Essays on Corporate Social and Environmental Performance

by

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Intellectual Property Statement

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Thesis Section	Jointly-authored Publication
Chapter 3. Financial constraints and employee satisfaction	Jing, C., Keasey, K., Lim, I. and Xu, B., 2019. Financial constraints and employee satisfaction. *Economics Letters*, *183*, p.108599.

This is a jointly-authored publication with my three PhD supervisors based on Chapter 3. I made significant contributions to the conceptualization, research design, execution, and writing of this publication. Specifically, I contributed to the development of the research idea, data collection, empirical analysis, and writing of a complete draft. My supervisors supervised the project, reviewed the findings, proofread and polished the draft, and managed the submission process.

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Abstract

This thesis consists of three essays on corporate social and environmental performance. The first chapter explores how capital markets shape corporate environmental policies. The last two chapters study the determinants and implications of employee satisfaction and gender differences at work.

The first chapter uses two quasi-natural experiments, brokerage closures and mergers, to explore the causal effect of analyst coverage on corporate environmental policies. I find firms significantly increase corporate pollution after an exogenous decrease in analyst coverage, suggesting that analyst monitoring plays a pivotal role in restricting environmentally harmful behaviors. This effect is more pronounced for firms with low initial analyst coverage, weaker corporate governance, less regulatory scrutiny, and incorporated in states where stakeholder constituency laws are not enacted. Reduced investment in pollution abatement, deteriorating environmental internal governance mechanisms, and a decreased role and influence of institutional investors are possible channels through which financial analysts influence corporate pollution.

The second chapter investigates the gender satisfaction gap at work. Using Glassdoor employer reviews, I find that females are less satisfied at work than males. In particular, females care more about work-life balance, while this difference in workplace preference vanishes at the manager level, illustrating the role of selection. Exploring further implications, I show that family-friendly workplaces with small gender satisfaction gaps exhibit superior firm performance. This finding is stronger in industries relying more on female employees, firms with stronger corporate governance, and financially unconstrained firms.

The third chapter studies the relation between financial conditions and employee satisfaction. Using Glassdoor data, this chapter documents employee satisfaction is substantially lower in financially constrained firms. Decomposing the employee ratings, I find financial constraints are negatively associated with employees' assessments of work-life balance, career opportunity, and senior leadership. Further analysis suggests employee-friendly workplaces and cultures are beneficial for firm valuation. Overall, this chapter highlights that employee satisfaction could be an important channel through which financial constraints reduce firm value.

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Introduction

Over recent decades, corporate social and environmental performance plays an increasingly important role in the business world. The determinants and implications of corporate social and environmental policies have received considerable attention from practitioners and academic researchers. This thesis consists of three essays exploring how corporate social and environmental performance (i.e., corporate environmental policies, gender gap, and employee satisfaction) can be shaped by corporate practices and capital markets, and the financial implications of socially responsible practices. The first chapter investigates the effect of capital markets on corporate pollution, while the last two chapters focus on the drivers and implications of employee satisfaction and gender differences at work.

The first empirical chapter studies how financial analysts, a crucial component of capital markets, shape corporate environmental policies. A major challenge of this study is how to identify the casual effect of financial analysts on corporate environmental performance due to reverse causality and omitted variable bias. To tackle this challenge, I take advantage of two quasi-natural experiments of brokerage exits (i.e., brokerage closures and brokerage mergers) to capture an exogenous decrease in analyst coverage that does not directly influence corporate environmental performance. After an exogenous decrease in analyst coverage, affected firms significantly increase toxic pollution as compared to control firms unaffected by brokerage exits. This finding supports the external monitoring hypothesis that analyst monitoring plays a pivotal role in restricting environmentally harmful behaviors (i.e., corporate pollution).

I further explore the monitoring role of financial analysts by studying how it interacts with alternative monitoring and governance mechanisms to influence corporate pollution. Specifically, the results are more pronounced for firms with poor corporate governance, facing less regulatory scrutiny, and incorporated in states where stakeholder constituency laws are not enacted. These results suggest that analyst monitoring acts as a substitute for traditional corporate governance mechanisms and regulatory oversight. Lastly, I investigate three non-mutually exclusive channels through which the changes in analyst coverage can shape corporate environmental policies. In particular, I document that decreases in analyst coverage lead to underinvestment in pollution abatement and green technologies, deteriorating environmental internal governance, and a decreased role and influence of institutional investors. Overall, this chapter highlights the important monitoring role financial analysts play in reducing negative externalities.

The second empirical chapter uses a novel database from Glassdoor to examine the gender differences in job satisfaction and workplace preferences. Using Glassdoor employer reviews I show that, on average, females are less satisfied at work than males (i.e., gender satisfaction gap). Specifically, females have a significantly lower rating on overall satisfaction and other workplace attributes including career opportunity, work-life balance, senior leadership, and corporate culture. I find that work-life balance is the attribute that contributes most to the gender satisfaction gap.

Moreover, I explore gender differences in workplace preferences by investigating the sensitivity of the overall satisfaction to each of the workplace attributes and find that females, relative to males, care more about work-life balance, senior leadership, and corporate culture, while care less about career opportunity and compensation benefits. Again, female and male employees differ most notably in their preferences for work-life balance. Further, I study whether the pattern of gender differences in workplace preferences carries over among mid-level managers. While most of the gender gaps among rank-and-file employees continue to hold for managers, the gender preferences for work-life balance vanishes. This evidence suggests females do not care more about work-life balance than males conditional on becoming a mid-level manager, indicating the role of selection. Given their dual roles in the home and the labor market, females are less likely to choose a career path to the managerial position when they have to sacrifice work-life balance to be promoted. Finally, I find that a family-friendly workplace with a lower gender satisfaction gap in work-life balance is positively associated with firm valuation and stock returns. In addition, cross-sectional analyses show that firms in industries relying more on female employees, with stronger corporate governance, and with less financial constraints may benefit more from workplace family-friendliness than others.

The third empirical chapter focuses on a key determinant of employee-friendly policy: corporate financing conditions. Specifically, I investigate the real effect of financial constraints on employee satisfaction using over 120,000 employee reviews collected by Glassdoor between 2008 and 2015. Financially constrained firms may have strong incentives to preserve internal cash flows through underinvestment in long-term projects (i.e., employee wellbeing) as the payoffs of such projects accrue slowly over time. Consistent with this view, I find an adverse impact of financial constraints on employee satisfaction. A one standard deviation increase in financial constraints reduces employee overall satisfaction by 3.3%.

By decomposing overall ratings, I document that the lower employee satisfaction in financially constrained firms is mainly driven by employee dissatisfaction about work-life balance, senior leadership, and career opportunity as those employees may be forced to work overtime and lose on-the-job perks, face increasing performance pressure from their superiors, and have a more uncertain career progression. Consequently, unsatisfied employees are reluctant to recommend their employer to others, hampering firms' competitiveness in the labor market. Lastly, I explore whether employee-friendly policies are beneficial for firms. Satisfied employees may be more motivated, productive, and loyal, which can improve firm performance. Indeed, I show a positive effect of employee-friendly workplaces, as measured by firm-level average employee satisfaction, on firm performance. This evidence suggests employee satisfaction is an important channel through which financial constraints reduce firm value.

1 Analyst Coverage and Corporate Environmental Policies: Evidence from Two Quasi-natural Experiments

1.1 Introduction

Over the last decade, on average, approximately 3.8 billion pounds of toxic chemicals were released into the environment each year by U.S. registered plants (EPA, 2019). When inhaled by the human body, toxic pollution is likely to lead to serious consequences such as birth defects, neurodevelopment disorders, illnesses, and even death. Globally, more than one in six deaths is linked to pollution and over nine million deaths were pollution-related in 2015 (Landrigan et al., 2018). In addition to risks to human health, economic activities are also significantly influenced by toxic pollution. In particular, literature has extensively documented the negative economic externalities of toxic pollution such as decreased worker productivity (Chang et al., 2016; Graff Zivin and Neidell, 2012), deterioration of labor supply (Hanna and Oliva, 2015), and lower home prices (Greenstone and Gallagher, 2008; Currie et al., 2015). Given the severe consequences of toxic pollution, increasing effort has been devoted to study the determinants of corporate environmental performance.[1] In this chapter, I focus on the role of financial analysts in shaping corporate environmental policies.

Financial analysts, as an important information intermediary and external monitor in capital markets, have real effects on a wide range of corporate policies (Bradshaw et al., 2017).[2] Building upon previous literature, I propose two competing

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[1] There is a small but fast-growing literature on how corporate environmental policy is determined by various firm characteristics such as organizational form (Akey and Appel, 2021), listed status (Shive and Forster, 2020), institutional ownership and activism (Akey and Appel, 2019; Chu and Zhao, 2019; Kim et al., 2019) and financing constraints (Goetz, 2019; Levine et al., 2018b; Xu and Kim, 2020).

[2] For instance, financial analysts could effectively reduce information asymmetry (Kelly and Ljungqvist, 2012) and earning management activities (Yu, 2008), mitigate agency problem (Chen et al., 2015), increase investment efficiency (Derrien and Kecskes, 2013), improve the quality of firm disclosure (Irani and Oesch, 2013), increase stock liquidity (Balakrishnan et al., 2014), and lead to more efficient investments in innovation (Guo et al., 2019), while the short-term pressure imposed by

hypotheses on how financial analysts shape corporate environmental policies. The first hypothesis is the *external monitoring hypothesis* predicting financial analysts have strong incentives to monitor corporate environmental behavior, resulting in lower toxic pollution. Firms in the U.S. are required to partially internalize environmental costs by allocating resources for environmental protection (Xu and Kim, 2020). Specifically, they are forced to allocate considerable attention and resources in pollution abatement activities such as resource reuse and recycling, updating and replacement of waste management facilities, and the development of green technologies.[3] More importantly, the payoffs of investments in pollution abatement accrue slowly over time and often sacrifice short-term performance. Therefore, the absence of external monitoring may induce managers to maximize short-term profit by avoiding or reducing the costs associated with pollution abatement and environmental protection. Indeed, managers are reluctant to invest in costly abatement processes and technologies to curb environmentally harmful behaviors if the detection probability is low (Hart and Zingales, 2016).

From this perspective, financial analysts may have strong incentives to monitor and influence corporate environmental policies because environmental performance is crucial to the firms they follow. Environmentally harmful behaviors (i.e., excessive corporate pollution) are explicitly linked to greater litigation risk and penalties by the regulatory agency (e.g., EPA), difficulties in attracting and retaining executives (Levine et al., 2018a) and principal customers (Banerjee et al., 2014), higher financing cost (Sharfman and Fernando, 2008; Chava, 2014), and ultimately lower firm value (Porter and Van der Linde, 1995; Konar and Cohen, 2001; Clarkson

financial analysts impedes firm's long-term projects such as innovation (He and Tian, 2013) and corporate social responsibility (Qian et al., 2019).

[3] For example, Clarkson et al. (2004) find the environmental capital expenditures of pulp and paper companies account for, on average, 9.77% of total capital expenditures.

et al., 2004; Karpoff et al., 2005). Given the importance of corporate environmental policies for firm performance, value-relevant environmental information has been increasingly incorporated in analyst reports (Jemel-Fornetty et al., 2011). For example, in 2013, there are approximately 27,000 financial analyst reports which include the analysis of corporate environmental performance (Dong et al., 2016).

As well-trained professionals with rich industry background knowledge, financial analysts can collect information through both public and private channels (e.g., tracking the financial reports; visiting the plants; surveying the customers) and directly monitor corporate policies by raising their concerns in conference calls (Chen et al. 2015). Essentially, financial analysts are regarded as important “whistle blowers” who play a major role in detecting corporate misbehaviors (Dyck et al., 2010). In addition, financial analysts also provide an indirect monitoring role by disseminating information to the capital market and external investors via research reports and social media like TV programs and newspapers (Miller, 2006), which reduces the cost of other stakeholders (e.g., institutional investors) to monitor managerial behaviors (Chen et al., 2018).

More importantly, direct and indirect monitoring by financial analysts not only increases the probability of detecting corporate environmental misbehaviors, but also the consequences of the misbehaviors. Anecdotal evidence suggests that firms’ environmental misbehaviors can lead analysts to issuing unfavorable stock recommendations and downgrades. For example, on January 27, 2020, an analyst at Zacks downgraded the recommendation of American Electric (NYSE: AEP) from “outperform” to “neutral”. The primary reason for the downgrade was AEP’s exposure to substantial environmental risks. Annually, 77 million tons of coal are burned by their plants, releasing large amounts of nitrogen, sulfur, mercury, and carbon dioxide into the air. Overall, the *external monitoring hypothesis* conjectures that analyst monitoring can reduce firm toxic pollution by increasing the ex-ante expected cost of a firm's environmentally harmful behaviors.

In contrast, the *short-termism hypothesis* predicts financial analysts often create excessive pressure on managers (Dechow et al., 2003; Graham et al., 2005; He and Tian, 2013), leading to an increase in toxic pollution. Financial analysts usually make earnings forecasts and stock recommendations based on the short-term perspective of firms (e.g., 1-year EPS forecast). The pessimistic view (e.g., "Sale" recommendation) or failure to meet earnings forecasts by analysts may lead to negative stock market reactions (Kasznik and McNichols, 2002), lower managerial compensation (Matsunaga and Park, 2001), and even forced managerial turnovers (Hazarika et al., 2012). Managers are forced to sacrifice long-term projects (He and Tian, 2013) to improve short-term performance to meet the analysts' forecasts (Irani and Oesch, 2016). Under the short-term pressure imposed by financial analysts, myopic managers are incentivized to reduce environmental-related investments or freeze current pollution abatement practices to increase short-term cash flows (Xu and Kim, 2020). Consequently, the *short-termism hypothesis* predicts an adverse impact of financial analysts on corporate environmental performance.

The main empirical challenge of this study is the relation between financial analysts and corporate environmental performance could be biased by the endogeneity problem (e.g., reversal causality or omitted variables). For instance, financial analysts focus the firms with better environmental performance, this may lead to a negative relation between analyst coverage and toxic pollution (Ioannou and Serafeim, 2015; Luo et al., 2015). In addition, unobservable firm heterogeneity correlated with both analyst coverage and environmental performance may also bias the estimations. To alleviate this concern, I take advantage of two natural experiments of brokerage exits (i.e., brokerage closures and brokerage mergers) to capture a plausibly exogenous decrease in analyst coverage (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; Derrien and Kecskes, 2013; Irani and Oesch, 2013; Chen et al., 2015).[4]

These two experiments can directly capture a decrease in analyst coverage and are exogenous to corporate environmental policies and individual characteristics, which help establish the causality. Kelly and Ljungqvist (2012) show that brokerage closures, which lead to a reduction in the number of analysts covering a firm, are largely due to business considerations rather than the heterogeneous characteristics of the firms they cover. Similarly, Hong and Kacperczyk (2010) show that when two brokers merge, analysts are often made redundant due to culture clashes and for reasons unrelated to any firm-specific characteristics (i.e., environmental policies). Accordingly, I can explore the effect of an exogenous decrease in analyst coverage on corporate environmental policies through these two quasi-natural experiments. In total, I identify 35 staggered brokerage exits that occurred during 2000 and 2010.

To investigate the environmental outcomes of analyst loss, I retain corporate firms that owned at least one plant in the Toxic Release Inventory (TRI) database constructed by Environmental Protection Agency (EPA). The TRI dataset reports the quantity of toxic pollution released to the environment by each U.S. registered plant and is extensively employed in previous studies (e.g., King and Lenox, 2000; Currie and Schmieder, 2009; Currie et al., 2015; Kim et al., 2019; Shive and Forster, 2020; Akey and Appel, 2021). Based on this dataset, I construct a pollution variable to measure corporate pollution in each firm-year observation. Further, I define the treated firms as the firms affected by the event of broker closures or mergers and then use propensity score matching (PSM) to match treatment firms to similar control firms.

[4] The validity of the two quasi-natural experiments has been extensively validated by prior studies who investigate the relation between analyst coverage and analyst bias (Hong and Kacperczyk, 2010), asset pricing (Kelly and Ljungqvist, 2012), firm investment (Derrien and Kecskes, 2013), innovation (He and Tian, 2013), and corporate governance (Chen et al., 2015)

To only capture the effect of analyst loss on corporate environmental performance, I construct a two-year estimation window to compare firm pollution in the one year before the brokerage exits with that in one year after. In total, my matching sample consists of 606 treatment (control) firm-year observations from 1999 to 2011.

Using difference-in-differences tests, I find that an exogenous decrease in analyst coverage significantly increases corporate pollution. In terms of economic magnitude, the total nominal (output scaled) toxic pollution of treated firms increases by approximately 13% (12.6%) of standard deviation as compared to matched control firms. The estimation results are robust to controls for industry-year fixed effects, a battery of firm characteristics, different estimation windows and subsamples, and alternative matching criteria. This evidence supports the *external monitoring hypothesis*, suggesting financial analysts play a pivotal role in restraining environmentally harmful behaviors.

I then investigate the effect of financial analysts on EPA violations. The *external monitoring hypothesis* argues that the absence of analyst monitoring may lead to more corporate environmentally harmful behaviors. From this perspective, I expect that firms affected by brokerage exits are more likely to violate EPA regulations. Consistent with my expectation, the number of EPA enforcements in treated firms increases by 7.3% after a decrease in analyst coverage, relative to control firms. Interestingly, this relation is mainly driven by an increase in non-judicial cases, while it is insignificant in the regression for judicial cases. It suggests managers strategically choose their environmental behaviors and only increase “their environmental misconduct” when there seems to be an absence of serious consequences for their career prospects and reputation (Aharony et al., 2015).

To sharpen my understanding of the monitoring hypothesis, I perform several cross-sectional tests to investigate how the monitoring role financial analysts play interacts with alternative monitoring mechanisms. Firstly, I find that the effect of an exogenous decrease in analyst coverage on corporate pollution is more pronounced in the subsample with low initial analyst coverage, as there is a relatively larger percentage drop in monitoring among such firms than those with high initial analyst coverage.

Second, I investigate the role of corporate governance in the relation between analyst coverage and corporate pollution. I find that firms with weaker corporate governance (as proxied by weaker market competition and a higher managerial entrenchment index) emit more toxic pollution after an exogenous decrease in analyst coverage. Third, I find the treatment effect is stronger in firms subject to less stringent regulatory monitoring (geographically more distant from EPA offices). The results indicate that analyst monitoring can act as a substitute for traditional corporate governance mechanisms and regulatory oversight (Irani and Oesch, 2013; Chen et al., 2015).

Fourth, I study whether the enactment of stakeholder constituency law can influence the results. Stakeholder constituency law requires the board of directors to consider the benefits of stakeholders when making corporate decisions. I find that firms incorporated in states without stakeholder constituency law tend to pollute more in the absence of analyst monitoring, suggesting analyst monitoring is particularly important in aligning shareholder-stakeholder conflicts over externalities caused by toxic pollution (Cheng et al., 2018).

In the final part of this chapter, I investigate the underlying mechanisms through which financial analysts shape corporate environmental policies. Specifically, I consider three non-mutually exclusive channels: (1) investments in pollution abatement; (2) environmental internal governance and; (3) role and influence of institutional investors. The first channel examines whether managers are incentivized to underinvest in pollution abatement and green technologies after an exogenous decrease in analyst coverage, leading to more corporate pollution. Since pollution abatement is costly, managers may be reluctant to allocate resources in abatement technologies or practices to curb environmental harmful behavior (Hart and Zingales, 2016). To test this channel, I employ corporate environmental expenditures and green patents as the proxies for investments in pollution abatement. I find that after experiencing an exogenous decrease in analyst coverage, the amount of environmental expenditures and the number of green patents in affected firms both significantly decrease relative to control firms. The underinvestment incentives consequently result in higher corporate pollution.

The second channel is internal environmental governance, suggesting a decrease in analyst coverage leads to higher corporate pollution through deteriorating environmental internal governance mechanisms. To the extent that the absence of analyst monitoring decreases the detection probability and consequences of environmentally harmful behaviors, managers may have strong incentives to lessen internal governance mechanisms associated with corporate environmental performance as such mechanisms require considerable attention and resources. In support of this view, I find that an exogenous decrease in analyst coverage reduces the probability of containing “pay for environmental performance” in executive contracts and having a sustainability board committee.

The last channel is the role and influence of institutional investors. Over recent years, an increasing number of institutional investors claim they monitor and influence corporate social and environmental policies (Krueger et al., 2020; Bolton and Kacperczyk, 2021), which induces managers to improve corporate social performance (Kim et al., 2019; Dyck et al., 2019; Chen et al., 2020). However, the role and influence of institutional investors rely on the corporate information environment. In the course of their duties, analysts disseminate information on a firm's environmental policies to capital markets (Miller, 2006). This reduces the monitoring cost for other stakeholders, in particular, institutional investors, when monitoring corporate behavior. Indeed, prior studies find that after decreases in analyst coverage, institutional investors are more likely to shy away from firms that become more opaque (Bushee and Noe, 2000; Chen et al., 2015). This weakens the role and influence of institutional shareholders in shaping corporate environmental policies, thereby incentivizing myopic managers to increase corporate pollution. Consistent with this view, I find a significant decrease in institutional ownership of affected firms after an exogenous decrease in analyst coverage. Further, I examine this channel across different institutional types. The decline in institutional ownership is mainly driven by the lower equity held by the quasi-indexers and public pension funds who have longer investment horizons and are under the pressure of social norms, thereby caring more about firm long-term performance and sustainability.

This chapter contributes to at least two strands of literature. First, this chapter contributes to the nascent but fast-growing literature on the determinants of corporate environmental policies. Previous studies have identified organizational form and ownership structure as crucial drivers of corporate pollution. For example, Akey and Appel (2021) present that the protection of limited liability leads to higher toxic emissions. Shive and Forster (2020) find that public firms tend to release more pollution than private firms. Kim et al. (2019) find that local institutional investor forces firms to reduce corporate pollution, while Akey and Appel (2019) and Chu and

Zhao (2019) document a positive relation between investor activism and target firms' pollution. In addition, financial resources are regarded as another key factor in determining corporate environmental policies (Cohn and Deryugina, 2018; Xu and Kim, 2020; Bartram et al., 2021). For instance, Xu and Kim (2020) suggest that financially constrained firms are more likely to reduce investments in pollution abatement and thus release more pollution into the environment. This chapter complements this line of literature by highlighting the monitoring role of financial analysts in reducing corporate pollution. More importantly, I provide three plausible mechanisms through which financial analysts shape corporate environmental policies. Specifically, I find that an exogenous decrease in analyst coverage may decrease firms' investments in pollution abatement, weaken the managerial incentives to establish internal environmental governance mechanisms, and reduce the monitoring role and influence of institutional investors.[5]

Second, this chapter contributes to the debate on the bright and dark sides of financial analysts. As an important information intermediary and external monitor, financial analysts could reduce information asymmetry (Kelly and Ljungqvist, 2012) and earnings management activities (Yu, 2008), mitigate agency problems (Chen et al., 2015), increase investment efficiency and stock liquidity (Derrien and Kecskes, 2013; Balakrishnan et al., 2014), and improve the quality of firm disclosure (Irani and

[5] To the extent that toxic emissions are a function of corporate social responsibility (CSR), my study is also related to extensive literature on CSR (e.g., Masulis and Reza, 2015). Most directly related are studies on how analysts influence a firms' CSR performance. However, the evidence is mixed on the effects of financial analysts on a firms' CSR ratings. For instance, Qian et al. (2019) find a negative relation between analyst coverage and firm CSR performance, while Dong et al. (2017) documents the opposite. Unlike these studies focusing on binary measures of aggregate CSR performance from the KLD database, my study takes advantage of the continuous measures of firm environmental performance from the TRI database which provides detailed information about corporate pollution (e.g. the quantity of toxic pollution released each year). Importantly, Kim et al. (2019) point out that the correlation between firm-level TRI toxic pollution and the KLD environmental score is relatively small (-0.17) and as such, capture very different elements of a firm's CSR. Therefore, my analysis allows me to more cleanly investigate an important aspect of CSR, corporate pollution, which has large negative externalities for society.

