]	[-4.03]
CAAR[-1,2]	-0.56%***	0.01%	-0.57%***
	[-6.07]	[0.07]	[-3.97]
CAAR[-1,0]	-0.24%***	0.04%	-0.29%***
	[-3.62]	[0.52]	[-2.72]
CAAR[-2,1]	-0.46%***	-0.08%	-0.38%**
	[-4.82]	[-0.75]	[-2.57]
Number of Observations	3,977	2,875	—

Panel C: Comparison of pre-event abnormal return between customers and matched firms

Variables	Customers (1)	Matched Firms (2)	Difference (1) - (2)
CAAR[-10,-5]	-0.02%	-0.07%	0.04%
	[-0.20]	[-0.42]	[0.22]

Panel D: Comparison of event abnormal return between customers and matched firms

Variables	Customers (1)	Matched Firms (2)	Difference (1) - (2)
CAAR[-1,1]	-0.30%***	-0.13%	-0.18%
	[-3.09]	[-1.25]	[-1.21]
CAAR[-1,2]	-0.34%***	-0.23%*	-0.12%
	[-3.26]	[-1.93]	[-0.72]
CAAR[-1,0]	-0.07%	-0.03%	-0.04%
	[-0.93]	[-0.39]	[-0.33]
CAAR[-2,1]	-0.38%***	-0.10%	-0.28%*
	[-3.60]	[-0.87]	[-1.77]
Number of Observations	2,801	1,873	—

Table 4.7: Reporting Party and Market Reactions

This table examines the effect of link reporting party on linked firms' stock market reactions. Suppliers (Customers) are divided into two categories: those with *links reported by themselves* and those with *links not reported by themselves* but reported by fraudulent firms. Panel A and C present the composition of supplier-customer links in terms of link reporting party. Panel B and D present market reactions of the above two types of suppliers and customers and their differences. Abnormal returns are calculated as the return in excess of expected return predicted by Carhart four-factor model. We also report the associated test statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Link Statisitcs of Suppliers (event study)			
	# of Links	*Percentage*	
Links reported by suppliers	3,518	85.58%	
Links not reported by suppliers	593	14.42%	
Total number of links	4,111	100.00%	
Panel B: Market Reactions (Suppliers)			
	[-1,1]	[-1,2]	[-1,10]
Links reported by suppliers	-0.56%***	-0.63%***	-0.62%***
	[-6.06]	[-6.15]	[-3.47]
Links not reported by suppliers	-0.07%	-0.04%	-0.47%*
	[-0.44]	[-0.23]	[-1.71]
Difference	-0.49%**	-0.59%**	-0.15%
	[-2.09]	[-2.26]	[0.34]
Panel C: Link Statisitcs of Customers (event study)			
	# of Links	*Percentage*	
Links reported by customers	1,254	42.41%	
Links not reported by customers	1,703	57.59%	
Total number of links	2,957	100.00%	
Panel D: Market Reactions (Customers)			
	[-1,1]	[-1,2]	[-1,10]
Links reported by customers	-0.47%**	-0.55%***	-0.33%
	[-2.55]	[-2.77]	[-1.07]
Links not reported by customers	-0.15%*	-0.20%**	-0.32%*
	[-1.70]	[-2.03]	[-1.95]
Difference	-0.32%*	-0.34%*	-0.01%
	[1.69]	[1.66]	[0.02]

Table 4.8: Cross-sectional Determinants of Suppliers' (Customers') Market Reactions

This table examines the cross-sectional determinants of suppliers' (Panel A) and customers' (Panel B) market reactions. The dependent variable is suppliers' (customers') three-day cumulative abnormal return $CAAR_S$. Independent variables are classified into four categories: fraud severity, fraudulent firms' product market conditions, suppliers' (customers') information environment, and corporate reputation or social capital of suppliers (customers). Fraud severity is measured by fraudulent firms' three-day cumulative abnormal return $CAAR_F$. Fraudulent firms' product market conditions include *TNIC_HHI* which is the Herfindahl-Hirschman index of fraudulent firms' TNIC industry, *TNIC_Similarity* which is average similarity score between fraudulent firms and their competitiors in the TNIC industry. Suppliers' (customers') information environment includes *Analyst Coverage* which is defined as the decile rank of the number of analysts following the firm, *Earnings Forecast Dispersion* which is defined as the vigintile rank of the firm's earnings forecast dispersion (standard deviation of analyst earnings forecasts scaled by prior year-end stock price), and *Stock Return Volatility* which is the standard deviation of the firm's monthly returns in past one year. Corporate reputation is measured by *CSR* which is defined as the firms's CSR score (the sum of the number of CSR strengths minus the sum of the number of CSR concerns). Control Variables include suppliers' (customers') book leverage, fraudulent firms' book leverage and book-to-market ratio. In each column, we report coefficient estimates, their heteroscedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Suppliers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]
Fraud Severity							
$CAAR_F$[-1,1]	0.0259***	0.0261***	0.0261***	0.0204**	0.0183*	0.0240**	0.0054
	[2.75]	[2.70]	[2.71]	[2.03]	[1.79]	[2.55]	[0.74]
Product Market Conditions							
TNIC_HHI		0.0044					
		[1.17]					
TNIC_Similarity			0.0113				
			[1.46]				
Information Environment							
Analyst Coverage				0.0003			
				[0.79]			
Earnings Forecast Dispersion					-0.0003*		
					[-1.71]		
Stock Return Volatility						-0.0407**	
						[-2.29]	
Reputation							
CSR							0.0005**
							[2.54]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3848	3751	3751	3446	3114	3830	2517
R^2	0.008	0.008	0.008	0.009	0.010	0.011	0.006