Oesch, 2013). Financial analysts, however, often impose short-term pressure on managers (Dechow et al., 2003; Graham et al., 2005), thereby forcing them to sacrifice long-term investments to meet short-term earnings forecasts and price targets (He and Tian, 2013; Irani and Oesch, 2016). This chapter provides strong evidence to support the bright side of financial analysts and their role in shaping corporate environmental policies and limiting corporate pollution. Prior studies regard financial analysts as the important external monitors who play a major role in detecting and restricting managerial misconduct (Dyck et al., 2010; Chen et al., 2015). My findings support this view and highlight that analyst monitoring works as a substitute for both traditional corporate governance mechanisms and regulatory oversight to refrain managers from environmentally harmful behaviors.

The remainder of this chapter is organized as follows. Section 1.2 describes the sample construction and identification strategy. Section 1.3 presents the main empirical results and robustness test. Section 1.4 provides various cross-sectional implications. Section 1.5 addresses the plausible underlying mechanisms. Section 1.6 concludes.

1.2 Sample Construction and Identification

1.2.1 Pollution data

The pollution data are collected from the Toxic Release Inventory (TRI) database that was constructed by the Environmental Protection Agency (EPA).[6] Beginning in 1986, the Emergency Planning and Community Right-to-Know Act (EPCRA) was created to provide information about toxic chemicals to governments and the public. Section 313 of EPCRA establishes the Toxic Release Inventory (TRI),

[6] More details about the Toxic Release Inventory database can be found at https://www.epa.gov/toxics-release-inventory-tri-program.

tracking the release and disposal of toxic chemicals that may threaten human health and the environment. Currently, this program covers data of the release or disposal of 755 individually listed chemicals and 33 chemical categories from roughly 60,000 plants (including both public and private owner plants).[7] All TRI plants are required to submit the annual report if a plant: (1) manufactures, processes, or otherwise uses one of the listed chemicals in an amount greater than the certain level of threshold; (2) owns more than 10 full-time employees; (3) operates in one of the 409 industries covered by EPCRA Section 313 and identified as six-digit North American Industry Classification System (NAICS) code. The TRI dataset is regarded as the primary source for plant environmental performance since its' first release (Prechel and Zheng, 2012) and is extensively employed in previous studies (e.g., King and Lenox, 2000; Currie and Schmieder, 2009; Currie et al., 2015; Kim et al., 2019; Shive and Forster, 2020; Akey and Appel, 2021).

As TRI data are self-reported by individual facilities, the main concerns are the potential errors and manipulations. To mitigate this concern, EPA provides stringent reporting instructions and guidelines to ensure the accuracy of the submission. EPA will assign an independent senior official to certify the accuracy and completeness of information for each submission. If any deliberately concealing and misreporting activities are detected, EPA can enforce enormous fines and potential criminal penalties on violators (Greenstone, 2003). For instance, EPA issued a $60,000 fine to a plant owned by Hexion Inc. as the plant "*failed to comply with reporting requirements*" in 2019.[8] Overall, there is little evidence that proves the misreporting of TRI data could bias the estimation results (Bui and Mayer, 2003).

[7] The list of covered toxic chemicals is shown in https://www.epa.gov/toxics-release-inventory-tri-program/tri-listed-chemicals
[8] See https://www.epa.gov/newsreleases/oregon-chemical-company-settles-epa-federal-chemical-reporting-violations

To analyse pollution outcomes, I keep firms that owned at least one plant in the Toxic Release Inventory (TRI) database. I then merge the TRI dataset with the Compustat and Institutional Brokers' Estimate System (I/B/E/S) database to retrieve the financial and analyst information of TRI pollution firms. The challenge in the matching is that there is no consistent and common identifier among the TRI, Compustat, and I/B/E/S databases. Following prior studies (Shive and Forster, 2020; Akey and Appel, 2021), I use a fuzzy string-matching technique to match the unique parent company name of each plant with the company names in the Compustat and I/B/E/S. To guarantee the accuracy of the matching, I manually verify the accuracy of each matched pair via the firm headquarter, company official website, Duns number, and Google search.[9] Similar to Akey and Appel (2019) and Chu and Zhao (2019), I drop the plants with zero toxic pollution. In addition, I exclude the firms in the financial (SIC 6000-6999) and utility industries (SIC 4900-4999). The initial pollution sample (prior to matching and criteria imposed for the identification strategy) consists of 765 unique firms with 5,872 plants from 1999 to 2011.

As the TRI pollution data are provided at the chemical-plant level, I further aggregate the release of all chemicals at the plant level and then sum up the plant-level releases to obtain firm-level pollution. More specifically, I follow prior studies (e.g., Gomez-Mejia, 2009; Delmas and Toffel, 2008; Kim et al., 2019) to identify a firm's total toxic pollution as the sum of total on-site pollution and total off-site pollution. On-site pollution is the amount of toxic pollution released onsite into the air, water, and ground, while off-site pollution is the quantity of toxic release transferred to an off-site location for further release or disposal at specialized waste

[9] Duns number is a unique nine-digit business identifier, issued by Dun & Bradstreet (D&B) and widely used in the U.S. and Europe.

management facilities.[10] To mitigate the concern of extreme values and skewness, I log-transform firm-level pollution. Consequently, I obtain the first measure for firm-level nominal pollution *Log(total),* the logarithm of total pollution. In addition, I construct a scaled measure to capture the firm's "eco-efficient". In particular, I scale each pollution variable by the total sales and then log-transform the adjusted pollution (Cordeiro and Sarkis, 1997; Konar and Cohen, 2001; Shive and Forster, 2020) to obtain the second measure for firm-level pollution *Log(total/sales)*, the logarithm of total pollution scaled by total sales.

1.2.2 Identification strategy

1.2.2.1 Two quasi-experiments: Brokerage closures and brokerage mergers

To investigate the effect of analyst coverage on corporate environmental performance, a major concern is that the relation between analyst coverage and corporate pollution is likely to be endogenous. For example, the estimation results may be biased by reverse causality, as financial analysts are more likely to cover environment-friendly firms (Ioannou and Serafeim, 2015; Luo et al., 2015). In addition, unobservable firm heterogeneity (e.g., corporate culture) correlated with both analyst coverage and corporate pollution can confound the estimation results. Therefore, the most straightforward way of regressing corporate pollution on the analyst coverage is inappropriate in this study. To overcome the obstacles, I take advantage of two unique quasi-natural experiments of brokerage exits (i.e., broker closures and mergers) to create a plausibly exogenous variation in analyst coverage (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; Derrien and Kecskes, 2013;

[10] Air pollution is composed of stack emissions and fugitive emissions. Stack emission refers to toxic chemical emissions to the air through confined air streams (such as stacks, ducts or pipes). Fugitive emissions are toxic air emissions that are not released through confined air streams (such as equipment leaks and evaporative losses). Water pollution is the total quantity of the toxic pollution released on-site as surface water discharges. Ground pollution is the total quantity of toxic pollution released to the on-site ground.

Irani and Oesch, 2013; 2016; Chen et al., 2015) and then use difference-in-differences (DiD) methodology to explore the effect of an exogenous change in analyst coverage on corporate environmental performance.

The first quasi-natural experiment is brokerage closures. Kelly and Ljungqvist (2012) find that the occurrences of broker closures are largely driven by increased market competition, reduced revenue, and more strict government regulation, rather than the heterogeneous firm characteristics covered by the closed brokers. In other words, this shock leads to a plausible exogenous decrease in analyst coverage for stocks they follow that is unrelated to corporate characteristics (i.e., environmental policies). Accordingly, the number of analysts coverage should be the only channel through which brokerage closures influence corporate pollution.

The second quasi-natural experiment is brokerage mergers, which is originally introduced by Hong and Kacperczyk (2010) to identify an exogenous reduction in analyst coverage due to coverage universes overlapping. When a stock is covered by both acquiring and target brokers before the merger, the acquiring broker often fires at least one analyst following the stock (usually from the target broker) due to redundancy and culture clashes (Wu and Zang, 2009; Hong and Kacperczyk, 2010). As with brokerage closures, brokerage mergers provide another ideal setting to capture an exogenous drop in analyst coverage of "covered" firms.

1.2.2.2 Identifying treatment and control firms

To construct my estimation sample, I start by creating the event list of brokerage exits. To identify brokerage closures, I follow the procedure of Chen et al. (2015) to identify the brokers that disappeared from the I/B/E/S database between 2000 and 2010. For each disappeared broker, I use BrokerCheck to collect the termination status and date of brokers and then manually check historical press releases in Bloomberg, LexisNexis, and Google to confirm the disappearance of listed brokers was attributed to the closure. Lastly, I supplement the event list with broker closures from Kelly and Ljungqvist (2012). Similar to Chen et al. (2015), I obtain a list of 30 brokerage closures events from 2000 to 2010.

To identify brokerage mergers, I follow the process of Hong and Kacperczyk (2010) and Chen et al. (2015) to construct the list of broker mergers using Thomson's SDC Mergers and Acquisition database. Specifically, I require the primary SIC code of both sides (the target and the acquirer) of one merge event to be 6211 or 6282, as sell-side financial analysts are more likely to be employed in these firms.[11] I consider only completed deals and deals that 100% of the target broker is acquired by the bidder broker. I then manually match the event list of broker mergers in Thomson's SDC Mergers and Acquisition database with the broker house in the I/B/E/S database and consequently produce 24 merge events. In total, I construct the event list of 54 brokerage exits (30 closures and 24 mergers) which is consistent with Chen et al. (2015) and similar to the combination of Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012).[12]

Next, I merge the event list with the I/B/E/S unadjusted historical detailed dataset to construct a sample of treated firms affected by brokerage exits and other information on brokers. From this, I construct the estimation window around the brokerage exits. Event dates are supposedly dates of brokerage exits. However, the termination date (month) of broker closure or merge from BrokerCheck or Thomson Reuters SDC Mergers and Acquisition database does not always exactly fall into the

[11] SIC code 6211 contains Security Brokers, Dealers, and Flotation Companies. SIC code 6282 is Investment Advice firms.

[12] Lehman is not in my sample, as it is not a suitable shock for identification purposes (Kelly and Ljungqvist, 2012; Chen et al., 2015). This is because Barclays, which had no U.S. equities business of its own, took over Lehman's entire U.S. research department. Untabulated test results show that all my results hold if I further exclude Bear Stearns following Kelly and Ljungqvist (2012)

same month with the disappearance date of the brokers in the I/B/E/S stop file, as the completion of one merger or closure event usually needs several months. Following Derrien and Kecskes (2013) and He and Tian (2013), I set a 6-month "event period" (denoted *t*) symmetrically around the disappearance date (three months before the event date and three months after).[13] For example, the Robertson Stephens analyst firm closed in July 2002, and I identify the time range from April 2002 to October 2002 as the event period of this closure event.

To ensure the results are only driven by the exogenous drop in analyst coverage, I identify a two-year estimation window around the event (*t-1 and t+1*) following previous studies (e.g., Derrien and Kecskes, 2013; Irani and Oesch, 2013; Chen et al., 2015; Chen and Lin, 2017; Li et al., 2019). Given the fact that the analyst loss for affected stock can be compensated for by new entries or other brokers in the long run, this estimation window ensures this study can directly capture the short-term decrease in analyst coverage and its effect on corporate environmental policies.[14] Since I identify six-month spans around the event, there is indeed a six-month gap between the year before the event *t-1* and the year after *t+1*. To avoid overlapping data, I identify the pre-event year *t-1* as the last fiscal year that ended before the disappearance date of brokers and the post-event year *t+1* as the first *complete* fiscal year after the event date. For instance, if a treatment firm has a December fiscal year-end and the event date is May 31, 2001, the year *t-1 (t+1)* would be December 31, 2000 (2002). In this way, this procedure produces two non-overlapping observations of each treated firm (i.e., *t-1* and *t+1*).

[13] I also employ 8-, 4-, and 0-month event period to replicate the main results, and do not find significant differences.
[14] In robustness tests in Section 1.3.2, I employ different estimation windows such as a 2-year (*t-2* to *t+2*) and 3-year (*t-3* to *t+3*) around the event and find the estimation results are not materially changed.

Next, I merge the affected firms by brokerage exits to the constructed pollution sample to identify the treated firms. I require all treated firms to have the financial information and pollution data from *t-1* to *t+1*, which means each treated firm must have observations in at least three consecutive years around the events. For the brokerage closures, I require firms to be covered by the closed broker in the pre-event year and then continue to exist in the I/B/E/S database in the post-event year. For the broker mergers, I constrain the treated firms to the stocks covered by both sides of mergers (target and acquirer) one year before the event and then continue to be covered by the acquirer broker house in the year after the event.[15] The unaffected firms by brokerage exits are allocated into the pool of control firms. Finally, the unmatched sample consists of 326 unique treatment firms (associated with 35 brokerage exits) and 764 control firms between 1999 and 2011.[16,17]

1.2.2.3 Matched treatment and control groups

Using this sample, I first examine the effect of an exogenous decrease in analyst coverage on corporate pollution and find that treated firms significantly emit more pollution into the environment after decreases in analyst coverage relative to control firms. However, the relation is likely to be biased as treated and control firms may differ along with various observable and unobservable firm characteristics which both affect the variation of analyst coverage and corporate pollution. For instance, if larger firms tend to be covered more by analysts (and thus more likely to be treated), these large firms could also find it more efficient to invest in pollution abatement

[15] For both broker closures and mergers, I further require that the estimate of the treated firm is not "stopped" in the I/B/E/S database before the disappearance date of the broker to ensure that the termination of analyst coverage is exogenous instead of being driven by firm-specific characteristics.
[16] A firm could be affected by more than one closure or merger events during my sample period
[17] The number of treated firms is relatively fewer than other studies (e.g., Derrien and Kecskes, 2013; Chen et al. 2015) as I require firms in my sample to own at least one registered plant in the TRI database to include pollution data.

technologies. To mitigate this concern, I use propensity score matching (PSM) to construct the matched sample.

Following prior studies (e.g., Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; He and Tian, 2013; Irani and Oesch, 2013; Derrien and Kecskes, 2013), I match on a set of firm characteristics in the pre-event year *t-1* which may predict the probability of being treated, including total assets (*Firm Size*), Return on assets (*ROA*), Tangibility (*Tangibility*), Book-to-Market ratio (*Book to Market*), and industry (*2-digit SIC*). I match on firm size, ROA, book-to-market ratio, as firms with larger size and better performance are more likely to be covered by financial analysts (Hong and Kacperczyk, 2010). In addition, I match on the tangible asset ratio which may lead to different environmental strategies and influence analysts' decisions on the coverage of a particular firm (Ioannou and Serafeim, 2015; Luo et al., 2015; Akey and Appel, 2021). Lastly, I match on the 2-digit SIC since the environmental policies and analyst coverage are significantly differ across industries.

After constructing the combinations of matching variables, I generate a logistic regression where the outcome variable is an indicator variable that equals one if the specific firm-year observation is identified as the treated firm and zero otherwise. Next, I employ a one-to-one nearest-neighbor match with replacement based on the propensity score of regression.[18] The matching sample consists of 254 unique treated firms and 116 unique control firms with 1,212 firm-year observations, including 606

[18] In the matching, there is a possibility that treated firms can be selected as control firms before (after) the three-year (t-1 to t+1) time window. To avoid the overlapping effects, treated firms could not be selected into the candidate pool of control firms to ensure a cleaner match.

treated (control) observations.[19, 20] That is 303 pairs of treated and control firms affected by brokerage exits (2 firm-year observations (*t-1* and *t+1*) each).

To ascertain the validity of the PSM matching, I perform a balance test to examine the differences in the mean of various firm characteristics between treated and control firms in the pre-event year (t-1).[21] The matching variables and other firm characteristics of treated and control firms are largely indistinguishable after PSM matching. Collectively, the balance test suggests that the matching process successfully controls for the ex-ante differences between treatment and control firms.

1.2.3 Empirical model

To investigate the effect of an exogenous decrease in analyst coverage on corporate pollution, I employ difference-in-differences estimates to compare the change in corporate pollution from pre-event year *t-1* to post-event year *t+1* in the treatment group versus the control group. The baseline regression is shown as follows:

$$y_{i,t} = \alpha + \beta_1(Treatment_{i,t} \times After_{i,t}) + \beta_2 Treatment_{i,t} + \beta_3 After_{i,t} + \delta X_{i,t} + \varepsilon_{i,t} \tag{1-1}$$

Where *t* indexes year and *i* indexes firm. *y* is one of two measures for firm total pollution, the logarithm of total nominal toxic pollution (*log(total)*) and the logarithm of output adjusted emission (*log(total/sale)*). $Treatment_{i,t}$ is an indicator variable which equals to one if the firm has experienced an exogenous drop in analyst coverage due to brokerage closures or broker mergers and zero otherwise, and $After_{i,t}$ is a dummy variable equal to one in the year after the events *t+1* and zero in the year

[19] As the number of firms with pollution data are relatively limited (765 unique firms) and my matching requires firms to be in a similar industry (SIC two-digit code), I lose about 100 treated firm-year observations.
[20] The number of unique control firms is smaller than treated firms because I use the PSM with replacement. The estimation results are not materially changed when employing non-replacement matching.
[21] The results are shown in panel B of Table 1-1.

before $t-1$. The variable of interest in this analysis is the interaction variable, $Treatment_{i,t} \times After_{i,t}$. The coefficient β_1 captures the change in corporate pollution of treated firms after an exogenous decrease in analyst coverage relative to before and relative to control firms. The vector $X_{i,t}$ contains a set of firm-specific variables employed in the prior studies, including firm size (*Firm size*), book-to-market ratio *(Book to Market)*, return on assets *(ROA)*, tangibility *(Tangibility)*, debt structure *(Book Leverage)*, Research and development expense *(R&D)*, dividend ratio *(Dividend ratio)*, and cash ratio *(Cash ratio)*. Details of the variables are presented in Appendix 1-A1. $\varepsilon_{i,t}$ is the error term and clustered at the firm level.

1.2.4 Summary statistics

After PSM matching, I obtain 1,212 firm-year observations including 606 firm-year observations per treated and control firms. To mitigate the effect of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

Panel A of Table 1-1 presents the descriptive statistics for all pollution and financial variables. On average, firms in my sample release 2.26 million pounds of toxic pollution into the environment, including 2.08 million pounds of on-site pollution and 0.18 million pounds of off-site pollution. The on-site pollution is composed of 0.74 million pounds air pollution, 0.17 million pounds water pollution, and 1.17 million pounds ground pollution. The control variables are largely similar to those reported in previous studies that use the TRI data (e.g., Kim et al., 2019; Chu and Zhao, 2019; Xu and Kim, 2020).

[Insert Table 1-1 here]

1.2.5 Diagnostics tests

The identification strategy of this paper is built upon the idea that firms affected by brokerage exits (treated firms) will lose financial analysts relative to unaffected firms (control firms). In Figure 1-1, I confirm this setting by plotting the mean difference in analyst coverage between the treatment and control group (treatment-control) for a six-year window symmetrically around the event of brokerage exits (from three years before the event *t-3* to three years after *t+3*). Figure 1-1 shows the mean difference in analyst coverage between treatment and control firms is roughly constant before an exogenous decrease in analyst coverage (from years $t-3$ to $t-1$) and then significantly decreases by approximately one analyst between year *t-1* and year *t+1*. The magnitude of the shock is consistent with prior studies (e.g., Derrien and Kecskes, 2013; Chen and Lin, 2017).[22, 23] This plot ascertains the validity of my setting that brokerage exits indeed result in an exogenous decrease in analyst coverage.

[Insert Figure 1-1 here]

Moreover, when employing difference-in-differences analysis, a key identifying assumption is the parallel trend assumption that requires the treatment and control firms to have a similar trend in corporate pollution before the brokerage exits. I follow prior studies (e.g., He and Tian, 2013; Derrien and Kecskes, 2013) to verify the satisfaction of the parallel trend assumption through plotting the mean difference in firm total pollution between treatment and control firms from three years before brokerage exits *t-3* to three years after *t+3*. Figure 1-2 shows that the net difference (treatment-control) in total pollution is stable prior to brokerage exits from the year *t-*

[22] The large gap in analyst coverage between the treatment and control groups is mainly explained by the fact that I do not allow the firms affected by brokerage exits to shift to the candidate pool of control firms, and I do not add analyst coverage as the matching variable due to the limited matching samples. The results are not materially changed if I include analyst coverage in the combination of matching criteria.

[23] To further confirm the validity of my settings, I generate a DID estimation with analyst coverage as the dependent variable. The coefficient of interation item (*Treatment*After*) is highly significant with a 4.58 t-value, which is consistent with my expectation that treated firms lose about one financial analyst after brokerage exits relative to control firms.

3 to year *t-1*, and then has a dramatic increase from the year *t-1* to year *t+1*, suggesting no differential pre-event trend in corporate pollution between treated and control firms and brokerage exits lead to a significant change in corporate pollution of treated firms relative to control firms. Overall, these two diagnostic tests lend confidence to the validity of my empirical strategy.

[Insert Figure 1-2 here]

1.3 Main Results

1.3.1 Baseline results

I begin the empirical analysis by examining the effect of exogenous decreases in analyst coverage on corporate pollution using the difference-in-differences estimation in Table 1-2.[24] The dependent variable is the nominal measure of total pollution (*log(total)*) in Columns (1) to (3) and sale-adjusted total pollution (*log(total/sales)*) in Columns (4) to (6).

[Insert Table 1-2 here]

I first estimate the DID regressions without control variables in Column (1) and then include control variables in Column (2). Firm and year fixed effects are included in Columns (1) and (2) to control for time-invariant heterogeneity across firm and time. In Column (3) I obtain firm and industry-year (SIC 2-digit) fixed effects to control for time-varying industry characteristics such as environmental regulatory changes and industry-technological shifts. Across all specifications the coefficient on the interaction term (*Treatment*After*) is positive and statistically significant at the 1% level. This increase in toxic pollution is economically large. As shown in Column (3), exogenous decreases in analyst coverage are associated with an increase of 36.1% in

[24] In the regression specification I omit the item of *Treat*, as I require that the treated firms cannot be shifted into candidate pool of control firms during my sample period and control for the firm fixed effects in all columns.

toxic emissions (approximately 13% of the dependent variable's standard deviation). The magnitude of the estimate is also comparable to the studies that explore the effect of decreases in analyst coverage on the long-term benefits of stakeholders. For example, He and Tian (2013) document that after an exogenous decrease in analyst coverage, treated firms generate 18.2% more patents and 29.4% more citations relative to control firms. Bradley et al. (2021) find that the workplace injury rate increases by 33.2% in response to analyst loss. Dong et al. (2016) show that the corporate social responsibility (CSR) score of treated firms decreases by 60% of the absolute sample mean value after decreases in analyst coverage.

In Columns (4) to (6), I use the output adjusted pollution (*log(total/sales)*) as an alternative firm-level pollution measure (Cordeiro and Sarkis, 1997; Konar and Cohen, 2001). The coefficient on *Treatment*After* remains positive and statistically significant at the 1% level. Overall, regardless of measures for corporate pollution, my results provide initial evidence in support of the *external monitoring hypothesis* that firms are more likely to increase environmentally harmful behaviors (i.e., corporate pollution) in the absence of analyst monitoring.

1.3.2 Robustness tests

In this section I conduct a battery of robustness tests to confirm the validity of my DID analysis. The estimation results are presented in Table 1-3. As with the baseline model, the dependent variable is nominal total pollution (*log(total)*) in Columns (1) to (3) and sale-adjusted total pollution (*log(total/sales*) in Columns (4) to (6). For brevity, I only report the coefficient and t-value of the interaction term (*Treatment*After*).

[Insert Table 1-3 here]

I start with different estimation windows. My baseline estimation employs a two-year window (*t-1* and *t+1*) around the event of brokerage exits, as it captures the short-term variation of analyst coverage and reduces the probability that the analyst loss may be filled by new entries or other brokers (Chen et al., 2015). Nonetheless, I replicate the results using 4-year (t-2 to t+2) and 6-year (t-3 to t+3) estimation windows in Rows (1) and (2) of Panel A. My findings remain robust to alternative estimation windows.

Second, a common concern is the estimation results may be driven by a specific set of matching variables when constructing my matching sample. To account for this concern, I start with the unmatched sample in Row 3 of Panel B. While the estimation may be biased by the difference in firm characteristics between treated and control firms, the results are highly robust to the unmatched sample. Next, in Rows (4) to (7), I use alternative combinations of matching variables to re-run my baseline estimation. In particular, I create a simple matched sample only with *Firm size* in Row (4). Row (5) is the combination used in the baseline model (*Firm size*, *ROA*, *Book-to-Market*, and *Tangibility*) and reproduced here for comparability. Row (6) adds *R&D* since the additional matching criteria since the investments in research and development may be associated with the input and output of corporate green technologies and pollution abatement (Chu and Zhao, 2019). Lastly, in Row (7) I further require treated and control firms to have the similar corporate monthly return (*Return*) and stock return volatility (*Volatility*) (Hong and Kacperczyk, 2010; He and Tian, 2013). Regardless of how to construct the combinations of matching variables, the coefficient on *Treatment*After* remains positive and statistically significant at the 5% level or better.

Third, I address the concern that the results could be driven by certain subsamples of firms. For example, the financial crisis (the internet bubble) may lead to brokerage exits and increases in corporate pollution due to financial constraints (He and Tian, 2013; Xu and Kim, 2020). Accordingly, I replicate the results after excluding all brokerage exits occurred between 2008 and 2010 in Row (8) and between 2001 and 2002 in Row (9) of Panel C, respectively. The results are not materially changed.

Fourth, prior studies (e.g., Shapiro and Walker, 2018; Akey and Appel, 2021) find a significant and persistent decrease in toxic pollution from the 1990s to the early 2000s due to the changes in environmental regulation (e.g., implicit pollution tax). In addition, approximately one-third of brokerage closures and mergers in my sample took place in 2000 and 2001. One potential worry is that this dramatic decrease in pollution and a large proportion of brokerage exits may distort my estimation results. To mitigate this concern, I re-estimate my regression after excluding the events in 2000 and 2001 in Row (10) of Panel D and obtain largely similar results.

Lastly, I note that roughly one-thirds of treated-firm-year observations are treated more than once in my sample, causing a reasonable concern that the potential confounding effect may bias the empirical results (Kim et al., 2019). To rule out this possibility, I only keep the observations affected by the first event of brokerage exits if they are treated more than once, and then replicate the DID estimation in Row (11) of Panel E.[25] The results are quantitatively similar.

[25] As an alternative robustness check, Chen et al. (2018) use a strategic sampling method to randomly select one treatment firm-year observation for firms treated more than once. I also employ their method to reproduce the estimation and the results remain robust.

1.3.3 Analyst coverage and sub-category pollution

I then investigate which specific component of toxic pollution is affected more by the analyst loss. Total pollution is composed of on-site pollution and off-site pollution. On-site pollution is the amount of toxic pollution released onsite into the air, water, and ground. Off-site pollution is the quantity of toxic release transferred to an off-site location for further release or disposal at specialized waste management facilities. In Panel A of Appendix 1-A2, I find the increases in toxic pollution of treated firms after decreases in analyst coverage are mainly driven by on-site pollution. This finding is not surprising. As the transfer and disposal of the off-site pollution are costly, firms are more likely to increase the emission of on-site pollution rather than transferring the pollution to costly off-site places for further disposal in the absence of external monitoring (Kim et al., 2019).

I further decompose on-site pollution into air, water, and ground pollution. Air pollution equals the sum of the onsite stack emissions and onsite fugitive emissions. Water pollution is the total quantity of the toxic pollution released onsite as surface water discharges. Ground pollution is the total quantity of toxic pollution released to the on-site ground. As shown in Panel B of Appendix 1-A2, analyst loss only significantly increases air pollution, while is unrelated to water and ground pollution.

1.3.4 EPA enforcements

The baseline results show that decreases in analyst coverage significantly increase corporate environmentally harmful behaviors (i.e., corporate pollution). In this section, I employ EPA enforcement as an alternative measure for environmentally harmful behaviors to investigate whether treated firms are more likely to violate the EPA regulations after decreases in analyst coverage.

EPA enforces environmental laws to protect the environment and takes civil or criminal enforcement action against non-compliance cases. [26] While non-compliance enforcement cannot directly measure the extent of toxic pollution, the advantage of this measure is linking toxic pollution to regulatory and litigation risks that may shape corporate environmental policies (Xu and Kim, 2020). The enforcement cases data are extracted from the Integrated Compliance Information System for Federal Civil Enforcement Case Data (ICIS FE&C). This provides plant-level information about individual enforcement cases such as the primary law violated, settlement date, and case number. More importantly, this dataset distinguishes the judicial and non-judicial cases, which allows me to observe how managers weigh the costs and benefits of corporate pollution.[27] If the costs (e.g., administrative corrections) are not sufficiently high as compared to judicial litigations that could lead to concerns of personal reputational damage, loss of board seats, and increased board turnover (Aharony et al., 2015; Fahlenbrach et al., 2017), managers might be more willing to engage in "stronger" forms of environmental misconduct.

As enforcement cases are at the plant level, I construct a firm-year count of enforcement cases by summing up the number of EPA enforcement cases. For the observations without non-compliance records, I treat the number of cases as zero. In my sample, the mean values of EPA enforcement cases, non-judicial cases, and judicial cases are 0.21, 0.18, and 0.03, respectively.[28] As the detection and settlement of non-compliance cases require time, I compare the non-compliance cases in the two years before the event (*t-2*) and two years after (*t+2*).[29] Firm and industry-year fixed

[26] See: https://www.epa.gov/enforcement/basic-information-enforcement
[27] Judicial cases are those formal lawsuits that take place in court, while non-judicial cases are those activities taken by the EPA but without the court process.
[28] As the distribution of non-compliance data has right-skewness, I log-transform the enforcement variables.
[29] The sample size reduces from 1,212 to 1,112 in this model since I use a different time window and there are some missing values in the financial or pollution data.

effects are included, as the enforcement data significantly vary across industries (Shive and Forster, 2020).

In Table 1-4, I investigate the effect of decreases in analyst coverage on EPA enforcement. The dependent variable is the natural logarithm of one plus the number of EPA enforcements in Columns (1) and (2), non-judicial enforcements in Columns (3) and (4), and judicial enforcements in Column (5) and (6). In Columns (1) and (2), the coefficients on the interaction terms (*Treatment*After*) are positive and statistically significant, suggesting a significant increase in the total number of EPA enforcement cases in the absence of analyst monitoring. The effects are also economically significant. As shown in Column (2), the number of non-compliance cases in treated firms increases by 7.3% after decreases in analyst coverage, relative to control firms. These results are consistent with Hart and Zingales (2016) that managers are more likely to increase environmental misbehaviors when the detection probability is low.

[Insert Table 1-4 here]

Then, I partition total enforcement cases into non-judicial and judicial ones. The coefficient on the interaction term (*Treatment*After*) is negative and statistically significant in the regression for non-judicial cases, while it is insignificant for judicial cases. This finding illustrates managers indeed strategically choose the types of environmental misbehaviors (Xu and Kim, 2020). Specifically, in the absence of external monitoring, managers are incentivized to increase environmental misconducts without serious consequences (i.e., non-judicial cases), while being more cautious in engaging in the misconduct that may threaten their individual reputation or career prospects (i.e., judicial cases).

1.4 Cross-sectional Analysis

My findings so far indicate that after an exogenous decrease in analyst coverage, firms significantly increase toxic pollution and non-compliance behaviors. In this section, I explore how financial analysts interact with cross-sectional heterogeneity to influence corporate pollution. To the extent that analysts reduce corporate pollution by playing an external monitoring role, which substitutes for alternative monitoring mechanisms, I expect the effect of decreases in analyst coverage to be more pronounced when alternative monitoring forces are weak. More specifically, I investigate whether the effect of analyst monitoring can be mitigated or exacerbated by *initial analyst coverage*, *corporate governance*, *the intensity of regulatory scrutiny*, and *stakeholder orientation laws*.

1.4.1 Analyst coverage and initial analyst coverage

I first examine the effect of initial analyst coverage before the brokerage exits on my results. Intuitively, if treated firms are followed by fewer financial analysts before the shock, the loss of an analyst should lead to a greater percentage reduction in external monitoring and thus have more effect on subsequent firm policies (Hong and Kacperczyk, 2010). Therefore, I conjecture that the effect of decreases in analyst coverage on corporate pollution is stronger in firms with low initial analyst coverage.

To test this conjecture, I split the treatment sample into two groups based on terciles sorted on initial analyst coverage of treated firms (He and Tian, 2013; Chen et al., 2015). In Table 1-5, treated firms are allocated to the group with low initial analyst coverage if they fall into the bottom tercile of analyst coverage in Columns (1) and (2). In a similar vein, treated firms are distributed into the group with high initial analyst coverage if they are in the top tercile in Columns (3) and (4).[30] As expected, I find that the effect of analyst coverage on pollution is more pronounced in the subsamples with low initial analyst coverage. The coefficients on the interaction terms (*Treatment*After*) are positive and statistically significant at the 5% level. In the group of low initial analyst coverage, the coefficients on the interaction term are small in magnitude and statistically weak. This evidence is consistent with the findings of previous studies (e.g., Hong and Kacperczyk, 2010; Irani and Oesch, 2013; He and Tian, 2013; Chen et al., 2015) that the effect of an exogenous decrease in analyst coverage on firm policies is mainly driven by the firms with low initial analyst coverage.

[Insert Table 1-5 here]

1.4.2 Analyst coverage and a firm's corporate governance

Next, I explore the effect of corporate governance on the relation between financial analysts and corporate pollution. Financial analysts play a crucially important monitoring role in mitigating managerial agency problems and may serve as a substitute for traditional corporate governance mechanisms (Irani and Oesch, 2013; Chen et al., 2015; Chen et al., 2018). Given that the rent-seeking behavior could be mitigated by corporate governance mechanisms, the marginal contribution of analyst monitoring might be smaller in firms with strong corporate governance.

I use two proxies for the quality of corporate governance. The first proxy is product market competition. High product market competition can lead to managers refraining from risk-seeking activities and not only motivates them to maximize firm profit (Jensen and Meckling, 1976; Hart, 1983), but also to improve corporate social

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[30] The average analyst coverage in the bottom (top) tercile group is 4.5 (17.4). The results are similar when I compare the top and bottom quartiles.

and environmental performance (Flammer, 2015), leading to better corporate governance. I conjecture that the monitoring role of financial analysts in reducing corporate pollution should be stronger for the firms with low product market competition. The competition measure employed in this analysis is *Fluidity*, as constructed by Hoberg et al. (2014), which captures the competitive threats faced by firms.[31] The greater fluidity indicates higher product market competition. I split treated firms into low and high market competition groups based on the median value of product market fluidity in the pre-event year (*t-1*).

My second proxy is the E-index of Bebchuk et al. (2009). E-index is the entrenchment index consisting of six anti-takeover provisions against takeovers and measures the rights a firm gives to shareholders as well as the ease of being acquired.[32] Under a takeover threat, managers are incentivized to avoid stock price declines caused by poor environmental performance (Kock et al., 2012). This perspective predicts that better corporate governance can restrain managers from harming the environment (Shive and Forster, 2020). The sample firms are divided into high E-index (poorly-governed) and low E-index (well-governed) groups based on the median value before the broker exits.

The estimation results are presented in Table 1-6. Using production market competition to partition my sample in Columns (1) to (4), I find that the coefficient on *Treatment*After* is positive and significant at the 5% level in firms facing less

[31] Fluidity is based on the words firms use to describe their products in the annual report (10-Ks) and the change in the words used by its competitors. As the words used by competitors become more similar to the firm's description, fluidity increases, which indicates a higher similarity between the products of the firm and its competitors. The product market fluidity measure is constructed using textual analysis of each firm's product descriptions obtained from their 10-K files. It captures changes in rival firms' products relative to the firm. The fluidity measure can be downloaded from: https://hobergphillips.tuck.dartmouth.edu/industryconcen.htm

[32] Six anti-takeover provisions are: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments.

competition (poor corporate governance), while it is insignificant for firms in competitive markets. The findings are largely similar when employing E-index as a measure for corporate governance in Columns (5) to (8).[33] The coefficient on *Treatment*After* is statistically significant only in poorly-governed firms (have a higher E-index).

[Insert Table 1-6 here]

Overall, using two proxies for the quality of corporate governance, my results are consistent with the notion that the monitoring role of financial analysts serves as a substitute for traditional corporate governance mechanisms (Irani and Oesch, 2013; Chen et al., 2015). In addition, my findings provide evidence supporting the view that corporate governance plays a crucial role in reducing toxic pollution (Shive and Forster, 2020).

1.4.3 Analyst coverage and the intensity of regulatory scrutiny

Then, I investigate the moderating effect of regulatory monitoring on my baseline results. Previous studies suggest regulators can be influential in shaping and enforcing corporate environmental policies (Delmas and Toffel, 2008). Specifically, firms monitored closely by regulators are more likely to comply with environmental regulations (Cohen, 1998) and join voluntary environmental programs (King and Lenox, 2000), thereby leading to better environmental performance (Earnhart, 2004; Short and Toffel, 2008). As with corporate governance, the monitoring role of financial analysts can also act as a substitute for regulatory oversight. Therefore, I expect the influence of financial analysts is exacerbated when firms are less monitored by regulators (i.e., EPA).

[33] The sample size in this model becomes much smaller since the IRRC database mainly covers S&P 1500 public firms.

To capture the intensity of regulatory scrutiny, I rely on the geographical distance between firms' plants and EPA regional office (Kedia and Rajgopal, 2011). EPA regional offices monitor the enforcement of environmental requirements. Intuitively, the cost of monitoring activities (e.g., site inspection) may significantly increase by the geographic distance between EPA regional office and firm plants. Accordingly, EPA regional office is less efficient in monitoring and detecting the environmental misconduct (i.e., toxic pollution) of distant plants.

I start by identifying the regional offices of the EPA. Figure 1-3 presents the geographical distribution of 10 regional offices and specific states covered by each office.[34] For example, regional office 1 is located in Boston, MA, and is responsible for the states of CT, MA, ME, NH, RI, and VT. As pollution and enforcement occur at the plant level, I calculate the geographical distance from each plant (belonging to a firm) to the EPA office that supervises it (Kim et al., 2019). More specifically, I use Coval and Moskowitz's (1999) formula to calculate the geographical distance for every facility-EPA regional office pair as follows:[35]

$$\begin{aligned} Distance_{i,j} = arccos\,\{&cos(lat_i)\,cos(lon_i)\,cos(lat_j)\,cos(lon_j) \\ &+ cos(lat_i)\,sin(lon_i)\,cos(lat_j)\,sin(lon_j) \\ &+ sin(lat_i)\,sin(lat_j)\}2\pi r/360 \end{aligned} \tag{1-2}$$

Where i denotes the TRI plant and j denotes EPA regional office. *Distance* is the geographic distance between the plant and the relevant EPA regional office. *lat* and *lon* are latitude and longitude measured in degrees. r is the radius of the earth (approximately 3963 statute miles).

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[34] Source: https://www.epa.gov/aboutepa/visiting-regional-office

[35] The location (longitude and latitude) of EPA regional offices and my sample plants are retrieved from EPA website and TRI database, respectively.

After calculating the distance between each plant- EPA office pair (*Distance*), I then construct a firm-level measure by taking its average (*Avg_Distance*). A larger average distance means weaker regulatory scrutiny by the EPA for a particular firm. The mean (median) value of *Avg_Distance* is 100.99 (100.42) miles. Then, I partition the sample into the high and low average distance subsamples based on the median *Avg_Distance* of treated firms in the pre-event year (*t-1*). The estimation results are presented in Table 1-7. I find the effect of analyst coverage on corporate pollution is mainly driven by distant firms farther away from the relevant EPA regional offices. This evidence suggests that financial analysts play a pivotal role in reducing corporate pollution in the absence of strong regulatory scrutiny, consistent with a substitution effect between analyst monitoring and regulatory oversight.

[Insert Table 1-7 here]

1.4.4 Analyst coverage and stakeholder orientation laws

Finally, I look at the state-level corporate constituency statutes. The traditional fiduciary duties of directors only require them to act in accordance with the interests of shareholders (Freeman, 1984). However, an increasing number of scholars criticize this view and argue modern firms should adopt stakeholder-oriented decision-making (see the review by Tirole (2001)). The proponents of the stakeholder-orientation view promote legislation to protect the stakeholder's interests rather than being merely shareholder-oriented, leading to the adoption of constituency statutes (Bainbridge, 1991). The enactment of state-level constituency statutes encourages corporate directors to consider a variety of stakeholders' interests (i.e., environment) in corporate decisions and thus to be more stakeholder-oriented. Indeed, Cheng et al. (2018) find a significant improvement in corporate social responsibility after the adoption of constituency statutes. To the extent the constituency statutes are effective in promoting environmental performance, I expect a stronger treatment effect of analyst coverage on corporate pollution among firms incorporated in states where such statutes are not enacted.

I partition the sample into firms incorporated in states with and without the constituency statutes, respectively. Over the sample period, 34 states have adopted these statutes.[36] The estimation results are reported in Table 1-8. Consistent with my expectation, the effect of decreases in analyst coverage on corporate pollution is more pronounced for firms incorporated in states without the constituency statutes law. The results suggest financial analysts play a crucial role in reducing corporate pollution in the absence of stakeholder orientation laws that empower boards to undertake environmentally friendly policies.

[Insert Table 1-8 here]

1.5 Potential Channels

The results to this point suggest a causal relationship between analyst coverage and corporate pollution, and support the argument that the monitoring role of financial analysts can restrain environmentally harmful behaviors. However, it is not clear how financial analysts shape corporate environmental policies. In this section, I explore three non-mutually exclusive channels: (1) *investments in pollution abatement*; (2) *internal environmental governance*; (3) *role and influence of institutional investors.*

1.5.1 Investments in pollution abatement

I first investigate whether underinvestment in pollution abatement is a potential channel through which analyst coverage influences corporate pollution. To reduce toxic pollution, firms can invest in pollution abatement activities such as

[36] See Flammer and Kacperczyk (2016) for a list of states that passed corporate constituency statutes. Firms incorporated in Texas are dropped as it introduced the statute during my sample period (i.e., in 2006).

developing green technologies or updating waste management facilities (Akey and Appel, 2021). However, investments in pollution abatement are costly. For instance, the cost of pollution abatement accounts for 5% -7% of capital expenditures for industrial firms (EPA, 2005). In the absence of analyst monitoring, managers may be reluctant to invest in pollution abatement activities if detection probability and the consequences of environmentally harmful behaviors are limited (Hart and Zingales, 2016). As such, the weaker monitoring caused by decreases in analyst coverage may induce managers to reduce investments in pollution abatement, leading to higher corporate pollution.

I employ two proxies for pollution abatement activities. The first proxy is total environmental capital expenditure. I search each sample firm in the Electronic Data Gathering, Analysis and Retrieval (EDGAR) database and manually collect the environmental expenditures data from 10-K files.[37, 38] In my sample, roughly 20% of firm-year observations disclose their environmental expenditures. On average, environmental expenditures account for 9.83% of total expenditures that is comparable to the 9.77% reported in Clarkson et al. (2004). Following Fernando et al. (2017), I set corporate environmental expenditures as zero if firms do not disclose the environmental expenditures in a particular year. To mitigate the concern of extreme values, I log-transform the environmental expenditures (*Log(environmental expenditure)*) as the dependent variable.

The estimation results are reported in Columns (1) and (2) of Table 1-9. The coefficients on *Treatment*After* are negative and statistically significant at the 10% level. The treatment effects are also economically significant. As shown in Column (2), the environmental expenditures of treated firms decrease by 34.7% after analyst

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[37] https://www.sec.gov/edgar/searchedgar/companysearch.html
[38] More specifically, I locate firms which mention environmental expenditures or environmental capital expenditures under the sections outlined “Environmental matters” or “Environment” in their 10-K files.

loss as compared to control firms. This suggests that increases in corporate pollution can be partly attributed to lower capital expenditures on activities and processes related to the environment.

[Insert Table 1-9 here]

The second proxy for pollution abatement is green innovation which captures the expense for research and development (R&D) related to green technologies (Chu and Zhao, 2019; Chu et al., 2020). The patent data are retrieved from Kogan et al. (2017).[39] I classify the green innovation following the classification of Carrión-Flores and Innes (2010) and Flammer et al. (2019), including innovation related to wind energy, solid waste prevention, water pollution, recycling, alternative energy, alternative energy sources, geothermal energy, air pollution control, solid waste disposal, and solid waste control.[40] I then calculate the number of green patents in each firm-year observation and set the missing value as zero (Chu and Zhao, 2019). Finally, I use the natural logarithm of one plus the number of green patents (*Log(Green patents)*) as the dependent variable. As there is a time gap between the initial investments in green innovation and subsequent innovation outputs, I employ a longer time window for this test.

Specifically, I compare the number of green patents two years before and after (*t-2* & *t+2*) broker exits in Columns (3) and (4) of Table 1-9.[41] As indicated by the

[39] More details are shown in https://paper.dropbox.com/home/recents

[40] The codes of classifications are shown as follows: Wind energy (242, 073, 180, 440, 340, 343, 422, 280, 104, 374), Solid waste prevention (137, 435, 165, 119, 210, 205, 405, 065), Water pollution (405, 203, 210), Recycling (264, 201, 229, 460, 526, 106, 205, 425, 060, 075, 099, 100, 162, 164, 198, 210, 216, 266, 422, 431, 432, 502, 523, 525, 902), Alternative energy (204, 062, 228, 248, 425, 049, 428, 242, 222, 708, 976), Alternative energy sources (062, 425, 222), Geothermal energy (060, 436), Air pollution control (123, 060, 110, 422, 015, 044, 423), Solid waste disposal (241, 239, 523, 588, 137, 122, 976, 405), and Solid waste control (060, 137, 976, 239, 165, 241, 075, 422, 266, 118, 119, 435, 210, 405, 034, 122, 423, 205, 209, 065, 099, 162, 106, 203, 431)

[41] For robustness, I also compare the innovation outputs 3 years before and after the events. The results are largely similar. In addition, I follow the study of He and Tian (2013) to build a seven-year time window around the event from three years (t-3) before broker exits to three years (t+3) after. The estimation results are robust to this alternative time window.

negative and significant coefficients on *Treatment*After* throughout the specifications, the number of green patents declines significantly after broker exits. Specifically, I find the number of green patents decreases by 12.2% relative to control firms. Taken together, my results suggest that treated firms facing less analyst monitoring tend to underinvest in pollution abatement and consequently result in higher toxic pollution.

1.5.2 The internal governance of environmental performance

The second channel is *environmental internal governance*. I examine whether the effect of analyst coverage on corporate pollution can be explained by the design of environmental internal governance that promotes firms' pro-environmental behavior. As discussed before, analyst monitoring increases the consequences of corporate environmental misbehaviors (e.g., issuing unfavorable analyst reports and stock recommendations), and firms (the board of directors in particular) could be motivated to establish internal governance mechanisms to improve corporate environmental performance. In contrast, in the absence of analyst monitoring, managers may lack incentives to design or maintain internal environmental mechanisms since such mechanisms require considerable attention and resources.