Panel B: Customers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]
Fraud Severity							
$CAAR_F$[-1,1]	-0.0001	-0.0058	-0.0052	0.0093	0.0069	0.0020	0.0018
	[-0.01]	[-0.71]	[-0.63]	[1.13]	[0.84]	[0.21]	[0.16]
Product Market Conditions							
TNIC_HHI		0.0040					
		[0.94]					
TNIC_Similarity			0.0080				
			[1.12]				
Information Environment							
Analyst Coverage				0.0016***			
				[2.92]			
Earnings Forecast Dispersion					-0.0006***		
					[-2.67]		
Stock Return Volatility						-0.0421**	
						[-2.07]	
Reputation							
CSR							0.0005*
							[1.78]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2727	2644	2644	2563	2428	2716	2009
R^2	0.001	0.001	0.001	0.008	0.007	0.007	0.002

Table 4.9: Clustering Standard Error by Firm-Year

This table re-estimate model 4.4 for suppliers (Panel A) and customers (Panel B) while clustering the standard error at the firm-year level. The dependent variables and independent variables are the same as in Table 4.7. In each column, we report coefficient estimates, their t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Suppliers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAARS[-1,1]	CAARS[-1,1]	CAARS[-1,1]	CAARS[-1,1]	CAARS[-1,1]	CAARS[-1,1]	CAARS[-1,1]
Fraud Severity							
CAARF[-1,1]	0.0259***	0.0261***	0.0261***	0.0204**	0.0183*	0.0240**	0.0054
	[2.71]	[2.67]	[2.68]	[2.01]	[1.77]	[2.52]	[0.72]
Product Market Conditions							
TNIC_HHI		0.0044					
		[1.18]					
TNIC_Similarity			0.0113				
			[1.44]				
Information Environment							
Analyst Coverage				0.0003			
				[0.81]			
Earnings Forecast Dispersion					-0.0003*		
					[-1.74]		
Stock Return Volatility						-0.0407**	
						[-2.16]	
Reputation							
CSR							0.0005**
							[2.55]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3848	3751	3751	3446	3114	3830	2517
R2	0.008	0.008	0.008	0.009	0.010	0.011	0.006

Panel B: Customers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAARC[-1,1]	CAARC[-1,1]	CAARC[-1,1]	CAARC[-1,1]	CAARC[-1,1]	CAARC[-1,1]	CAARC[-1,1]
Fraud Severity							
CAARF[-1,1]	-0.0001	-0.0058	-0.0052	0.0093	0.0069	0.0020	0.0018
	[-0.01]	[-0.71]	[-0.63]	[1.13]	[0.84]	[0.21]	[0.16]
Product Market Conditions							
TNIC_HHI		0.0040					
		[0.94]					
TNIC_Similarity			0.0080				
			[1.12]				
Information Environment							
Analyst Coverage				0.0016***			
				[2.96]			
Earnings Forecast Dispersion					-0.0006***		
					[-2.70]		
Stock Return Volatility						-0.0421**	
						[-2.08]	
Reputation							
CSR							0.0005*
							[1.79]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2727	2644	2644	2563	2428	2716	2009
R2	0.001	0.001	0.001	0.008	0.007	0.007	0.002

Table 4.10: Regressions after Elimination of Clustered Company Events

This table re-estimates regression models in Table 4.7 after eliminating events that are preceded by another event in the same company within two-year window prior to the event date. In each column, we report coefficient estimates, their heteroscedasticity-robust t-statistics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Suppliers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]	$CAAR_S$[-1,1]
Fraud Severity							
$CAAR_F$[-1,1]	0.0230**	0.0235**	0.0237**	0.0205*	0.0182	0.0211*	0.0067
	[2.12]	[2.12]	[2.14]	[1.78]	[1.54]	[1.95]	[0.84]
Product Market Conditions							
TNIC_HHI		0.0047					
		[1.12]					
TNIC_Similarity			0.0103				
			[1.16]				
Information Environment							
Analyst Coverage				0.0006			
				[1.51]			
Earnings Forecast Dispersion					-0.0004*		
					[-1.76]		
Stock Return Volatility						-0.0499**	
						[-2.52]	
Reputation							
CSR							0.0008***
							[3.85]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3137	3052	3052	2816	2538	3121	2069
R^2	0.008	0.008	0.008	0.009	0.010	0.013	0.008

Panel B: Customers' Market Reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]	$CAAR_C$[-1,1]
Fraud Severity							
$CAAR_F$[-1,1]	-0.0014	-0.0080	-0.0074	0.0088	0.0069	0.0009	0.0001
	[-0.13]	[-0.90]	[-0.82]	[0.97]	[0.78]	[0.09]	[0.01]
Product Market Conditions							
TNIC_HHI		0.0036					
		[0.82]					
TNIC_Similarity			0.0062				
			[0.83]				
Information Environment							
Analyst Coverage				0.0014**			
				[2.36]			
Earnings Forecast Dispersion					-0.0008***		
					[-3.04]		
Stock Return Volatility						-0.0407**	
						[-2.00]	
Reputation							
CSR							0.0004
							[1.51]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2402	2328	2328	2263	2146	2394	1771
R^2	0.001	0.002	0.002	0.006	0.009	0.007	0.002

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