To test this conjecture, I use two proxies for environmental internal governance, executives' compensation contracts and sustainability committees. The first proxy is the executives' compensation contract which is regarded as an effective tool to align interests between managers and shareholders (John and John, 1993; Frydman and Jenter, 2010). The intuition is that if the managers' compensation is linked with corporate environmental performance, they may have strong incentives to develop green technologies and reduce toxic pollution (Flammer et al., 2019). Over recent years, an increasing number of managerial compensation contracts tend to link executive pay with social and environmental goals. The ratio of social and environmental-related compensation in S&P 500 firms increases from 12% in 2004 to 37% in 2013 (Flammer et al., 2019).

Following previous studies of performance-based compensation (Bennett et al., 2017; Bradley et al., 2021), I obtain the information of executives' compensation contracts from the ISS Incentive Lab Database for the largest 750 public firms. Specifically, I search for the environmental-related keywords in their compensation contract and construct a dummy variable with one if the incentive contract of any executive is linked with environmental performance, and zero otherwise.[42] In my sample, approximately 5% of firm-year observations have environment-related incentives in their compensation contracts. I then employ the probit model to examine whether an exogenous decrease in analyst coverage may reduce the probability of containing environmental incentives in the compensation contract in Columns (1) of Table 1-10.[43] I find that the coefficient on *Treatment*After* is negative and statistically significant, suggesting in the absence of analyst monitoring, firms have less incentives to link executives' pay to environmental performance.

[Insert Table 1-10 here]

Second, I examine the establishment of a sustainability committee as another internal environmental governance mechanism. Firms create various board committees for different strategic goals (Singh and Harianto, 1989) and may set up the sustainability committee to be responsible for sustainability issues (e.g., environmental performance). The presence of a sustainability committee may serve to motivate managers to create sustainability goals in the board meeting (Fu et al.,

[42] The environment-related keywords include: "environment", "emission", "waste", "toxic", and "release".

[43] In this regression, my sample size becomes much smaller because I only collect the compensation data of largest 750 public firms and lose some observations when using probit regression.

2020), leading to better corporate environmental performance (Dalton et al. 1998; Dixon-Fowler et al., 2017). However, the creation and maintenance of the sustainability committee are costly, which may require considerable attention, effort, and resources on the operation of the sustainability committee and subsequent sustainability activities (Greening and Gray, 1994). When the consequences of environmental misbehaviors decrease due to analyst loss, firms could be reluctant to establish or maintain such committees.

The board committee information is retrieved from the BoardEx database. I flag the committees whose title contains the words “sustainability”, “sustainable”, “responsibility”, “ethics” or “environment” as sustainability committees and construct an indicator variable *Sustainability committee* that equals one if a firm has a sustainability committee in a particular year, and zero otherwise. Similar to my test for compensation contract, the probit model is employed to compare the probability of having a sustainability committee in two years before and after broker exits, given the fact that setting up a new board committee may require more time than other firm policy responses. The results are presented in Column (2) of Table 1-10. The negative and significant coefficient on *Treatment*After* suggests treatment firms are less likely to set up the sustainability committee after decreases in analyst coverage, relative to control firms.

Taken together, regardless of proxy for the internal environmental governance mechanisms, I find the weaker external monitoring caused by decreases in analyst coverage induce firms to reduce the quality of environmental internal governance. This could be a potential channel through which financial analysts shape corporate environmental policies.

1.5.3 Role and influence of institutional investors

Finally, I examine the last channel of role and influence of institutional investors. In recent years, institutional investors increasingly incorporate environmental issues into their investment decisions (Krueger et al., 2020) and exert pressure on managers to enhance environmental performance (Kim et al., 2019; Dyck et al., 2019; Chen et al., 2020). For instance, Kim et al. (2019) document local investors have strong incentives to force firms they invest in to reduce corporate pollution. However, the monitoring role and influence of institutional investors rely on the corporate information environment. As an important information intermediary, analysts disseminate information on a firm's environmental policies to capital markets (Miller, 2006), which reduces the monitoring cost for other stakeholders, in particular, institutional investors, when monitoring corporate behavior. Indeed, prior studies find that after decreases in analyst coverage, institutional investors are more likely to shy away from firms after analyst coverage decreases, as they anticipate these firms becoming harder to monitor (O'Brien and Bhushan, 1990; Bushee and Noe, 2000; Chen et al., 2015). Thus, the analyst loss may weaken the role and influence of institutional shareholders in shaping corporate environmental policies, thereby incentivizing myopic managers to increase corporate pollution.

To test this channel, I collect information on institutional ownership from the Thomson Reuters Institutional Holdings (13F) database. I first investigate the effect of analyst coverage on equity ownership of all institutional investors in Columns (1) and (2) of Table 1-11. As shown in Column (2), the institutional ownership of treatment firms decreases by 2.2% after decreases in analyst coverage as compared to control firms. This evidence suggests the increased monitoring costs pertaining to environmental policies may lead institutional investors to shy away from treated firms.

[Insert Table 1-11 here]

To sharpen my analysis, I further focus on groups of institutional investors that are more long-term oriented and environmentally conscious, as different institutional investors have heterogeneous preferences and investment strategies (Hong and Kacperczyk, 2009; Hong and Kostovetsky, 2012). If environmental monitoring cost matters to institutional investors, the results should be more pronounced among investors who care more about corporate environmental performance. Specifically, I identify two such groups of institutional investors, quasi-indexers and public pension funds.

Quasi-indexers are passive investors with long-term investment horizons and low trading turnover (Bushee, 2001). They can monitor and influence corporate policies through large voting (Appel et al., 2016) and impose pressure on managers to improve environmental performance (Kim et al., 2019; Chen et al., 2020). I use the identifications by Bushee (2001) to classify quasi-indexers and calculate the percentage of shares held by quasi-indexers as the dependent variable in Columns (3) and (4) of Table 1-11. I find an exogenous decrease in analyst coverage leads to a significantly lower quasi-indexers ownership of 3.6% percent in treated firms relative to control firms.

Next, I examine the equity ownership of public pension funds. Public pension funds have a relatively long investment horizon and are under the pressure of social norms, leading to their stronger preference for social and environmental investments (Kim et al., 2019). For instance, pension funds are more likely to initiate social and environmental shareholder proposals (Chidambaran and Woidtke, 1999) and are reluctant to invest in “sin” stocks (Hong and Kacperczyk, 2009). As with quasi-indexers, I follow Bushee’s (2001) classification to identify public pension funds and calculate the proportion held by such investors. The estimation results are shown in

Columns (5) and (6) of Table 1-11. I find that the ownership of public pension funds in treatment firms decreases by 0.3% after an exogenous decrease in analyst coverage relative to control firms. Given the mean value of ownership by public pension funds in my sample (2.57%), this decrease is not only statistically but also economically significant (0.3/2.57 is 11.67%).

Overall, the results suggest that as environmental monitoring cost increases after analyst loss—institutional investors, in particular, longer-termed and environmentally conscious investors, become more reluctant to hold shares in these firms. This weakens the role and influence of institutional investors in monitoring corporate environmentally harmful behaviors.

1.6 Conclusions

In this chapter, I explore the casual effects of financial analysts on corporate environmental policies. Using two quasi-natural experiments (i.e., brokerage closures and mergers), I find that firms experiencing an exogenous decrease in analyst coverage significantly increase their toxic pollution relative to control firms. My results suggest the pivotal monitoring role financial analysts play in restraining corporate pollution. In cross-sectional tests, I find the effect is more pronounced for firms with low initial analyst coverage, poor corporate governance, less regulatory scrutiny, and incorporated in states without stakeholder constituency laws.

Finally, I explore three non-mutually exclusive channels through which analyst coverage shapes corporate environmental policies. First, I find after an exogenous decrease in analyst coverage, firms are more likely to underinvest in pollution abatement and green technologies, leading to higher corporate pollution. Second, analyst loss reduces firms' incentives to establish and maintain internal environmental governance mechanisms (i.e., linking executive pay to environmental goals and establishing sustainability committees). Lastly, firms after decreases in analyst coverage may face less environmental pressure from institutional investors, especially environmentally conscious investors.

My results highlight the pivotal monitoring role financial analysts play in restraining environmentally harmful behaviors (i.e., toxic pollution). As well-trained professionals with industry-specific knowledge, financial analysts can directly monitor and influence corporate environmental policies by collecting information through both public and private channels (e.g., tracking corporate disclosures and corporate site visits) and raise their concerns in corporate conference calls. In addition, analysts can also play an indirect monitoring role by disseminating information to capital markets through media and research reports, which reduce the monitoring costs for other stakeholders (i.e., institutional investors). The absence of analyst monitoring (an exogenous decrease in analyst coverage) may induce managers to increase corporate pollution. Overall, my evidence uncovers a bright side of financial analysts in reducing corporate pollution and suggests external oversight (i.e., analyst monitoring) can decrease negative externalities.

Figure 1-1. Differences in analyst coverage between treatment and control firms

This figure shows the mean difference in analyst coverage (the number of analysts covering a firm) between treatment and control firms (treatment-control) three years before (t-3) and after (t+3) brokerage exits. Control firms are matched by total assets, the book to market ratio, return on assets (ROA), tangibility, and two-digit SIC code.

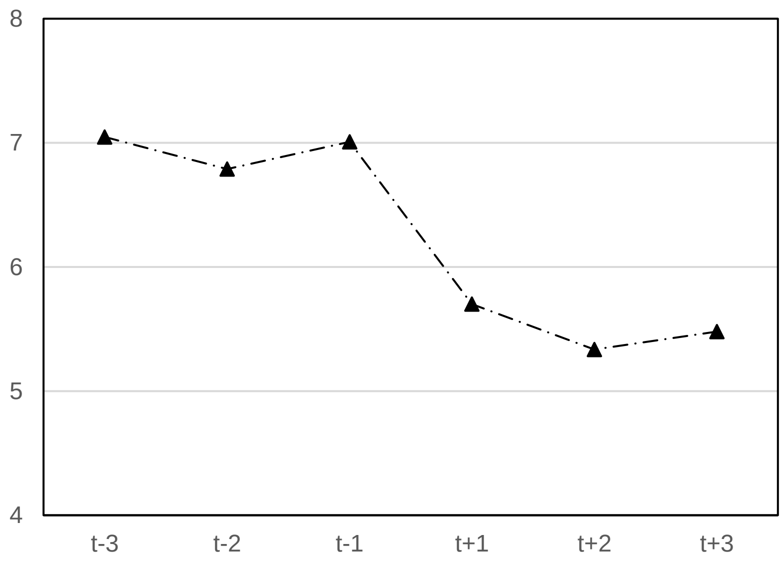


Figure 1-2. Differences in total pollution between treatment and control firms

This figure shows the mean difference in total pollution (the natural logarithm of one plus the total pollution) between treatment and control firms (treatment-control) three years before (t-3) and after (t+3) brokerage exits. Control firms are matched by total assets, the book to market ratio, return on assets (ROA), tangibility, and two-digit SIC code.

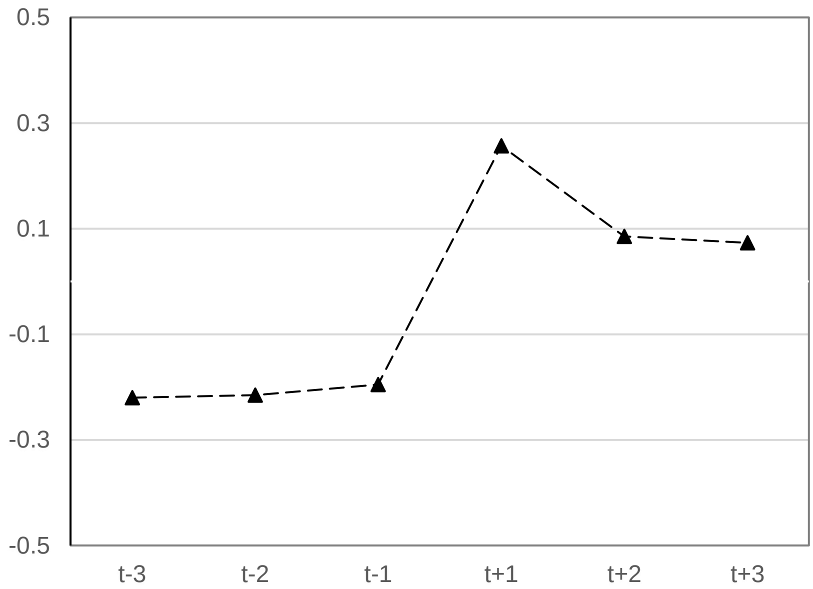
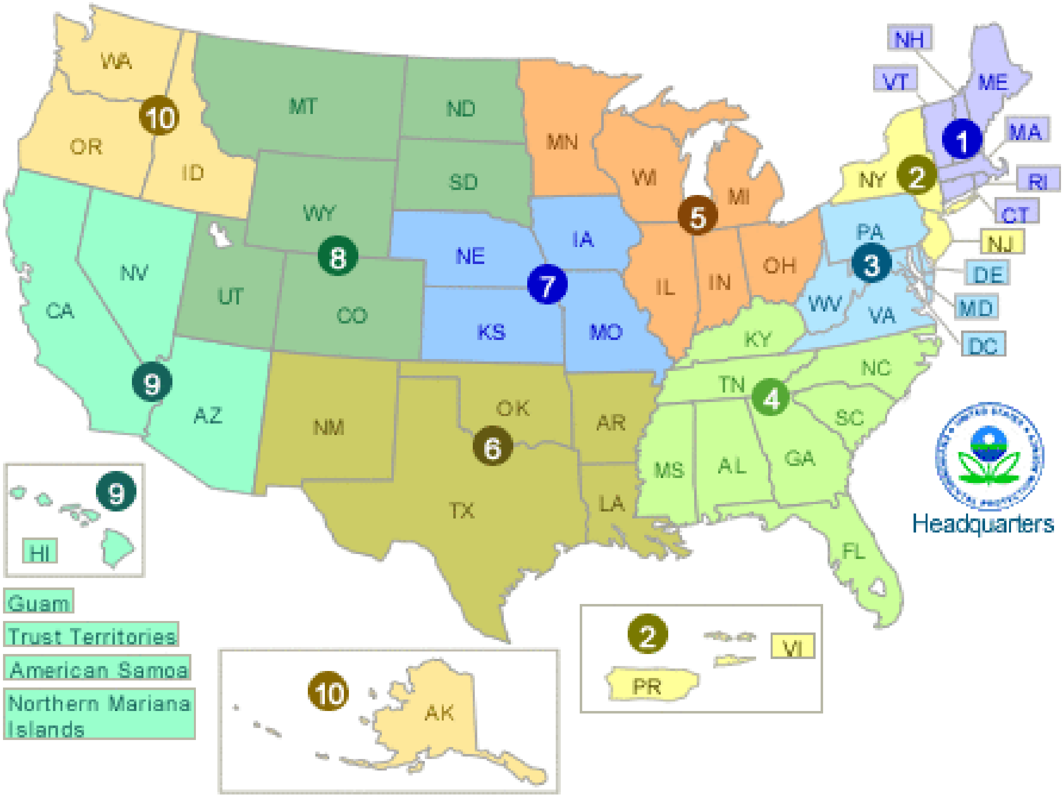


Figure 1-3. Distribution of EPA regional offices

This figure shows the distribution of EPA regional offices across the U.S. The EPA owns 10 regional offices (named EPA region 1 to 10). Each regional office is responsible for several neighboring states and monitors the plant operations in these states.



Source : https://www.epa.gov/aboutepa/visiting-regional-office

Table 1-1. Descriptive statistics

This table reports descriptive statistics for treated and control firms. The sample consists of 1,212 firm-year observations (606 treatment and control firm-year observations) from 1999 to 2011. Panel A presents summary statistics of the matched sample. Panel B reports means and t-tests for differences between treated and control firms in the pre-event year (t-1). All variables are defined in Appendix 1-A1.

Panel A. Descriptive statistics (matched sample)

Variable	Obs	Mean	Median	Std. Dev.	25th	75th
Pollution variables						
Total Pollution (1000s)	1,212	2262.770	64.033	22538.130	8.451	464.547
On-site Pollution (1000s)	1,212	2086.881	41.868	22444.550	2.553	314.087
Off-site pollution (1000s)	1,212	175.889	1.930	1152.640	0.000	41.485
Air pollution (1000s)	1,212	738.782	31.681	2235.939	2.262	244.257
Water pollution (1000s)	1,212	174.215	0.000	1409.633	0.000	0.677
Ground pollution (1000s)	1,212	1173.884	0.000	22103.92	0.000	0.021
Log(total)	1,212	10.709	11.067	3.493	9.042	13.049
Log(on-site)	1,212	9.920	10.642	4.097	7.845	12.657
Log(off-site)	1,212	6.484	7.566	4.889	0.000	10.633
Log(air)	1,212	9.606	10.363	4.082	7.724	12.406
Log(water)	1,212	3.401	0.000	4.629	0.000	6.519
Log(ground)	1,212	2.436	0.000	4.502	0.000	3.092
Log(total/sales)	1,212	-10.867	-10.358	3.156	-12.415	-8.782
Log(on-site/sales)	1,212	-11.656	-10.940	3.727	-13.452	-9.162
Log(off-site/sales)	1,212	-15.092	-14.113	4.478	-19.891	-11.412
Log(air/sales)	1,212	-11.970	-11.114	3.711	-13.638	-9.351
Log(water/sales)	1,212	-18.175	-19.788	4.129	-21.097	-16.184
Log(ground/sales)	1,212	-19.140	-20.757	4.415	-21.643	-18.230
Firm characteristics						
Firm size	1,212	7.784	7.621	1.482	6.763	8.537
ROA	1,212	0.036	0.045	0.082	0.009	0.074
Book to Market	1,212	0.492	0.456	0.528	0.279	0.693
Tangibility	1,212	0.281	0.249	0.152	0.164	0.366
Book leverage	1,212	0.277	0.265	0.171	0.165	0.373
R&D ratio	1,212	0.024	0.016	0.032	0.000	0.030
Dividend ratio	1,212	0.013	0.008	0.017	0.000	0.019
Cash ratio	1,212	0.087	0.052	0.099	0.020	0.115
Analyst coverage	1,212	6.868	5.250	6.410	2.083	9.458

Panel B. Difference in means in t-1 between treated and control firms

Variable	Mean (Treated)	Mean (Control)	Diff.	P-value
Firm characteristics				
Firm size	7.700	7.761	-0.061	0.615
ROA	0.050	0.049	0.000	0.956
Book to Market	0.469	0.454	0.015	0.667
Tangibility	0.291	0.273	0.017	0.154
Book leverage	0.278	0.279	0.000	0.988
R&D ratio	0.026	0.022	0.004	0.160
Dividend ratio	0.013	0.014	-0.001	0.519
Cash ratio	0.083	0.078	0.005	0.472

Table 1-2. Decreases in analyst coverage and corporate pollution

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on corporate pollution. The sample consists of 1,212 firm-year observations (606 treatment and control firm-year observations) from 1999 to 2011. The dependent variable is *Log(total)* in Columns (1) to (3) and *Log(total/sales)* in Columns (4) to (6). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Log(total)			Log(total/sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	**0.452*** **	**0.443*** **	**0.361*** **	**0.458*** **	**0.462*** **	**0.397*** **
	(2.86)	**(2.79)**	**(2.60)**	**(2.91)**	**(2.92)**	**(2.82)**
After	-0.290	-0.295	-0.125	-0.311*	-0.305	-0.143
	(-1.58)	(-1.59)	(-0.73)	(-1.67)	(-1.63)	(-0.81)
Firm size		0.479**	0.581**		-0.175	-0.161
		(2.32)	(2.41)		(-0.84)	(-0.64)
ROA		0.364	0.344		-0.272	-0.140
		(0.39)	(0.41)		(-0.30)	(-0.17)
Book to Market		-0.002	-0.050		0.046	-0.024
		(-0.02)	(-0.33)		(0.42)	(-0.16)
Tangibility		0.914	0.906		0.547	-0.057
		(0.76)	(0.63)		(0.46)	(-0.04)
Book leverage		0.740	1.612*		0.813	1.771**
		(1.02)	(1.84)		(1.11)	(1.99)
R&D ratio		2.969	2.787		1.030	0.691
		(0.41)	(0.34)		(0.14)	(0.08)
Dividend ratio		7.260	4.063		4.929	1.770
		(1.10)	(0.66)		(0.74)	(0.28)
Cash ratio		0.060	-0.273		0.347	-0.082
		(0.06)	(-0.20)		(0.35)	(-0.06)
Industry-Year FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
N	1,212	1,212	1,212	1,212	1,212	1,212
R-sq	0.119	0.137	0.448	0.195	0.201	0.481

Table 1-3. Robustness tests

This table reports various robustness tests for my baseline DiD regression. Panel A uses different estimation windows. Panel B shows results with alternative matching criteria. Panel C excludes brokerage exits that occurred during the financial crisis or the internet bubble. Panel D excludes observations in 2001 and 2002 due to large decreases in pollution. Panel E retains observations only for their first treatment (if treated more than once). The dependent variable is *Log(total)* in Columns (1) to (3) and *Log(total/sales)* in Columns (4) to (6). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). For brevity, only the coefficients of interaction terms *Treatment*After* are reported. All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Log(total)			Log(total/sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Different DiD estimation windows						
(1) t-2 to t+2 years	0.377**	0.371**	0.294**	0.356**	0.368**	0.308**
	(2.25)	(2.27)	(2.09)	(2.16)	(2.26)	(2.17)
(2) t-3 to t+3 years	0.353**	0.336*	0.271*	0.300*	0.325*	0.280*
	(2.01)	(1.94)	(1.75)	(1.74)	(1.89)	(1.81)
Panel B: Alternative matching criteria						
(3) Unmatched sample	0.248***	0.242***	0.295***	0.238***	0.250***	0.303***
	(3.70)	(3.65)	(4.36)	(3.60)	(3.84)	(4.51)
(4) Firm size only	0.337**	0.321**	0.420***	0.344**	0.371**	0.466***
	(2.01)	(2.02)	(3.04)	(2.05)	(2.30)	(3.34)
(5) Firm size/ROA/Book-to-Market/Tangibility	0.452***	0.443***	0.361***	0.458***	0.462***	0.397***
	(2.86)	(2.79)	(2.60)	(2.91)	(2.92)	(2.82)
(6) Firm size/ROA/Book-to-Market/Tangibility/R&D	0.383**	0.397**	0.436**	0.341**	0.401***	0.456***
	(2.31)	(2.52)	(2.45)	(2.18)	(2.62)	(2.61)
(7) Firm size/ROA/Book-to-Market/Tangibility/Return/Volatility	0.409**	0.441***	0.560***	0.428***	0.478***	0.594***
	(2.44)	(2.71)	(3.20)	(2.66)	(2.95)	(3.38)

Panel C. Excluding brokerage exits in financial crises						
(8) Exclude events after 2008	0.459***	0.445***	0.371**	0.448***	0.458***	0.402***
	(2.89)	(2.70)	(2.51)	(2.83)	(2.76)	(2.66)
(9) Exclude events in the 2001 and 2002	0.391**	0.355**	0.369**	0.387**	0.374**	0.408**
	(2.18)	(2.10)	(2.28)	(2.19)	(2.21)	(2.49)
Panel D. Excluding the period of rapid pollution decline						
(10) Exclude events in the 2000 and 2001	0.601***	0.613***	0.394**	0.640***	0.647***	0.436**
	(2.90)	(2.87)	(2.30)	(3.12)	(3.04)	(2.52)
Panel E. First treatment						
(11) Retain only firm-year obs. impacted by first exit	0.374**	0.369**	0.335**	0.382**	0.389**	0.370**
	(2.34)	(2.28)	(2.10)	(2.39)	(2.39)	(2.31)
Controls	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No

Table 1-4. Decreases in analyst coverage and EPA enforcements

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on EPA enforcement. The dependent variable *Log(total enforcement)* is the natural logarithm of one plus the total number of EPA enforcements (non-judicial + judicial) in Columns (1) and (2). *Log(non-JDC)* is the natural logarithm of one plus the number of non-judicial cases in Columns (3) and (4), while *Log(JDC)* is the natural logarithm of one plus the number of judicial cases in Columns (5) and (6). I use EPA cases for two years before (t-2) and after (t+2) brokerage exits as the investigation and settlements of EPA enforcements require time. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+2) brokerage exits and 0 for the year before (t-2). For brevity, control variables are not reported. All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Log(total enforcement)		Log(non-JDC)		Log(JDC)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	**0.077****	**0.073***	**0.094****	**0.089****	**-0.014**	**-0.014**
	(2.02)	**(1.96)**	**(2.54)**	**(2.48)**	**(-0.90)**	**(-0.93)**
After	-0.052	-0.051	-0.052	-0.051	-0.010	-0.009
	(-1.07)	(-1.07)	(-1.23)	(-1.23)	(-0.44)	(-0.38)
Controls	No	Yes	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,112	1,112	1,112	1,112	1,112	1,112
R-sq	0.393	0.408	0.366	0.381	0.464	0.473

Table 1-5. Cross-sectional analysis: Initial analyst coverage

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on initial analyst coverage. The sample is divided into two subsamples (low and high initial analyst coverage). Treated firms are partitioned into the low (Columns (1) and (2)) initial analyst coverage subsample if initial analyst coverage is in the bottom tercile for treated firms in the year prior to brokerage exits (t-1). Treated firms are partitioned into the high (Columns (3) and (4)) initial analyst coverage subsample if initial analyst coverage is in the top tercile for treated firms in the year prior to brokerage exits (t-1). The dependent variable is *Log(total)* in Columns (1) and (3) and *Log(total/sales)* in Columns (2) and (4). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Low initial coverage		High initial coverage	
	Log(total)	Log(total/sales)	Log(total)	Log(total/sales)
	(1)	(2)	(3)	(4)
Treatment*After	**0.669****	**0.680****	**0.338**	**0.409***
	(2.05)	**(2.10)**	**(1.55)**	**(1.89)**
After	-0.662*	-0.686**	-0.115	-0.122
	(-1.94)	(-2.02)	(-0.39)	(-0.42)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	392	392	420	420
R-sq	0.168	0.190	0.327	0.374

Table 1-6. Cross-sectional analysis: Corporate governance

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on the firms' corporate governance. The sample is divided into two subsamples (poor and good corporate governance) based on product market competition and the E-index. Treated firms are partitioned into the low (Columns (1) and (2)) product market competition subsample if the product market fluidity is higher than the median value for treated firms in the year prior to brokerage exits (t-1). Treated firms are partitioned into the high (Columns (3) and (4)) product market competition subsample if the product market fluidity is lower than the median value for treated firms in the year prior to brokerage exits (t-1). Treated firms are partitioned into the high (Columns (5) and (6)) managerial entrenchment subsample if the E-index is higher than the median value for treated firms in the year prior to brokerage exits (t-1). Treated firms are partitioned into the low (Columns (7) and (8)) managerial entrenchment subsample if the E-index is lower than the median value for treated firms in the year prior to brokerage exits (t-1). The dependent variable is *Log(total)* in Columns (1), (3), (5) and (7) and *Log(total/sales)* in Columns (2), (4), (6) and (8). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Low competition		High competition		High E-index		Low E-index	
	Log(total)	Log (total/sales)	Log(total)	Log (total/sales)	Log(total)	Log (total/sales)	Log(total)	Log (total/sales)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment*After	**0.664****	**0.672****	**0.217**	**0.251**	**0.526****	**0.537****	**0.178**	**0.205**
	(2.50)	**(2.53)**	**(1.38)**	**(1.58)**	**(2.54)**	**(2.58)**	**(0.99)**	**(1.13)**
After	-0.519*	-0.511*	-0.087	-0.104	-0.177	-0.159	-0.123	-0.171
	(-1.71)	(-1.68)	(-0.41)	(-0.48)	(-0.77)	(-0.68)	(-0.53)	(-0.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	580	580	596	596	552	552	320	320
R-sq	0.190	0.238	0.152	0.210	0.155	0.212	0.364	0.397

Table 1-7. Cross-sectional analysis: Regulatory monitoring

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on the intensity of regulatory monitoring. The sample is divided into two subsamples (low and high regulatory scrutiny) based on the average physical distance from the firm's plants to the regional EPA office that supervises it. Treated firms are partitioned into the long distance (Columns (1) and (2)) subsample if the average firm level distance of plant-EPA pairs is higher than the median value for treated firms in the year prior to brokerage exits (t-1). Treated firms are partitioned into the short distance (Columns (3) and (4)) subsample if the average firm level distance of plant-EPA pairs is lower than the median value for treated firms in the year prior to brokerage exits (t-1). The dependent variable is *Log(total)* in Columns (1) and (2) and *Log(total/sales)* in Columns (3) and (4). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Long distance		Short distance	
	Log(total)	Log(total/sales)	Log(total)	Log(total/sales)
	(1)	(2)	(3)	(4)
Treatment*After	**0.553****	**0.565*****	**0.300**	**0.322**
	(2.58)	**(2.62)**	**(1.49)**	**(1.62)**
After	-0.570***	-0.556**	-0.415	-0.447*
	(-2.62)	(-2.51)	(-1.60)	(-1.72)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	608	608	604	604
R-sq	0.150	0.193	0.155	0.211

Table 1-8. Cross-sectional analysis: State stakeholder orientation laws

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on corporate pollution conditional on the passage of state stakeholder orientation laws. My sample is divided into two subsamples ("No Law" and "Has Law") based on if a firm is incorporated in a state that has passed the stakeholder orientation law. As of 2011 (the end of my sample period), 34 states have adopted stakeholder orientation laws. With the exception of the state of Texas, the stakeholder orientation laws were passed prior to 1999 (the start of my sample period). Therefore, I drop firms that are incorporated in Texas (passed the law in 2006). Treated firms are partitioned into the "No Law" (Columns (1) and (2)) subsample if they are incorporated in states that have not passed stakeholder orientation laws. Treated firms are partitioned into the "Has Law" (Columns (3) and (4)) subsample if they are incorporated in states that have passed stakeholder orientation laws. The dependent variable is *Log(total)* in Columns (1) and (2) and *Log(total/sales)* in Columns (3) and (4). *Log(total)* is the natural logarithm of one plus the amount of total pollution. *Log(total/sales)* is the natural logarithm of one plus the amount of sales-adjusted total pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	No Law		Has Law	
	Log(total)	Log(total/sales)	Log(total)	Log(total/sales)
	(1)	(2)	(3)	(4)
Treatment*After	**0.536****	**0.581*****	**0.237**	**0.197**
	(2.49)	**(2.72)**	**(1.32)**	**(1.05)**
After	-0.390*	-0.415*	-0.049	-0.025
	(-1.66)	(-1.77)	(-0.15)	(-0.07)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	846	846	360	360
R-sq	0.150	0.203	0.268	0.357

Table 1-9. Channels: Investments in pollution abatement

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on investments in pollution abatement technologies and processes. The dependent variable is *Log(environmental expenditure)* in Columns (1) and (2) and *Log(green patents$_{-2,+2}$)* in Columns (3) and (4). *Log(environmental expenditure)* is the natural logarithm of one plus the amount of environmental expenditures on pollution abatement. *Log(green patents)* is the natural logarithm of the number of green patents. I use green patents for two years before (t-2) and after (t+2) brokerage exits as there is a time lag between initial investments in green technology and innovation outputs. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Log(environmental expenditure)		Log(green patents$_{-2,+2}$)	
	(1)	(2)	(3)	(4)
Treatment*After	**-0.373***	**-0.347***	**-0.121***	**-0.122***
	(-1.80)	**(-1.69)**	**(-1.88)**	**(-1.88)**
After	0.238	0.224	0.024	0.008
	(1.06)	(1.03)	(0.30)	(0.11)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,212	1,212	1,112	1,112
R-sq	0.040	0.061	0.212	0.221

Table 1-10. Channels: Compensation contracts and sustainability committees

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on managerial compensation contracts and the presence of a sustainability committee. Probit models are used in this estimation. The dependent variable is *Environmental compensation* in Column (1) and *Sustainability committee*$_{-2,+2}$ in Column (2). *Environmental compensation* is an indicator variable that equals 1 if firms set environmental targets in the executives' performance-based compensation and 0 otherwise. *Sustainability committee* is an indicator variable which equals 1 if firms have a specialized sustainability committee and 0 otherwise. I use the presence of sustainability committees for two years before (t-2) and after (t+2) brokerage exits as there is a time lag as committees require time to be formed. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Probit model	Environmental compensation	Sustainability committee$_{-2,+2}$
	(1)	(2)
Treatment*After	**-0.576***	**-0.778****
	(-1.87)	**(-2.45)**
After	1.063*	0.955***
	(1.90)	(2.70)
Treatment	2.117***	1.398***
	(5.14)	(3.40)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	213	406
pseudo R-sq	0.357	0.504

Table 1-11. Channels: Institutional ownership

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on institutional ownership. The dependent variable is the % of equity a firm owned by: institutional investors (*IO*) in Columns (1) and (2); quasi-indexers (*Quasi-indexers*) in Columns (3) and (4), and; public pension funds (*Public pension funds*) in Columns (5) and (6). *IO* is the percentage of shares held by intuitional investors. *Quasi-indexers* is defined following Bushee (2001) and is calculated as the percentage of shares held by quasi-indexers. *Public pension funds* is defined following Bushee (2001) and is calculated as the percentage of shares held by public pension funds. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	IO		Quasi-indexers		Public pension funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	**-0.024***	**-0.022***	**-0.039*****	**-0.036*****	**-0.003****	**-0.003****
	(-1.97)	**(-1.74)**	**(-2.96)**	**(-2.67)**	**(-2.30)**	**(-2.28)**
After	0.047***	0.044***	0.047***	0.043***	0.001	0.001
	(3.83)	(3.56)	(3.67)	(3.43)	(1.23)	(1.09)
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	848	848	848	848	848	848
R-sq	0.443	0.465	0.731	0.738	0.096	0.126

Appendix 1-A1. Variable definitions

Variable	Definition	Data Source
Pollution variables		
Total pollution	Total quantity of on- and off-site toxic emission at the firm level	TRI
On-site pollution	Total quantity of toxic pollution released onsite into the air, water, and ground at the firm level	TRI
Off-site pollution	Total quantity of toxic release transferred to off-site locations for further release or disposal at the firm level	TRI
Air pollution	Total quantity of onsite stack emissions and on-site fugitive emissions at the firm level	TRI
Water pollution	Total quantity of toxic pollution released on-site as surface water discharges at the firm level	TRI
Ground pollution	Total quantity of toxic pollution released to on-site grounds at the firm level	TRI
Log(total)	Natural logarithm of (one plus) the total pollution	TRI
Log(on-site)	Natural logarithm of (one plus) the on-site pollution	TRI
Log(off-site)	Natural logarithm of (one plus) the off-site pollution	TRI
Log(air)	Natural logarithm of (one plus) the air pollution	TRI
Log(water)	Natural logarithm of (one plus) the water pollution	TRI
Log(ground)	Natural logarithm of (one plus) the ground pollution	TRI
Log(total/sales)	Natural logarithm of (one plus) the sales adjusted total pollution (total pollution/sales)	TRI
Log(on-site/sales)	Natural logarithm of (one plus) on-site pollution scaled by sales	TRI
Log(off-site/sales)	Natural logarithm of (one plus) off-site pollution scaled by sales	TRI
Log(air/sales)	Natural logarithm of (one plus) air pollution scaled by sales	TRI
Log(water/sales)	Natural logarithm of (one plus) water pollution scaled by sales	TRI
Log(ground/sales)	Natural logarithm of (one plus) ground pollution scaled by sales	TRI
Log(total enforcement)	Natural logarithm of (one plus) the number of EPA enforcement cases) at the firm level	ICIS FE&C
Log(non-JDC)	Natural logarithm of (one plus) the number of non-judicial cases at the firm level	ICIS FE&C
Log(JDC)	Natural logarithm of (one plus) the number of judicial cases at the firm level	ICIS FE&C
Firm characteristics		
Firm size	Natural logarithm of (one plus) total assets	Compustat
ROA	Operating income divided by total assets	Compustat
Book to Market	Book value of equity divided by the market value of equity	Compustat
Tangibility	Net property, plant, and equipment divided by total assets	Compustat

Book leverage	The sum of current liabilities and long-term debt divided by the total assets	Compustat
R&D ratio	Research and development expenses divided by total assets.	Compustat
Dividend ratio	The sum of common dividends and preferred dividends divided by total assets	Compustat
Cash ratio	Cash and short-term investments divided by total assets	Compustat
Cross-sectional analysis		
Analyst coverage	Arithmetic mean of the 12 monthly numbers of earnings forecasts over the fiscal year	I/B/E/S
Fluidity	Fluidity is defined as the dot product between the words used in a firm's product description and the change in the words used by its competitors. As the words used by competitors become more similar to the firm's description, fluidity increases, which indicates a higher similarity between the products of the firm and its competitors.	Hoberg et al. (2014)
E-index	The sum of six anti-takeover provisions introduced by Bebchuk et al. (2009)	IRRC
Average distance	Average geographic distance between plants owned by a firm and the EPA regional offices at the firm level using the formula of Coval and Moskowitz's (1999)	TRI
Channels analysis		
Institutional ownership (IO)	Fraction of a firm's shares held by institutional investors	Thomson Reuters 13-F
Quasi-indexers	Fraction of a firm's shares held by quasi-indexers (defined following Bushee (2001))	Thomson Reuters 13-F
Public pension funds	Fraction of a firm's shares held by public pension funds (defined following Bushee (2001))	Thomson Reuters 13-F
Log(environmental expenditure)	Natural logarithm of (one plus the amount of a firm's environmental expenditures on pollution abatement)	10-K
Log(green patents)	Natural logarithm of (one plus the number of green patents)	Kogan et al. (2017)
Environmental compensation	Indicator variable that equals one if firms set environmental performance-based compensation contracts for any named-executive and zero otherwise	DEF 14A
Sustainability committee	Indicator variable equals one if firms have a sustainability committee and zero otherwise	BoardEx

Appendix 1-A2. Decreases in analyst coverage and sub-categories of corporate pollution

This table reports the results of the DiD regression on the effects of decreases in analyst coverage on sub-categories of pollution. The sample consists of 1,212 firm-year observations (606 treatment and control firm-year observations) from 1999 to 2011. Panel A investigates the decreases in analyst coverage on firms' on-site and off-site pollution. On-site pollution is the quantity of toxic chemicals released into the air, water, and ground on-site at the plant. Off-site pollution is the quantity of toxic release transferred to off-site locations for further release or disposal at specialized waste management facilities. *Log(on-site)* is the natural logarithm of one plus the amount of on-site pollution. *Log(on-site/sales)* is the natural logarithm of one plus the amount of sales adjusted on-site pollution. *Log(off-site)* is the natural logarithm of one plus the amount of off-site pollution. *Log(off-site/sales)* is the natural logarithm of one plus the amount of sales adjusted off-site pollution. Panel B splits on-site pollution into air, water, and ground pollution. Air pollution is the total quantity of on-site stack emissions and on-site fugitive emissions. Water pollution is the total quantity of toxic pollutions released on-site as surface water discharges. Ground pollution is the total quantity of toxic pollution released on-site on grounds. *Log(air)* is the natural logarithm of one plus the amount of air pollution. *Log(air/sales)* is the natural logarithm of one plus the amount of sales adjusted air pollution. *Log(water)* is the natural logarithm of one plus the amount of water pollution. *Log(water/sales)* is the natural logarithm of one plus the amount of sales adjusted water pollution. *Log(ground)* is the natural logarithm of one plus the amount of ground pollution. *Log(ground/sales)* is the natural logarithm of one plus the amount of sales adjusted ground pollution. *Treatment* is a dummy variable that equals 1 if the firm has experienced an exogenous decrease in analyst coverage as a result of brokerage exits and 0 otherwise. *After* is a dummy variable that equals 1 for the year after (t+1) brokerage exits and 0 for the year before (t-1). All variables are defined in Appendix 1-A1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Impact of an exogenous drop in analyst Coverage on on-site pollution and off-site pollution

	On-site pollution		Off-site pollution	
	Log(on-site)	Log(on-site/sales)	Log(off-site)	Log(off-site/sales)
	(1)	(2)	(3)	(4)
Treatment*After	**0.470*** **	**0.489*** **	**0.278**	**0.297**
	(2.67)	**(2.79)**	**(1.31)**	**(1.39)**
After	-0.243	-0.252	-0.259	-0.268
	(-1.23)	(-1.27)	(-1.24)	(-1.28)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,212	1,212	1,212	1,212
R-sq	0.191	0.271	0.080	0.068

Panel B. Impact of an exogenous drop in analyst Coverage on air, water, and ground pollution

	Air pollution		Water pollution		Ground pollution	
	Log(air)	Log (air/sale)	Log(water)	Log (water/sales)	Log (ground)	Log (ground/sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*After	**0.402****	**0.421*****	**-0.076**	**-0.057**	**-0.021**	**-0.002**
	(2.52)	**(2.65)**	**(-0.54)**	**(-0.40)**	**(-0.10)**	**(-0.01)**
After	-0.189	-0.199	0.030	0.020	-0.389	-0.399
	(-1.05)	(-1.10)	(0.31)	(0.20)	(-1.57)	(-1.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,212	1,212	1,212	1,212	1,212	1,212
R-sq	0.200	0.284	0.070	0.161	0.054	0.088

2 Gender, Workplace Preferences, and Firm Performance: Looking Through the Glass Door

2.1 Introduction

Over recent years, gender differences in the labor market have attracted the attention of many scholars (e.g., Adams and Funk, 2012; Tate and Yang, 2015; Adams and Kirchmaier, 2016; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Zandberg, 2021). While the gender gap has been significantly narrowed in various aspects such as the gender wage gap (Blau and Kahn, 2017), female labor force participation (Blau and Kahn, 2007), and gender leadership gap (Field et al., 2020), gender differences in female's choices and preferences are persisted (Bertrand et al., 2010; Stevenson and Wolfers, 2009; Mas and Pallais, 2017; Wiswall and Zafar, 2018). In this chapter, I explore the gender differences in job satisfaction and workplace preferences, and the financial implications of the gender satisfaction gap at work using 96,983 Glassdoor employer reviews from 2,301 U.S. public firms between 2008 and 2015.

Glassdoor is an employer review and online recruitment platform where employees can anonymously review their companies, interview experience, compensation and benefits, and other workplace practices. Each company review includes the rating of employee overall satisfaction, as well as other workplace attributes such as career opportunity, compensation and benefits, work-life balance, senior leadership, and corporate culture. In addition, Glassdoor also provides a rich set of information about employee characteristics including employee gender, highest education level, job title, and age. Such information enables this chapter to examine the dynamics of gender differences in job satisfaction and workplace attribute preferences, and investigate whether these differences matter for firm performance.

I start with the gender gap in job satisfaction. I find, on average, female employees are less satisfied at work than male employees. Specifically, females have a significantly lower rating on overall satisfaction and most workplace attributes and the workplace attribute with the highest gender satisfaction gap is work-life balance. Moreover, I explore gender differences in workplace preferences, where the greater sensitivity of the overall job satisfaction rating to each of the workplace attributes indicates higher preferences. The results indicate that females, relative to males, care more about work-life balance, senior leadership, and corporate culture, while they care less about career opportunity and compensation benefits. Again, the largest gender difference in workplace preference is in work-life balance, suggesting the balance between work and personal life contributes most to the gender satisfaction gap at work. This evidence is consistent with prior studies that females demand and value the flexibility at work more than males do (e.g., Mas and Pallais, 2017; Wiswall and Zafar, 2018).

The workplace preference in work-life balance reflects the career-family conflict female employees face. While females have made remarkable progress in the labor market over recent decades (Blau and Kahn, 2006; Blau and Kahn, 2007; Blau and Kahn, 2017), they remain the main providers of family commitments (e.g., household production and childcare). Such conflict increases their difficulty in balancing work and family life and influences their career path selection, especially when having children (Bertrand et al., 2010; Mas and Pallais, 2017). To further explore the role of selection in female career development, I compare gender gaps in workplace preferences between rank-and-file employees and mid-level managers. It is worth noting that the work-life balance is the only dimension along which the manager gender gap significantly differs from the employee gender gap. Among rank-and-file employees, females significantly care more about work-life balance than males, while this gender gap appears to vanish when becoming a mid-level manager. This evidence indicates females do not care more about work-life balance than males at the manager level, suggesting the crucial role work-life balance plays in females' career progression. Given their dual roles in the home and the labor market, females are less likely to choose a career path to the managerial position when they have to sacrifice work-life balance to be promoted.

Having established the gender gap in job satisfaction, I then examine whether this gap matters for firm performance. Given the crucial role work-life balance plays in the gender satisfaction gap at work, I focus on the financial implications of the gender gap in work-life balance in this section.[44] Specifically, I calculate the gender gap as the difference between the average work-life balance rating of male and female employees for each firm-year observation. The lower gender satisfaction gap in work-life balance represents a more family-friendly workplace. A family-friendly orientation helps create a more positive work environment that improves employee morale and productivity, leading to a higher firm valuation (Bloom et al., 2011). Indeed, I show that firms with lower gender gaps in work-life balance have higher firm value. This finding is robust to controls for employee average satisfaction (Green et al., 2019) and "100 Best Companies to Work for" (Edmans, 2011). Moreover, I examine the underlying mechanism of this gender gap-firm value relation. Firms with low gender satisfaction gaps exhibit superior operating performance and higher labor productivity, consistent with the view that family-friendly workplaces are beneficial for firm valuation through employee productivity.

[44] As a robustness test, I calculate the gender satisfaction gap using overall rating. The results are shown in Appendix 2-A8 and my findings are largely similar.

To better understand the relation between the gender satisfaction gap and firm valuation, I conduct several cross-sectional tests on how the value implications vary across different industries and different types of firms. First, I examine whether some industries benefit more from workplace family-friendliness. If family-friendly workplaces can indeed improve firm value, the results should be more pronounced in industries relying more on female employees. Consistent with this conjecture, I find the negative effect of the gender satisfaction gap on firm value is stronger in industries with a higher female proportion. Second, I investigate whether corporate governance can affect the relation between the gender gap and firm value. I find that this relation is mainly driven by firms with stronger corporate governance proxied by blockholder ownership, product market competition, and co-opted directors. Third, I find the estimation results are only significant in financially unconstrained firms, suggesting firms subject to financing difficulties are less likely to benefit from family-friendly policies.

Finally, I investigate whether the information in the gender satisfaction gap at work is fully incorporated into stock prices by capital markets. In particular, my analysis uncovers a significant negative relation between the gender gap in work-life balance and stock returns. For instance, equal-weighted portfolios consisting of firms with the lowest gender gap (bottom quintile) outperform firms with the highest gender gap (top quintile) by a four-factor alpha of 0.89% per month. The magnitude of this estimate is similar to that reported by Green et al. (2019).[45] This finding is robust to controlling for a range of firm characteristics and "100 Best Companies to Work for" (Edmans, 2011) using the Fama-MacBeth regressions.

[45] Using the change in overall employer rating from Glassdoor, Green et al. (2019) report a 0.88% per month alpha estimate for the long-short portfolio that buy firms with improving rating and sell firms with declining rating.

This chapter contributes to at least two strands of literature. First, this chapter adds to the literature on gender differences in job satisfaction and workplace preferences. I document that females are less satisfied at work than males, largely due to their preferences for work-life balance. This finding is consistent with Mas and Pallais (2017) and Wiswall and Zafar (2018) that females value work flexibility more than males. Moreover, I find this workplace preference in work-life balance vanishes among mid-level managers, illustrating the role of selection. Since females remain the main providers of family commitments, female employees are less likely to choose a career path to the managerial position if they care about work-life balance. This result complements the evidence of Adams and Funk (2012) that female directors in less family-friendly workplaces are less likely to be married and have fewer children.

Second, this chapter contributes to the literature on the relation between employee satisfaction and firm performance. Human capital plays an increasingly important role in the modern company (Edmans, 2011) and employees are regarded as a key ingredient of the human capital that can create substantial value for companies through building client relationships or inventing new products and patents (Maslow, 1943; McGregor, 1960; Becker and Gerhart, 1996). Accordingly, maintaining employee satisfaction can effectively improve employee morale and productivity, leading to higher firm value. Consistent with this view, Edmans (2011) finds the portfolio with firms in the list of "100 Best Companies to Work For in America" can earn a positive abnormal return. Using Glassdoor employer reviews, Green et al. (2019) suggest a positive effect of the change in employee overall satisfaction on stock returns, while Hales et al. (2018) and Sheng (2019) find employees' assessment on company business outlook can predict future performance. To the best of my knowledge, this chapter is the first study to examine the value implications of the gender satisfaction gap at work. I show that family-friendly workplaces with smaller gender satisfaction gaps are associated with a higher firm valuation after controlling for employee overall satisfaction. Moreover, this chapter explores how this gender gap-firm value relation varies across different industries and firms. I find firms in industries relying more on female employees, with stronger corporate governance, and with less financial constraints may benefit more from workplace family-friendliness than others.

The remainder of this chapter is organized as follows. Section 2.2 describes the Glassdoor data, sample construction, and descriptive statistics. Section 2.3 presents the results about gender differences in job satisfaction and workplace preference. Section 2.4 explores the value implications of the gender satisfaction gap. Section 2.5 concludes this chapter.

2.2 Data and Summary Statistics

2.2.1 Glassdoor data

I obtain employee reviews from Glassdoor to measure employee satisfaction. Glassdoor (www.glassdoor.com) is one of the largest online review and recruiting platforms with 60 million monthly visits that launched in 2008.[46] As of 2015, the platform contains approximately three million reviews from 280,000 firms (including public and private firms) covering the majority of U.S. public firms. In Glassdoor, employees can anonymously review their companies, interview experience, compensation and benefits, and other workplace practices. From each employer review, I extract one-to-five point employees' overall rating (*Overall rating*), as well as the assessments of various workplace attributes regarding career opportunities (*Career*), compensation benefits (*Compensation*), work-life balance (*Work-life*), senior leadership (*Leadership*), and corporate culture (*Culture*), ranging from 1 (least

[46] Source: https://www.glassdoor.com/about-us/

satisfied) to 5 (most satisfied). In addition, such a review also provides information of employee characteristics, including employee gender (*Female)*, the highest education level (*Education*), age (*Age*), and job title (*Manager*). *Female* is an indicator variable that equals one if the review is posted by a female, and zero otherwise. *Age* is the employee's age in years. *Education* is the employee's highest education level, coded as 0 for employees who do not own a bachelor or higher degree, 1 for bachelor's, 2 for master's and MBA, 3 for PhD. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. Details of the Glassdoor variables are presented in Appendix 2-A1.

To ensure data quality, Glassdoor implements various requirements for employee reviews. First, a priority concern when using online reviews is the sample selection bias, that is, the extremely satisfied or unsatisfied employees are more likely to post online reviews. For instance, the customer reviews from Amazon are a strongly skewed distribution with a large proportion of 5-star and 1-star ratings. To alleviate this concern, the Glassdoor platform employs a "give-to-get" model to attract more neutral and balanced reviews. The model is such that new users can only access limited information in Glassdoor until they make a contribution such as posting a "company review". In this way, Glassdoor induces more employees who hold moderate opinions to evaluate their employer and workplace practices, which in turn mitigates the self-selection concern. In addition, Liu et al. (2017) compare the Glassdoor data to nationally representative data collected by the U.S. Census Bureau and show that the Glassdoor wage distribution matches that of the Census Bureau wage distribution for major metropolitan areas and industries. This suggests that nonrandom selection into the site is unlikely to be a severe threat to the validity of the results.[47]

Second, Glassdoor adopts tight scrutiny for submitted reviews. To distinguish the authenticity of reviews, Glassdoor requires that each review must be submitted through an active email address or valid social media account. Moreover, Glassdoor uses proprietary technology filters and algorithm programs to detect multiple reviews from the same IP address. In addition, platform editors are responsible for the scrutiny and removal of inappropriate content or fake news.[48] Finally, these successfully posted reviews will be censored by users. To maintain the integrity of reviews, Glassdoor encourages users to flag the review with inappropriate content. Such reviews will be deleted after the verification by Glassdoor.

Third, the community guidelines of Glassdoor claim "Glassdoor strives to be the most trusted and transparent place for today's candidate to search for jobs and research companies". It assures users that Glassdoor never deletes, revises, or selectively discloses the contents or ratings of company review once a review is in line with community guidelines. Furthermore, the company review is completely anonymous and prohibits any exact names, reducing the risk of reprisal and coercion.

To further validate the quality of Glassdoor data, I empirically compare the Glassdoor rating with the KLD employee relation score and the list of "100 Best Companies to Work" which are two of the most widely used proxies for employee satisfaction.[49] In untabulated analysis, I regress Glassdoor *Overall rating* on KLD

[47] As a robustness test, I replicate my results after excluding extreme reviews in Section 2.3.4. The results remain robust.

[48] Roughly 15% reviews are removed by editors in this process.

[49] The employee relation score is the difference between the number of employee relation strengths and the number of employee relation concerns. The list of "100 Best Companies to Work" is collected from https://alexedmans.com/data

employee relation score and "100 Best Companies to Work" separately and find both measures are positively associated with the contemporaneous rating, confirming the validity of Glassdoor rating in capturing employee satisfaction at work.

2.2.2 Sample construction and summary statistics

My sample begins with Glassdoor employee reviews for U.S. public firms from 2008 to 2015. To ensure the informativeness of the ratings, I first remove the reviews posted by "former" employees since the exact departure date of former employees is not presented in Glassdoor.[50] In addition to timeliness, the former employees, especially the dismissed employees, are more likely to post irrational reviews on their employer.[51] Second, I drop reviews posted by senior managers (e.g., CEO, CFO, director, and executive) to mitigate the bias of potential self-promotion.[52] The remaining reviews are completed by either current rank-and-file employees or mid-level managers. Finally, I exclude incomplete reviews with at least one missing employee characteristic such as employee gender, education, age, and job title. In total, my sample consists of 96,983 reviews from 2,301 U.S. public firms.

In Figure 2-1, I compare the overall satisfaction (*Overall rating*) of female and male employees across industries using the Fama-French 12-industry classification. It is apparent that employee overall satisfaction and gender satisfaction gap vary across industries. The *Enrgy* (Oil, Gas, and Coal Extraction and Products) and *Chems* (Chemicals and Allied Products) firms have the highest employee overall satisfaction, while the industries with relatively low employee satisfaction are *Shops* (Wholesale,

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[50] Employees are required by Glassdoor to claim the employee status (current or previous employee) when they post a company review.
[51] Indeed, the ratings by former employees are substantially lower than those by current employees. In Section 2.3.4, I replicate my main finding after adding back former employee reviews and the results remain robust.
[52] More specifically, I remove the reviews with the job title that includes any of the following words: "President", "CFO", "CEO", "Chairman", "Director", "Executives", and "Head".

Retail, and Some Services) and *Telcm* (Telephone and Television Transmission). Regarding the gender satisfaction gap (the difference in overall satisfaction between male and female employees), females are less satisfied with their job than males in most industries. Industries with the largest gender gaps are *Hlth* (Healthcare, Medical Equipment, and Drugs) and *Money* (Finance), whereas those with the smallest gender gaps are *Telcm* (Telephone and Television Transmission) and *Chems* (Chemicals and Allied Products), respectively.

[Insert Figure 2-1 here]

Next, I present the trend of female and male overall satisfaction across years in Figure 2-2. During the sample period, there is a downward trend in overall satisfaction for both male and female employees in the early years, while it rebounds after 2010. The initial decline trend may be driven by the recent financial crisis which leads both male and female employees to be under the threat of unemployment and to have more pessimistic expectations about their career prospects. As a robustness test, I regenerate my main results after excluding the reviews between 2008 and 2010. My results are not driven by this particular period.[53]

[Insert Figure 2-2 here]

I then present descriptive statistics for Glassdoor variables in Panel A of Table 2-1. My final sample consists of 92,915 reviews from 2,163 U.S. public firms between 2008 and 2015. The number of reviews in sub-category ratings is slightly lower than that in the overall rating because the filling of such reviews is not compulsory.[54] The average *Overall rating* is 3.425, suggesting employees tend to post a generally positive opinion on the company. The mean values of other workplace attributes vary

[53] The details are shown in section 2.3.4 Robustness check.

[54] The number of reviews in *Culture* is substantially smaller than that in other ratings since this assessment is added by Glassdoor from 2012.

from 3.045 for *Leadership* to 3.522 for *Culture*. With respect to employee characteristics, 32.1% and 26.9% of the reviews are posted by female employees and mid-level managers respectively. The average education level in my sample is a bachelor's degree and the average employee age is 33.

[Insert Table 2-1 here]

Panel B of Table 2-1 presents the correlation matrix across Glassdoor ratings. It is not surprising that overall rating is highly correlated with all sub-category ratings, with correlations ranging from 0.576 (*Work-life*) to 0.742 (*Culture*). The correlations among sub-category ratings vary from 0.387 (*Work-life* & *Compensation*) to 0.709 (*Culture* & *Leadership*). These numbers are comparable to those reported in Huang et al. (2015) and Green et al. (2019).

Then, I perform a univariate analysis to compare the differences in Glassdoor variables, stratified by female and male employees in Panel C of Table 2-1. I find females have substantially lower overall satisfaction (3.347) relative to males (3.461), leading to an unconditional gender satisfaction gap of 0.114. Female employees are also less satisfied with all other workplace practices. The largest gender satisfaction gap exists in the assessment of *Work-life* with 0.180 difference, suggesting female employees, relative to male employees, are subject to more challenges in the balance of career and family commitments. The rating with the smallest gap is *Leadership* with only 0.071 disparity. In terms of employee characteristics, female employees have the same age and a similar proportion of mid-level managers relative to male employees, while they are significantly less educated.

2.3 Gender Differences in Job Satisfaction and Workplace Preferences

2.3.1 Gender gaps in employer ratings

In this section, I investigate the gender satisfaction gaps at work using the following baseline regression:

$$Y_{ijt} = \alpha + \beta\ Female_i + \gamma\ Z_{ijt} + \varepsilon_{ijt} \qquad (2\text{-}1)$$

Where i indexes individual, j indexes firm, and t indexes year. The dependent variable is employee job satisfaction measured by *Overall rating* and various other workplace practices related to *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*. The variable of interest is *Female*, an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. The vector *Z* denotes a set of employee characteristics such as *Age*, *Education*, and *Manager*. *Age* is the employee's age in years. *Education* is the employee's highest education level, coded as 0 for employees who do not own a bachelor or higher degree, 1 for bachelor's, 2 for master's and MBA, 3 for PhD. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise.[55] Details of Glassdoor variables are presented in Appendix 2-A1. I include firm-year fixed effects to account for any time-varying heterogeneity at the firm level correlated with workplace gender gaps.[56] Standard errors are clustered at the firm level.

Table 2-2 presents the estimation results. I begin my analysis by examining the gender gap in overall satisfaction in Column (1). The coefficient on *Female* is negative and statistically significant at the 1% level. Specifically, the average overall satisfaction of female employees is 0.039 points lower than that of male employees. The magnitude of the estimated gender satisfaction gap is much smaller as compared

[55] Employee is identified as a mid-level manager if his/her job title contains one of the following words: "manager", "officer", and "controller".
[56] The results are not materially changed if I control for firm and year fixed effects separately.

to the unconditional differential (0.114) shown in Panel C of Table 2-1, implying about 66% of the unconditional differential can be accounted for by the set of control variables and time-varying heterogeneity at the firm level.

[Insert Table 2-2 here]

I then investigate which specific workplace practice females are least satisfied with versus males. In Columns (2) to (6), I examine the gender satisfaction gap in five sub-dimensions: career opportunity (*Career*), compensation benefit (*Compensation*), work-life balance (*Work-life*), senior leadership (*Leadership*), and culture value (*Culture*). Across all specifications, I find that the coefficient on *Female* remains negative and four of the five coefficients are significant at the 5% level or better. The only exception is *Compensation* in Column (4), which provides the "correct" sign while it is insignificant. It suggests the gender pay gap is limited at lower levels of the corporate hierarchy.[57] In contrast, female employees are significantly less satisfied with career opportunity, work-life balance, and corporate culture. The magnitudes of coefficients for the regression of career opportunity (-0.032), senior leadership (-0.028), and culture value (-0.038) are largely similar to that of the overall rating (-0.038). It is worth noting that female employees are least satisfied with work-life balance as compared to male employees with 0.071 points gender gap which is about twice as large in magnitude as those for other workplace attributes, highlighting the important role work-life balance plays in the gender gap at work.

2.3.2 Gender gaps in workplace preferences

The above evidence suggests females, on average, are less satisfied at work than males, and the highest gender gap exists in the assessment of work-life balance.

[57] According to the Bureau of Labor Statistics (BLS, 2019), women earn 82% of men's income on average. Despite the lower income relative to men, women have similar satisfaction with compensation, pointing to gender differences in preferences.

I then examine how female employees differ from their male counterparts in preferences for workplace attributes. I compare employee preferences for various workplace attributes by estimating the sensitivity of the overall job satisfaction to each of the subcategory ratings separately, with greater sensitivities indicating higher preferences. For example, if female employees care more about work-life balance than male employees, then females' overall job satisfaction should be more sensitive to changes in work-life balance satisfaction. That is, a reduction (rise) in the work-life balance rating should lower (increase) females' job overall satisfaction to a larger extent relative to that of males. Specifically, I use the following model to investigate the employee gender gap in workplace preferences:

$$Overall_{ijt} = \alpha + \beta_1 Female_i + \beta_2 Sub\ rating_{ijt} + \beta_3 Sub\ rating \times Female_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt} \quad (2\text{-}2)$$

Where i denotes individual, j denotes firm, and t denotes year. *Overall* is employee overall job satisfaction and *Sub rating* is one of five sub-category ratings including *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*. *Female* is an indicator variable that takes the value one if the reviewer is female, and zero otherwise. The variable of interest in this model is the interaction variable *Sub rating*×*Female*. The coefficient β_3 identifies the gender satisfaction gap in workplace preference.

The estimation results are presented in Table 2-3. Regressions for Columns (1) to (5) include the workplace attributes, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively.[58] The results show significantly different workplace preferences between female and male employees. In Columns (1) and (2), the coefficients on *Career* × *Female* and *Benefit* × *Female* are negative and statistically

[58] As a robustness check, I examine how female and male employees value each attribute after taking other attributes into account in Appendix 2-A2. My findings are not materially changed.

significant, indicating female employees care less about career opportunities and compensation and benefits relative to male employees. In contrast, females care more about work-life balance, senior leadership, and corporate culture as shown by the positive and significant coefficients on interaction variables in Columns (3) to (5).

[Insert Table 2-3 here]

Again, the workplace attribute with the largest preference gap is *Work-life* (0.032), while the corresponding magnitudes are much smaller for other attributes. These findings are consistent with prior studies that females value the flexibility at work more than males do. Mas and Pallais (2017) find that females tend to select and place a higher valuation on more flexible work arrangements. In a similar vein, Wiswall and Zafar (2018) estimate the preferences of undergraduates for workplace attributes and indicate female undergraduates have a higher willingness to pay for work flexibility. My study complements this strand of literature by emphasizing the pertinence of work-life balance as the most important workplace attribute, responsible for gender gaps in job satisfaction and workplace preferences.

2.3.3 Gender gaps in workplace preferences among mid-level managers

The previous sections suggest the work-life balance is the main contributor to the gender gap in job satisfaction and workplace preferences. The workplace preference in work-life balance reflects the career-family conflict female employees face. While females have made remarkable progress in the labor market over recent decades (Blau and Kahn, 2006; Blau and Kahn, 2007; Blau and Kahn, 2017), they remain the main providers of household production (Hersch and Stratton, 2002). Such conflict leads to difficulty in balancing their work and family life and is likely to influence the selection of a female's career path, especially when having children (Bertrand et al., 2010; Mas and Pallais, 2017). For example, Bertrand et al. (2010)

find many qualified female employees choose to leave the job market after having children. To further explore the role of selection in female career development, I investigate whether the pattern of gender differences in job satisfaction and workplace preferences carries over in mid-level managers.

I first compare the differences in gender satisfaction gaps between mid-level managers and rank-and-file employees by estimating the following model:

$$Y_{ijt} = \alpha + \beta_1 Manager_{it} + \beta_2 Female_i + \beta_3 Female \times Manager_{it} + \gamma Z_{ijt} + \varepsilon_{ijt} \qquad (2\text{-}3)$$

Where i denotes individual, j denotes firm, and t denotes year. *Y* stands for the overall and subcomponent ratings. *Manager* (*Female)* is an indicator variable that equals to one if the review is posted by a mid-level manager (female), and zero otherwise. The variable of interest is the interaction variable *Female×Manager*. The coefficient β_3 shows the difference in gender gap between the mid-level managers and rank-and-file employees.

The estimation results are presented in Table 2-4. On average, managers are more satisfied with *Overall rating, Career, Benefit, Leadership, and Culture* than non-managerial employees. The only workplace attribute that managers are less satisfied with is *Work-life*. It is perhaps not surprising because the increasing additional tasks and responsibilities associated with managerial roles may crowd out the attention devoted to their life and family. It is worth noting that the coefficients on *Female×Manager* suggest that the position of mid-level manager widens the gender satisfaction gap in *Work-life*, which is offset by the reduced gender gaps in satisfaction regarding *Career* and *Benefit*, leading to an insignificant coefficient for the *Overall rating* in Column (1).

[Insert Table 2-4 here]

Next, to further examine whether gender gaps in workplace preference for mid-level managers differ from those of rank-and-file employees, I employ a triple-difference analysis as follows:

$$\begin{aligned} Overall_{ijt} = \alpha &+ \beta_1 Manager_{it} + \beta_2 Female_i + \beta_3 Sub\ rating_{ijt} \\ &+ \beta_4 Female \cdot Manager_{ijt} + \beta_5 Sub\ rating \cdot Female_{ijt} \\ &+ \beta_6 Sub\ rating \cdot Manager_{ijt} \\ &+ \beta_7 Sub\ rating \cdot Female \cdot Manager_{ijt} + \gamma\ Z_{ijt} + \varepsilon_{ijt} \qquad (2\text{-}4) \end{aligned}$$

Where i denotes individual, j denotes firm, and t denotes year. *Overall* is employee overall job satisfaction and *Sub rating* is one of five sub-category ratings including *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*. *Manager* (*Female*) is an indicator variable that equals to one if the review is posted by a mid-level manager (female), and zero otherwise. The coefficient of interest in this analysis is β_7, which captures the difference of gender gap in workplace preferences between mid-level managers and rank-and-file employees.

In Table 2-5, I find that while most of the gender gaps among rank-and-file employees continue to hold for managers, the gender preference for work-life balance is significantly changed. Specifically, among rank-and-file employees, females care more about work-life balance than males. However, this preference appears to vanish or even reverse at the manager level, as indicated by the negative and statistically significant coefficient on the triple interaction term *Work-life* × *Female* × *Manager* in Column (3). This evidence indicates that the managerial position narrows the gender gap in the preference for work-life balance. In other words, females do not care more about work-life balance relative to males when becoming mid-level managers.

[Insert Table 2-5 here]

This evidence suggests a particularly important role work-life balance plays in female career progression. Given their dual roles in the home and the labor market, females are less likely to choose a career path to the managerial position when they have to sacrifice work-life balance to be promoted. This finding echoes the view of Bertrand et al. (2010) and Adams and Funk (2012) that the selection cost of leadership career path is much higher for females.

2.3.4 Robustness check

In this section, I conduct a series of robustness tests to confirm the validity of my main results. First, in the previous analysis, I identify the employee highest education level as a single linear variable, coded as 0 for employees who do not own a bachelor or higher degree, 1 for bachelor's, 2 for master's and MBA, 3 for PhD. To account for the potential nonlinearity in the relation between employee satisfaction and education, I replace *Education* with a set of indicator variables: *Bachelor* is an indicator that equals one if the employee has a bachelor's degree, and zero otherwise; *Master (MBA)* is an indicator that equals one if the employee has a Master's or MBA degree, and zero otherwise; *PhD* is an indicator that equals one if the employee has a PhD degree, and zero otherwise. In Appendix 2-A3, I re-estimate my main results (Tables 2, 3, and 5) and find the results are not materially affected when replacing *Education* with the three indicator variables.

Second, as discussed in 2.2.2, there is a downward trend in overall satisfaction for both male and female employees during the financial crisis (2008 to 2010). To alleviate the concern that the results are driven by this particular period, I exclude the reviews between 2008 and 2010 and re-run the main regressions in Appendix 2-A4. The estimation results are qualitatively similar. Third, I drop all reviews from former employees in sample construction as such reviews are less informative and more likely to be irrational. In addition, I delete reviews with missing data on the employee-specific controls (i.e., age, education, and manager). These procedures result in a large loss of observations. As a robustness check, I add back reviews by former employees and exclude the controls for employee characteristics. The results are presented in Appendix 2-A5 and are robust to this expanded sample.

Fourth, when using online reviews, a common concern is the sample selection bias that the extremely satisfied or unsatisfied employees are more likely to post an online review than moderate one leads to heavily skewed review distributions. For example, the product reviews of Amazon are concentrated in 1-star and 5-star (Leah-Martin, 2017; Huang, 2018). To account for this concern, Glassdoor uses a Give-to-Get policy to encourage moderate employees to express their voice.[59] Moreover, I calculate the mode of each rating to mitigate the concern of selection bias. The mode for each rating is 4.0 with the exception of 3.0 for *Career* and *Leadership*, suggesting that a majority of Glassdoor reviews are posted by moderate employees. As a further robustness check, I drop the extreme reviews with 1 or 5 ratings and re-estimate the main results. As shown in Appendix 2-A6, the main findings are not materially changed after excluding the extreme reviews. Thus, the results are unlikely to be affected by selection bias.

Lastly, employees are identified as mid-level managers and rank-and-file employees according to their job titles. One possible concern is that different positions (job titles) may afford different levels of flexibility, resulting in the gender satisfaction gap (Goldin, 2014). To rule out the possibility that the findings are driven by unobserved differences across positions, I re-generate estimation results after controlling for the more stringent firm-position-year fixed effects in Appendix 2-A7.

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[59] The specific description for Give-to-Get policy has been provided in Section 2.2.1.

For those rank-and-file employees, I use the last word in the job title provided by Glassdoor to categorize employees into different position groups. For instance, employees identified as “Business Analyst”, “Analyst”, or “Financial Analyst” by Glassdoor are classified into the “Analyst” group. Finally, I identify all groups that account for less than 1% of the total observations to the “others” group.[60] In total, there are 13 unique position groups. The results remain robust after controlling for firm-position-year fixed effects

2.4 Performance Implications

2.4.1 Gender satisfaction gap and firm value

My findings so far indicate a significant gender gap in their workplace preferences between male and female employees, especially when it comes to the preference for work-life balance. Next, I explore whether the gender gap in job satisfaction matters for firm performance. Hereafter, I focus on the gender satisfaction gap in work-life balance rating because the previous results suggest that female and male employees differ the most in their satisfaction with and preferences for work-life balance.[61] In particular, I examine the relation between the gender gap in work-life balance and firm valuation at the firm level as follows:

$$Tobin's\ Q_{it} = \alpha + \beta Gender\ gap\_WL_{it} + \delta Z_{it} + \varepsilon_{it} \qquad (2\text{-}5)$$

Where i denotes firm, and t denotes year. The dependent variable is *Tobin' s Q* defined as the market value of equity plus total assets minus the book value of equity, divided by total assets. For each firm-year observation, I compute *Gender gap_WL* as the difference between the average work-life balance rating of male and female employees. The vector Z contains a rich set of firm, governance, and CEO

[60] I also try to use 0.5% and 0.1% to identify the “others” group. The results are not significantly changed.
[61] My findings are largely similar when using overall satisfaction gender gap.

characteristics, including innovation (*R&D*), firm size (*Ln(Sales)*), cash holding (*Cash*), capital structure (*Leverage*), annual return (*Return*), the number of employees (*Ln(Employee)*), the fraction of female directors (*% of Female director*), board size (*Board size*), CEO duality (*CEO chair*), CEO gender (*Female CEO*), and the tenure *(Ln(CEO tenure))* and age (*Ln(CEO age)*) of CEO.[62] In addition, I further control for *Average overall rating* and *Best100*. *Average overall rating* is the average overall rating that may capture firm fundamental information and predict firm performance (Huang et al., 2015; Green et al., 2019). *Best100* is an indicator variable that equals one if the firm is in the list of "the 100 Best Companies to Work For", and zero otherwise. Edmans (2011) shows the portfolio with firms included in the list of "100 Best Companies to Work For in America" exhibits positive abnormal returns. Details of all variables are presented in Appendix 2-A1. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level.

The estimation results are presented in Table 2-6. I start with the regression of Tobin's Q on *Gender gap_WL*, *Average overall rating*, and other firm, governance, and CEO characteristics in Column (1) and further control for *Best100* in Column (2). In both columns, the coefficient on *Gender gap_WL* is negative and statistically significant at the 5% level, suggesting family-friendly workplaces with smaller gender gaps in work-life balance enhance firm value. In Appendix 2-A8, I also examine the effect of the gender satisfaction gap in overall rating on Tobin's Q. There is a consistently significant negative relation between gender gap and firm valuation.

[Insert Table 2-6 here]

While my results suggest a positive effect of family-friendly workplaces on firm valuation, it does not rule out the possibility of reverse causality that firms with

[62] To mitigate the effects of outliers, I winsorize all accounting variables at the 1st and 99th percentiles.

higher values may have more resources to afford more flexibility in work arrangements, resulting in a smaller gender satisfaction gap. To mitigate this potential endogeneity concern, I adopt an instrumental variable approach to support the causal relation between the gender satisfaction gap and firm valuation. Specifically, I estimate a two-stage least squares regression using the *Average cost childcare* as an instrument for work-life balance gender gap (*Gender gap_WL*). *Average cost childcare* is defined as the average employee-specific *Cost childcare under 3* in a firm in a year based on the employee's work location (State), where *Cost childcare under 3* is the cost of childcare for children under three years old in a state as a percentage of the state's personal income per capita. The idea is since females are the main providers of family commitments (i.e., childcare), the expensive childcare services may force females to pay more attention to the family, thereby deteriorating the balance between work and personal life and leading to a higher gender satisfaction gap in work-life balance. Under this view, firms with higher average costs of childcare services tend to have larger gender satisfaction gaps. More importantly, the average childcare costs based on employee work location are unlikely to be correlated with firm valuation other than through the gender satisfaction gap. The results presented in Appendix 2-A9 confirm the causal effect of the gender gap at work on firm valuation.

2.4.2 Potential channels through which gender satisfaction gap drives firm value

The above results confirm that family-friendly workplaces and cultures are beneficial to firm value. I then explore how such gaps influence firm performance. A family-friendly orientation helps create a more positive work environment that improves employee morale and productivity, leading to an improved firm valuation (Bloom et al., 2011). To provide direct evidence on this channel, I investigate whether family-friendly firms exhibit superior operating performance and higher labor productivity.

I start by examining the relation between the work-life balance gender gap and operating performance (*ROA*) in Column (1) of Table 2-7. The coefficient on *Gender gap_WL* is negative and statistically significant at the 5%, suggesting family-friendly workplaces with smaller gender gaps are associated with improved operating performance. I then study the effect of family-friendly workplaces on employee productivity. Production per employee (*Production/Emp*) and revenue per employee (*Revenue/Emp*) are used as proxies for employee productivity (Schoar, 2002; Brynjolfsson and Hitt, 2003; Caskey and Ozel, 2017). *Production/Emp* is defined as the firm's sum of the cost of goods sold and change of inventory divided by the total number of employees. *Revenue/Emp* is defined as the firm's sum of total annual sales and change of inventory divided by the total number of employees. The estimation results are shown in Columns (2) and (3) of Table 2-7. In both columns, I find a significant negative relation between the gender gap and employee productivity.

[Insert Table 2-7 here]

Overall, my results suggest operating performance and employee productivity are two underlying channels through which gender satisfaction gaps at work influence firm valuation, providing further support for the labor productivity channel. In addition to this channel, family-friendly workplaces and cultures may retain key employees and achieve greater innovation success, resulting in a higher firm valuation. To rule out alternative explanations, I further investigate whether employee turnover and corporate innovation are significantly influenced by the work-life gender gap. The results presented in Appendix 2-A10 show that the effects of *Gender gap_WL* on *employee turnover* and *ln(Patents)* are insignificant.

2.4.3 Cross-sectional analysis of the relation between gender satisfaction gap and firm value

Having established a negative relation between the gender satisfaction gap in work-life balance and firm value, I further investigate how this effect varies cross-sectionally using sub-sample analysis related to industry and firm characteristics. Specifically, family-friendly workplaces are unlikely to add value to all firms equally. Firms facing higher costs and constraints to implement family-friendly policies are less likely to benefit from family-friendliness than others. In particular, I investigate how the gender gap interacts with industry characteristics, corporate governance, and financial constraints to influence firm valuation.

I first look at the industries that tend to rely on females. My results have indicated females value work-life balance more than males. Intuitively, if family-friendly workplaces indeed increase labor productivity and firm valuation, this relation should be more pronounced in industries relying more on female employees. To test this argument, I partition my sample into two groups based on whether the firm's industry is female-dominated in Panel A of Table 2-8. An industry is identified as being female-dominated if the proportion of females in such an industry is above the sample median. I use the two-digit NAICS industry classification in Columns (1) and (2) and the Fama-French 12-industry classification in Columns (3) and (4). Regardless of how industries are classified, the coefficient on *Gender gap_WL* is only negatively significant in female-dominated industries.

[Insert Table 2-8 here]

I then consider the role of corporate governance in the relation between the gender gap in job satisfaction and firm valuation. Under the agency framework, Jensen and Meckling (1976) argue that managers' nonpecuniary private benefits may include their personal relations with employees. For example, entrenched managers might care more than shareholders about worker loyalty and employee relations. One way for managers to strengthen employee relations and secure loyalty is to make workplaces more employee-friendly and promote gender equality (Edmans, 2011). Moreover, in the spirit of Bertrand and Mullainathan (2003), fostering family-friendly workplaces could be a way for quiet-life managers to buy peace with employees and making their job easier. Together, these arguments point to the potential agency problems associated with workplace practices, implying a key role of corporate governance in mitigating these problems and enhancing the value of family-friendly workplaces.

I use three proxies for corporate governance. The first proxy is *Institutional blockholding*, defined as the percentage of shares owned by all institutional investors who own 5% or more of the firm's equity. Higher blockholder ownership means stronger corporate governance. The second proxy is the product market fluidity developed by Hoberg et al. (2014) which captures the competitive threats faced by firms. A higher value of *fluidity* represents greater market competition.[63] The third proxy is a measure of board monitoring effectiveness developed by Coles et al. (2014). *TW Co-option* is the sum of the tenure of co-opted directors divided by the total tenure of all directors, where co-opted directors are directors who join the board after the CEO assumes office.[64] Lower *TW Co-option* implies stronger corporate governance. For each proxy, I partition firms into groups with weak and strong corporate

[63] Fluidity is defined as the dot product between the words used in a firm's product description and the change in the words used by its competitors. As the words used by competitors become more similar to the firm's description, fluidity increases, which indicates a higher similarity between the products of the firm and its competitors. Therefore, fluidity is a measure of the competitive threats faced by a firm. The product market fluidity measure is constructed using textual analysis of each firm's product descriptions obtained from their 10-K files. It captures changes in rival firms' products relative to the firm. The fluidity measure can be downloaded from: https://hobergphillips.tuck.dartmouth.edu/industryconcen.htm

[64] Data source: https://sites.temple.edu/lnaveen/data/

governance groups based on the median value of my sample. I expect the value implications of the gender satisfaction gap to be stronger in subsamples with stronger corporate governance.

The results are presented in Panel B of Table 2-8. Regardless of the governance proxy, *Gender gap_WL* has a significantly negative coefficient only in strong governance firms. These results confirm that family-friendly practices are not equally beneficial for all firms. In the face of severe agency problems, the benefits of such a policy for firm valuation could be much less, suggesting the quality of corporate governance plays a crucial role in the value implications of the gender satisfaction gap.

Finally, I investigate whether financial constraints can influence the relation between the gender satisfaction gap and firm valuation. Investments in family-friendly workplaces such as flexible working hours, parental leave provisions, and formal childcare support are costly. Such investments may reduce firms' capital and other critical resources and force firms to forgo positive NPV projects, especially when facing financing constraints. Hence, I conjecture that financially constrained firms are unlikely to benefit greatly from family-friendly workplaces.

To test this conjecture, I use two proxies for financial constraints: *WW index* and *Equity constraints*. The WW index is an accounting-based measure constructed by Whited and Wu (2006). The construction of the WW index loads on six accounting variables, including cash flow to total assets, an indicator variable of dividend policy, long-term debt to total assets, firm size, sales growth, and industry sales growth. The less profitable, highly leveraged, smaller, and lower growth firms will have a larger WW index, indicating a higher degree of financial constraints. *Equity constraints* is a text-based financial constraints measure developed by Hoberg and Maksimovic

(2015).[65] Through analysing the mandatory disclosure of liquidity in the Management Discussion and Analysis (MD&A) section in the 10-K file, Hoberg and Maksimovic (2015) evaluate corporate financing constraints using the objective algorithm, with higher values indicating that firms are more at risk of delaying their investments due to issues with equity liquidity. I partition firms into financially constrained (unconstrained) firms based on the median value of the *WW index* and *Equity constraints*. The estimation results are shown in Panel C of Table 2-8. Consistent with the expectation, I find the coefficient on *Gender gap_WL* is negative and statistically significant in financially unconstrained firms, while it is insignificant in the subsample of constrained firms. This evidence suggests that investing in family-friendly workplaces could add undesirable strain to the already tight financial situation facing constrained firms.

2.4.4 Gender satisfaction gap and stock returns

In the final part of my analysis, I further explore whether the information in the gender satisfaction gap is fully incorporated into stock prices. In particular, I employ a portfolio approach to examine the relation between the gender gap and stock returns. Following Green et al. (2019), sample firms are partitioned into quintile portfolios based on the average gender gap in work-life balance at end of each calendar quarter. For each firm-quarter observation, I calculate the average gender gap as the difference between the average male and female employee ratings. The firms with the highest (lowest) quintile quarterly gender gap are assigned into the high (low) gap portfolio and the rest are in the middle portfolio. To alleviate the concern that the results are driven by the firms with few reviews, I further require each firm-quarter observation to include at least 15 reviews in Glassdoor posted by employees

[65] The data are shared by Hoberg and Maksimovic: http://faculty.marshall.usc.edu/Gerard-Hoberg/MaxDataSite/index.html

(Green et al., 2019).[66] I then track the equal-weighted and value-weighted portfolio returns of the three portfolios in the subsequent quarter and use the Fama-French-Carhart four-factor model (Carhart, 1997) to ensure the outperformance of female-friendly firms does not result from risk.[67] The regression specification is as follows:

$$R_{it} = \alpha + \beta_{MKT}MKT_t + \beta_{HML}HML_t + \beta_{SMB}SMB_t + \beta_{MOM}MOM_t + \varepsilon_{it} \qquad (2\text{-}6)$$

Where R_{it} is the excess return (in excess of a risk-free rate) on portfolio i in month t using equal-weighted and value-weighted approaches. α is an intercept capturing the abnormal risk-adjusted return. MKT_t, HML_t, SMB_t, and MOM_t are risk factor returns of market, value, size, and momentum extracted from Ken French's website.[68] Newey-West standard errors are used in the estimation.

The results are presented in Table 2-9. The dependent variable is equal-weighted portfolio excess return in Columns (1) to (4) and value-weighted portfolio excess return in Columns (5) to (8). The first three columns of each approach (Columns (1) to (3) and Columns (5) to (7)) include the portfolio with low, middle, and high workplace gender gaps, respectively. Columns (4) and (8) report the results for the long-short portfolio. For value-weighted returns, the alpha is 0.561% per month for a low gender gap portfolio and -0.328% per month for a high gender gap portfolio. The alpha estimate for the long-short portfolio that buys the low gender gap portfolio and sells the high gender gap portfolio is 0.889% each month with a t-statistic of 2.42. The returns are qualitatively similar but slightly larger when using the value-weighted approach. The long-short portfolio of the value-weighted approach yields an alpha of 0.906% with a t-statistic of 2.98. Importantly, it is

[66] For robustness, I also try other review threshold (e.g., 5, 10, and 20) which do not significantly influence my results.
[67] As a robustness check, I also use Fama-French three-factor and five-factor model and the results are qualitatively similar.
[68]Data source: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

reassuring that the magnitudes of alpha estimates in my analysis are close to those reported by Green et al. (2019). Using the change of overall employer rating from Glassdoor, they show that the long-short alpha for firms with improving and declining ratings is 0.88% per month when equal-weighted and 0.77% per month when value-weighted. Taken together, my findings suggest family-friendly workplaces are positively associated with the future stock returns. This evidence complements the recent studies by Edmans (2011) and Green et al. (2019) who find a positive relation between employee satisfaction and stock performance.

[Insert Table 2-9 here]

The above portfolio sorting approach indicates a positive abnormal return associated with family-friendly workplaces, while it does not control for firm characteristics which may influence the return predictability of the workplace gender gap. To address this concern, I estimate Fama and MacBeth (1973) regressions to control for a rich set of characteristics as a robustness check. In particular, I conduct the following cross-sectional regression of the monthly stock return on the lagged quarterly gender gap in work-life balance and a battery of control variables:

$$R_{i,t+1} = \alpha + \beta_1 Gender\ gap_{i,t} + \gamma\ Z_{it} + \varepsilon_{it} \qquad (2\text{-}7)$$

Where *i* denotes the firm, and *t* denotes the month. *R* is the excess return adjusted by a risk-free rate. *Gender gap* is the difference between the average male and female employee ratings in the lagged quarter. The vector *Z* denotes a vector of firm-level characteristics taken from Brennan et al. (1998), Gompers et al. (2003), and Edmans (2011): *Size* is the natural logarithm of the firm's market capitalization (in $ billions) in month t-2; *BM* is the natural logarithm of the book-to-market ratio at the end of the previous fiscal year; *Return2–3, Return4–6,* and *Return7–12* are the natural logarithm of the compounded returns in month t-3 to month t-2, month t-6 to month t-4, and month t-12 to month t-7, respectively; *Price* is the natural logarithm of the stock price of a particular firm at the end of month t-2; *Volume* is the natural logarithm of the dollar volume of trading (in $ millions) in month t-2; *Div. Yield* is the dividend yield of a particular firm at the end of the previous fiscal year. In addition, I further control for the employee average satisfaction by using the *Best 100* that is an indicator variable equaling one if the firm is nominated as the "100 Best Companies to Work for" on Fortune's list, and zero otherwise. Standard errors are calculated following Newey and West (1987).

The results are presented in Table 2-10. I first estimate the regression of the monthly excess return on the lagged gender gap without controls in Column (1). The coefficient on *Gender gap_WL* is -0.428 with Newey-West t-statistic of 2.49, suggesting firms with family-friendly workplaces are positively associated with superior future stock returns. In Column (2), I introduce other control variables to the model and find the coefficient on *Gender gap_WL* remains negative and statistically significant at the 5% level. Notably, I also examine the return predictability of the *Top100* ("100 Best Companies to Work for"). While Edmans (2011) finds firms in this list have a persistent long-term outperformance during 1984 to 2009, Column (2) shows that the coefficient estimate on *Top100* is positive but insignificant, which is consistent with empirical findings of recent Glassdoor studies (e.g., Green et al., 2019; Sheng, 2019; Welch and Yoon, 2020) and support the view of McLean and Pontiff (2016) that investors can learn the information of mispricing from academic publication, leading to a decline of post-publication return predictability.

[Insert Table 2-10 here]

2.5 Conclusions

In this chapter, I explore the gender satisfaction gap at work using 96,983 Glassdoor reviews from 2,301 U.S. public firms between 2008 and 2015. I find that females are significantly less satisfied at work than males and they differ systematically in their workplace preferences, particularly those regarding work-life balance. In particular, female employees care more about work-life balance but this gender difference vanishes at the manager level, illustrating the role of selection. Given the crucial role of the gender satisfaction gap in work-life balance, I further investigate the value implications of family-friendliness. The results suggest family-friendly workplaces with low gender satisfaction gaps lead to a higher firm valuation.

This chapter supports the persistence of gender differences in females' choices and preferences at work, particularly those regarding work-life balance. This evidence is consistent with the view that females value work flexibility more than males. More importantly, such preference for work-life balance vanishes at the manager level, reflecting the career-family conflict female employees are facing. Given the fact that females remain the main providers of family commitments, females are less likely to choose a career path to the managerial position when they have to sacrifice work-life balance to be promoted. Accordingly, it is plausible that family-friendly workplaces play a particularly important role in career progression, which can enhance employee morale and productivity and consequently benefit firm performance.

Figure 2-1. Average overall rating by industry and gender

This figure shows the average overall ratings of male and female employees of firms in Fama-French 12 industries: *NoDur* for non-durables; *Durbl* for durables; *Manuf* for manufacturing; *Enrgy* for oil, gas, and coal extraction and products; *Chems* for chemicals and allied products; *BusEq* for business equipment; *Telcm* for telephone and television transmission; *Utils* for utilities; *Shops* for wholesale, retail, and some services; *Hlth* for healthcare, medical equipment, and drugs; *Money* for finance; and *Other* for others, e.g., mines, construction, hotels, business service, and entertainment.

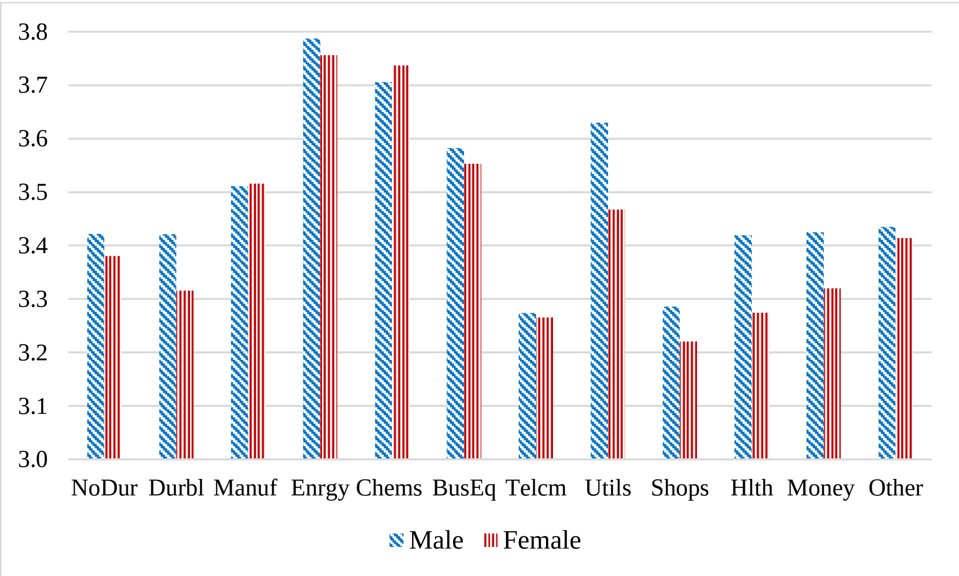

Figure 2-2. Average overall rating by year and gender

This figure compares the average overall ratings of male employees and those of female employees across years.

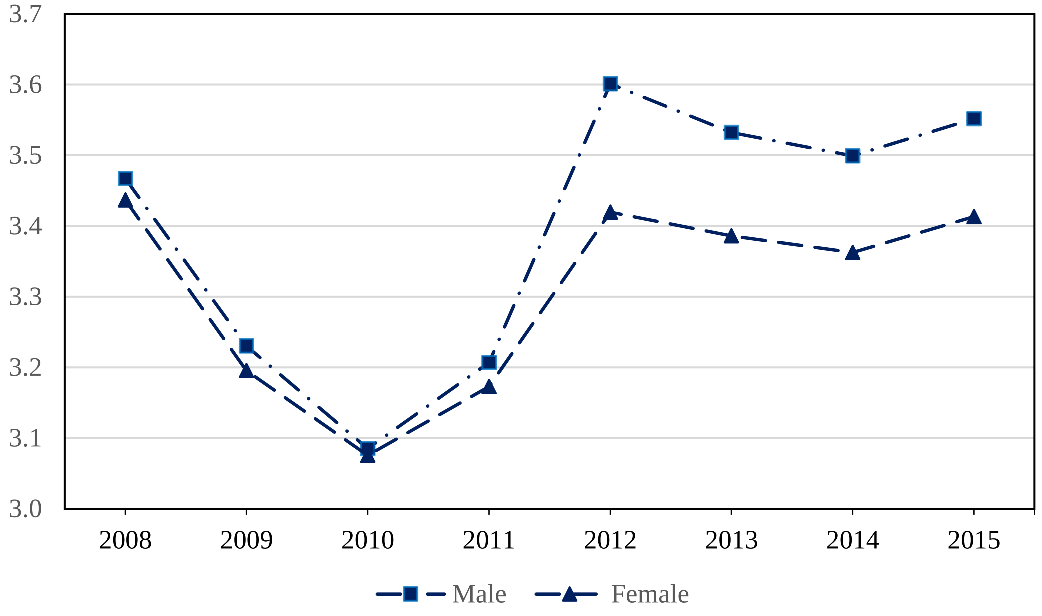

Table 2-1. Descriptive statistics

This table reports descriptive statistics for the main variables used in my study. Panel A presents descriptive statistics based on the whole sample. Panel B shows the correlation matrix. Panel C reports the univariate analysis results by gender. All variables are defined in Appendix 2-A1.

Panel A. Descriptive statistics

Variable	Obs.	Mean	Stdev	25th	Median	75th
Overall rating	96,983	3.425	1.169	3.000	4.000	4.000
Career	94,994	3.250	1.208	2.000	3.000	4.000
Benefit	94,907	3.321	1.145	3.000	3.000	4.000
Work-life	94,879	3.437	1.234	3.000	4.000	4.000
Leadership	94,470	3.045	1.281	2.000	3.000	4.000
Culture	71,100	3.522	1.292	3.000	4.000	5.000
Female	96,983	0.321	0.467	0.000	0.000	1.000
Age	96,983	33.313	10.055	25.000	31.000	39.000
Education	96,983	1.093	0.656	1.000	1.000	1.000
Manager	96,983	0.269	0.444	0.000	0.000	1.000

Panel B. Correlation matrix

	Overall rating	Career	Benefit	Work-life	Leadership	Culture
Overall rating	1.000					
Career	0.716***	1.000				
Benefit	0.589***	0.526***	1.000			
Work-life	0.576***	0.421***	0.387***	1.000		
Leadership	0.739***	0.627***	0.469***	0.534***	1.000	
Culture	0.742***	0.599***	0.464***	0.538***	0.709***	1.000

Panel C. Univariate analysis by gender

	Male		Female		Difference	
	Mean	Median	Mean	Median	Mean	Median
Overall rating	3.461	4.000	3.347	3.000	0.114***	1.000***
Career	3.284	3.000	3.177	3.000	0.107***	0.000***
Benefit	3.360	3.500	3.239	3.000	0.121***	0.500***
Work-life	3.495	4.000	3.314	3.000	0.180***	1.000***
Leadership	3.068	3.000	2.997	3.000	0.071***	0.000***
Culture	3.558	4.000	3.450	4.000	0.108***	0.000***
Age	33.317	31.000	33.303	30.000	0.014	1.000***
Education	1.144	1.000	0.987	1.000	0.157***	0.000***
Manager	0.269	0.000	0.271	0.000	-0.002	0.000

Table 2-2. Gender differences in job satisfaction

This table reports gender differences in employer overall and subcategory ratings. The dependent variables include the overall job satisfaction rating, *Overall rating*, in Column (1), and the five subcategory ratings, *Career*, *Benefit*, *Work-life*, *Leadership*, and *Culture* in Columns (2) to (6), respectively. The variable of interest, *Female*, is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Age* is the employee's age in years. *Education* is the employee's highest education level, coded as 0 for employees who do not own a bachelor or higher degree, 1 for bachelor's, 2 for master's and MBA, 3 for PhD. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall rating	Career	Benefit	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Female	**-0.039*** **	**-0.032*** **	**-0.010**	**-0.071*** **	**-0.029** **	**-0.039*** **
	(-3.51)	**(-2.92)**	**(-0.87)**	**(-5.88)**	**(-2.32)**	**(-3.12)**
Age	-0.010***	-0.013***	-0.001**	-0.010***	-0.013***	-0.013***
	(-12.64)	(-16.72)	(-1.96)	(-11.44)	(-13.64)	(-12.28)
Education	0.019***	-0.016*	-0.040***	0.065***	0.039***	0.047***
	(2.59)	(-1.77)	(-4.51)	(6.03)	(4.53)	(4.78)
Manager	0.067***	0.214***	0.154***	-0.126***	0.052***	0.060***
	(5.01)	(10.82)	(7.08)	(-6.11)	(3.71)	(3.81)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	96,983	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.154	0.117	0.171	0.129	0.119	0.145

Table 2-3. Gender differences in workplace attribute preferences

This table examines the gender differences in workplace preferences. The dependent variable is *Overall rating*. *Female* is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture* are the five subcomponent ratings. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	0.026	0.027	-0.114***	-0.065***	-0.074***
	(1.20)	(1.11)	(-4.71)	(-3.34)	(-2.92)
Career	0.657***				
	(128.03)				
Career × Female	-0.013**				
	(-2.15)				
Benefit		0.578***			
		(103.28)			
Benefit × Female		-0.019***			
		(-2.69)			
Work-life			0.510***		
			(71.47)		
Work-life × Female			0.033***		
			(5.12)		
Leadership				0.630***	
				(123.72)	
Leadership × Female				0.015***	
				(2.75)	
Culture					0.627***
					(96.05)
Culture × Female					0.014**
					(2.07)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.554	0.413	0.418	0.580	0.572

Table 2-4. Gender gaps in job satisfaction among mid-level managers

This table examines the differences in gender satisfaction gaps for mid-level managers and those of rank-and-file employees. The dependent variables include the overall employer rating, *Overall rating*, as well as the five subcomponent ratings, namely, *Career*, *Benefit*, *Work-life*, *Leadershi*p, and *Culture*. *Female* is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall rating	Career	Benefit	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Manager	0.073***	0.200***	0.138***	-0.111***	0.062***	0.068***
	(4.72)	(9.74)	(6.22)	(-5.02)	(3.67)	(3.73)
Female	-0.034***	-0.045***	-0.024*	-0.058***	-0.020	-0.032**
	(-2.70)	(-3.39)	(-1.68)	(-4.25)	(-1.37)	(-2.25)
Female × Manager	**-0.018**	**0.044****	**0.050****	**-0.047***	**-0.031**	**-0.024**
	(-0.88)	**(2.18)**	**(2.05)**	**(-1.80)**	**(-1.44)**	**(-0.98)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	96,983	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.154	0.117	0.171	0.129	0.119	0.145

Table 2-5. Gender gaps in workplace preferences among mid-level managers

This table examines the difference of gender gap in workplace preferences between mid-level managers and those of rank-and-file employees. The dependent variable is *Overall rating*. *Female* is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture* are the five subcomponent ratings. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Manager	-0.132***	-0.082**	0.133***	-0.058*	-0.055*
	(-4.27)	(-2.13)	(3.24)	(-1.91)	(-1.65)
Female	0.032	0.038	-0.159***	-0.075***	-0.089***
	(1.29)	(1.38)	(-5.28)	(-3.14)	(-2.83)
Female × Manager	-0.032	-0.054	0.148***	0.032	0.055
	(-0.66)	(-1.00)	(2.88)	(0.74)	(1.13)
Career	0.650***				
	(117.77)				
Career × Female	-0.012*				
	(-1.68)				
Career × Manager	0.023***				
	(3.04)				
Career × Female × Manager	-0.003				
	(-0.24)				
Benefit		0.572***			
		(95.09)			
Benefit × Female		-0.019**			
		(-2.34)			
Benefit × Manager		0.022**			
		(2.27)			
Benefit × Female × Manager		0.004			
		(0.29)			
Work-life			0.511***		
			(65.09)		
Work-life × Female			0.045***		
			(5.79)		
Work-life × Manager			-0.001		
			(-0.11)		
Work-life × Female × Manager			-0.041***		
			(-2.95)		
Leadership				0.621***	
				(109.64)	
Leadership × Female				0.017***	
				(2.58)	
Leadership × Manager				0.030***	
				(3.72)	
Leadership × Female × Manager				-0.009	
				(-0.70)	
Culture					0.621***
					(87.40)
Culture × Female					0.019**
					(2.23)
Culture × Manager					0.024***
					(2.73)
Culture × Female × Manager					-0.018
					(-1.37)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.554	0.413	0.419	0.580	0.572

Table 2-6. Gender satisfaction gap and firm value

This table examines the relation between the gender satisfaction gap in work-life balance and firm value. The dependent variable is *Tobin's q*, defined as the market value of equity plus total assets minus the book value of equity, all divided by total assets. For each firm in a particular year, I compute *Gender gap_WL* as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. I include a rich set of firm, governance, and CEO controls. *Average overall rating* is the average overall rating of all employees in a firm. *Best100* is an indicator that equals one if a firm is included in the "100 Best Companies to Work For in America" list, and zero otherwise. *R&D* is the ratio of R&D expenditures to total assets. *Ln(Sales)* is the natural logarithm of sales. *Cash* is cash and short-term investments divided by total assets. *Leverage* is total debt divided by total assets, where total debt is defined as current liabilities plus long-term debt. *Return* is the annual stock return. *Ln(Employee)* is the natural logarithm of the total number of employees. *% of Female director* is the fraction of female directors on the board. *Board size* is the number of directors on the board. *CEO chair* is an indicator variable that equals one if the CEO also chairs the board, and zero otherwise. *Female CEO* is an indicator that equals one if the CEO is female, and zero otherwise. *Ln(CEO tenure)* is the natural logarithm of the number of years the CEO has been in office. *Ln(CEO age)* is the natural logarithm of CEO age in years. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Tobin's Q	
	(1)	(2)
Gender gap_WL	**-0.025****	**-0.025****
	(-1.97)	**(-1.97)**
Average overall rating	0.132***	0.132***
	(3.79)	(3.80)
Best100		0.096
		(0.73)
R&D	3.556	3.580
	(0.63)	(0.63)
Ln(Sales)	0.609**	0.610**
	(2.39)	(2.39)
Cash	0.655**	0.664**
	(1.96)	(2.01)
Leverage	-0.219	-0.210
	(-0.74)	(-0.72)
Return	0.597***	0.597***
	(10.08)	(10.09)
Ln(Employee)	-0.253	-0.256
	(-1.39)	(-1.41)
% Female director	-0.303	-0.306
	(-0.95)	(-0.96)
Board size	-0.001	-0.001
	(-0.11)	(-0.12)
CEO chair	-0.011	-0.012
	(-0.16)	(-0.17)
Female CEO	0.015	0.015
	(0.13)	(0.13)
Ln(CEO tenure)	0.062*	0.062*
	(1.82)	(1.82)
Ln(CEO age)	-0.609**	-0.610**
	(-2.38)	(-2.38)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	3,758	3,758
Adjusted R-sq	0.217	0.217

Table 2-7. Channels in the relation between gender satisfaction gap and firm value

This table examines whether the gender satisfaction gap influences firm value through labor productivity. The dependent variable in Panel A is *Tobin's q*, defined as the market value of equity plus total assets minus the book value of equity, all divided by total assets. In Panel B, the dependent variables include: *Production/Emp* is the sum of the cost of goods sold and change of inventory divided by the total number of employees. *Revenue/Emp* is the sum of annual sales and change of inventory divided by the total number of employees. *ROA* is the return on assets. For each firm in a particular year, I compute *Gender gap_WL* as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. *High (Low) labor intensity* is an indicator that equals one if the industry *Labor intensity* is above (below) the sample median and zero otherwise, where *Labor intensity* is the average ratio of labor and pension expenses to sales in an industry in a year. All other variables are defined in Appendix 2-A1. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	ROA	Production/Emp	Revenue/Emp
	(1)	(2)	(3)
Gender gap_WL	**-0.002****	**-0.007****	**-0.006****
	(-2.49)	**(-2.10)**	**(-2.22)**
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	3,750	3,392	3,392
Adjusted R-sq	0.158	0.025	0.219

Table 2-8. Cross-sectional analysis in the relation between gender satisfaction gap and firm value

This table explores the cross-sectional heterogeneity in the relation between the gender satisfaction gap and firm value. The dependent variable is *Tobin's q*, defined as the market value of equity plus total assets minus the book value of equity, all divided by total assets. For each firm in a particular year, I compute *Gender gap_WL* as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. Panel A partitions firms into two subsamples based on whether the firm's industry is female-dominated. An industry is noted as being female-dominated if its percentage of women employed is above the sample median. Panel B split firms into strong and weak governance firms based on the sample median of the corporate governance measure in question. I use three measures of corporate governance. *Institutional blockholding* is the percentage of shares owned by all institutional investors who own 5% or more of the firm's equity. *Product market fluidity* captures changes in a firm's product space due to moves made by its rivals, based on a textual analysis of the firm's business descriptions in 10-K filings. *TW Co-option* is the sum of the tenure of co-opted directors divided by the total tenure of all directors, where co-opted directors are directors who join the board after the CEO assumes office. Panel C split firms into high and low financing constraints firms based on the sample median of the financing constraints measure in question. I use two measures. *WW Index*, proposed by Whited and Wu (2006), is a linear combination of six empirical factors, with higher values indicating more severe financing constraints. *Equity constraints* is a text-based financial constraints measure from Hoberg and Maksimovic (2015), with higher values indicating that firms are more at risk of delaying their investments due to issues with equity liquidity. All other variables are defined in Appendix 2-A1. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Industry female employee representation

	Female-dominated industry			
	Two-digit NAICS		Fama-French 12	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Gender gap_WL	**-0.009**	**-0.043***	**-0.012**	**-0.039****
	(-0.61)	**(-1.92)**	**(-0.71)**	**(-2.04)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2,213	1,498	1,998	1,760
Adjusted R-sq	0.187	0.288	0.184	0.278

Panel B. Corporate governance

	Institutional blockholding		Product market fluidity		TW Co-option	
	Low	High	Low	High	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Gender gap_WL	**0.007**	**-0.043****	**-0.012**	**-0.038****	**-0.023**	**-0.036****
	(0.38)	**(-2.18)**	**(-0.66)**	**(-2.18)**	**(-1.00)**	**(-2.04)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,858	1,853	1,845	1,842	1,747	1,752
Adjusted R-sq	0.238	0.251	0.266	0.214	0.258	0.254

Panel C. Financial constraints

	WW Index		Equity constraints	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Gender gap_WL	**-0.049****	**-0.003**	**-0.049***	**-0.011**
	(-2.39)	**(-0.28)**	**(-1.84)**	**(-0.38)**
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,864	1,859	1,082	1,078
Adjusted R-sq	0.279	0.191	0.223	0.257

Table 2-9. Returns for stock portfolios sorted on the gender satisfaction gap

This table reports the return results of a sorted portfolio using the Fama-French-Carhart 4-factor model, MKT, HML, SMB, and MOM. The sample is partitioned into three portfolios based on the quarterly work-life balance gender gap, including low (bottom 20%), middle (middle 60%), and high (top 20%) gender gap portfolios. I then track the returns of the three portfolios over the following quarter. The dependent variable is the monthly portfolio excess return (raw return less the risk-free rate). Portfolio results are reported using equal- and value-weighted portfolio weights. Newey–West adjusted t -statistics are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Equal-Weighted				Value-Weighted			
	Low	Middle	High	L-H	Low	Middle	High	L-H
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	**0.561****	**0.054**	**-0.328**	**0.889****	**0.568****	**0.132**	**-0.338**	**0.906*****
	(2.12)	**(0.25)**	**(-1.21)**	**(2.42)**	**(2.45)**	**(0.62)**	**(-1.33)**	**(2.98)**
MKT	0.906***	0.947***	0.949***	-0.043	0.957***	0.901***	0.952***	0.006
	(10.15)	(16.90)	(16.22)	(-0.55)	(12.76)	(17.68)	(14.73)	(0.07)
SMB	0.012	-0.050	0.210**	-0.197*	-0.233*	-0.157**	0.138	-0.371***
	(0.10)	(-0.64)	(2.16)	(-1.90)	(-1.92)	(-2.32)	(1.49)	(-2.98)
HML	0.205	-0.089	-0.173	0.378**	0.132	0.023	-0.158	0.291*
	(1.57)	(-1.04)	(-1.11)	(2.37)	(1.21)	(0.30)	(-0.99)	(1.83)
MOM	-0.049	-0.110**	-0.085	0.036	0.027	-0.084***	-0.044	0.071
	(-0.79)	(-2.31)	(-1.15)	(0.63)	(0.43)	(-2.87)	(-0.77)	(1.10)

Table 2-10. Gender satisfaction gap and stock returns: Fama-MacBeth regressions

This table reports the average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of monthly stock returns on the gender satisfaction gap. *Gender gap_WL* is defined as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. The set of controls follows those of Brennan et al. (1998), Gompers et al. (2003), and Edmans (2011). *Best100* is an indicator that equals one if a firm is included in the "100 Best Companies to Work For in America" list, and zero otherwise. *Size* is the natural logarithm of the firm's market capitalization (in billions) in month *t*-2. *BM* is the natural logarithm of the firm's book-to-market ratio at the end of the previous fiscal year. *Return2–3*, *Return4–6*, and *Return7–12* are the natural logarithms of the compounded returns in month *t*-3 to month *t*-2, month *t*-6 to month *t*-4, and month *t*-12 to month *t*-7, respectively. *Price* is the natural logarithm of the stock price at the end of month *t*-2; *Vol* is the natural logarithm of the dollar trading volume (in millions) in month *t*-2; *Div. Yield* is the firm's dividend yield at the end of the previous fiscal year. Newey–West adjusted *t*-statistics are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

	Return	
	(1)	(2)
Gender gap_WL	**-0.428****	**-0.470****
	(-2.49)	**(-2.31)**
Best100		0.816
		(0.93)
Size		0.104
		(0.35)
BM		0.023
		(0.06)
Return2-3		-2.282
		(-1.02)
Return4-6		-2.978
		(-1.49)
Return7-12		1.211
		(0.85)
Div. Yield		-0.082
		(-0.78)
Price		0.266
		(0.63)
Vol		-0.543
		(-1.02)
N	6,665	6,665

Appendix 2-A1. Variable definitions

Variable	Definition	Data source
Glassdoor rating components		
Overall rating	Employee's overall rating of employer ranked on a five-point scale, with five (one) being most favorable (unfavorable).	Glassdoor
Career	Employee's opinion of his or her opportunities for career prospects at the company ranked on a five-point scale, with five (one) being most favorable (unfavorable).	Glassdoor
Compensation	Employee's opinion of his or her compensation and benefits package ranked on a five-point scale, with five (one) being most favorable (unfavorable).	Glassdoor
Work-life	Employee's opinion of his or her work-life balance ranked on a five-point scale, with five (one) being most favorable (unfavorable).	Glassdoor
Leadership	Employee's opinion of employer's senior management ranked on a five-point scale, with five (one) being most favorable (unfavorable).	Glassdoor
Culture	Employee's opinion of employer's culture and values ranked on a five-point scale, with five (one) being most favorable (unfavorable). This rating is available in Glassdoor only from 2012 onwards.	Glassdoor
Employee characteristics		
Female	An indicator that equals one if the review is completed by a female employee, and zero otherwise.	Glassdoor
Gender gap_WL	Difference in the average work-life balance rating between female and male employees in a firm.	Glassdoor
Gender gap_Overall	Difference in the average overall rating between female and male employees in a firm.	Glassdoor
Education	Employee's highest education level, coded as 0 (below bachelor), 1 (bachelor), 2 (Master's and MBA), and 3 (PhD).	Glassdoor
Age	Employee's age in years.	Glassdoor
Average overall rating	Average overall rating of all employees in a firm.	Glassdoor
Manager	An indicator that equals one if the review is completed by a mid-level manager (e.g., group, regional or divisional managers), and zero otherwise.	Glassdoor
Firm characteristics		
Best100	An indicator that equals one if a firm is included in the "100 Best Companies to Work For in America" list, and zero otherwise.	Great Place to Work®
Ln(Sales)	Natural logarithm of sales. Sales is converted into year 2008 dollars using the Consumer Price Index obtained from the Bureau of Labor Statistics.	Compustat

Leverage	Total debt divided by total assets, where total debt is defined as current liabilities plus long-term debt.	Compustat
Cash	Cash and short-term investments divided by total assets.	Compustat
R&D	Ratio of R&D expenditures to total assets.	Compustat
Tobin's q	Market value of equity plus total assets minus the book value of equity, all divided by total assets, where market value of equity is the product of fiscal year-end closing price and number of shares outstanding.	Compustat
ROA	Return on assets.	Compustat
Production/Emp	Sum of cost of goods sold and change of inventory divided by total number of employees.	Compustat
Revenue/Emp	Sum of total annual sales and change of inventory divided by total number of employees.	Compustat
Return	Annual stock return.	Compustat
Ln(Employee)	Natural logarithm of the number of employees.	Compustat
Governance and CEO characteristics		
CEO chair	An indicator that equals one if the CEO also chairs the board, and zero otherwise.	Execucomp
Ln(CEO tenure)	Natural logarithm of the number of years the CEO has been in office.	Execucomp
Ln(CEO age)	Natural logarithm of the age of the CEO in years.	Execucomp
Female CEO	An indicator that equals one if the CEO is female, and zero otherwise	Execucomp
% Female director	Number of female directors on the board divided by board size.	RiskMetrics
Board size	Number of directors on the board.	RiskMetrics
Variables for endogeneity		
Average cost childcare	Average employee-specific *Cost childcare under 3* in a firm in a year, based on the employee's work location.	Childcare Aware® of America
Cost childcare under 3	Cost of childcare for children under three years old in a state as a percentage of the state's personal income per capita.	Childcare Aware® of America; Bureau of Economic Analysis

Appendix 2-A2. Robustness tests: Including all subcomponent ratings in the same regression

This table reproduces my main results (Tables 4 and 6) after including all of the subcategory ratings in the same specification. The dependent variable is *Overall rating*. *Female* is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture* are the five subcomponent ratings. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-1A. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively

Panel A. Gender differences in job attribute preferences

	Overall rating	
	(1)	(2)
Female	0.051**	0.035
	(2.38)	(1.51)
Career	0.317***	0.242***
	(59.67)	(43.44)
Career × Female	-0.040***	-0.035***
	(-5.85)	(-4.66)
Benefit	0.184***	0.170***
	(38.18)	(31.19)
Benefit × Female	-0.022***	-0.024***
	(-3.49)	(-3.74)
Work-life	0.166***	0.115***
	(38.30)	(25.51)
Work-life × Female	0.026***	0.025***
	(4.77)	(4.13)
Leadership	0.304***	0.204***
	(65.93)	(45.81)
Leadership × Female	0.019***	-0.000
	(2.93)	(-0.01)
Culture		0.238***
		(45.64)
Culture × Female		0.019**
		(2.30)
Controls	Yes	Yes
Firm-Year FE	Yes	Yes
N	90,080	67,288
Adjusted R-sq	0.715	0.731

Panel B. Gender gaps in workplace preferences among mid-level managers

	Overall rating	
	(1)	(2)
Manager	-0.104***	-0.099***
	(-4.34)	(-3.64)
Female	0.051**	0.031
	(2.24)	(1.15)
Female × Manager	-0.023	-0.007
	(-0.56)	(-0.15)
Career	0.318***	0.247***
	(51.43)	(36.77)
Career × Female	-0.039***	-0.034***
	(-5.13)	(-4.02)
Career × Manager	-0.003	-0.016*
	(-0.41)	(-1.65)
Career × Female × Manager	-0.001	-0.003
	(-0.08)	(-0.19)
Benefit	0.189***	0.173***
	(38.38)	(29.88)
Benefit × Female	-0.031***	-0.033***
	(-4.24)	(-4.37)
Benefit × Manager	-0.016**	-0.013
	(-2.19)	(-1.48)
Benefit × Female × Manager	0.038***	0.036***
	(2.89)	(2.63)
Work-life	0.164***	0.113***
	(35.46)	(23.81)
Work-life × Female	0.033***	0.030***
	(4.96)	(4.15)
Work-life × Manager	0.006	0.007
	(0.90)	(0.99)
Work-life × Female × Manager	-0.024**	-0.017
	(-2.04)	(-1.31)
Leadership	0.291***	0.196***
	(57.12)	(37.97)
Leadership × Female	0.021***	0.002
	(2.68)	(0.16)
Leadership × Manager	0.044***	0.028***
	(5.50)	(3.11)
Leadership × Female × Manager	-0.009	-0.005
	(-0.65)	(-0.31)
Culture		0.232***
		(37.34)
Culture × Female		0.021**
		(1.98)
Culture × Manager		0.022**
		(2.28)
Culture × Female × Manager		-0.009
		(-0.50)
Controls	Yes	Yes
Firm-Year FE	Yes	Yes
N	90,080	67,288
Adjusted R-sq	0.716	0.732

Appendix 2-A3. Robustness tests: Replacing the education variable with education dummies

This table reproduces my main results (Tables 3, 4, and 6) after replacing the education variable with a set of education dummies. *Bachelor* is an indicator variable that equals one if the employee has a bachelor's degree and zero otherwise. *Master(MBA)* is an indicator variable that equals one if the employee has a Master's or MBA degree and zero otherwise. *PhD* is an indicator variable that equals one if the employee has a PhD degree and zero otherwise. The holdout group consists of those who do not have a bachelor's or above degree. The dependent variables include the overall job satisfaction rating, *Overall Rating*, and the five subcomponent ratings, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively in Panel A. The variable of interest, *Female*, is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Gender differences in job satisfaction after replacing the education variable with education dummies

	Overall rating	Career	Compensation	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Female	**-0.039*****	**-0.032*****	**-0.010**	**-0.071*****	**-0.029****	**-0.039*****
	(-3.51)	**(-2.91)**	**(-0.87)**	**(-5.88)**	**(-2.31)**	**(-3.15)**
Age	-0.010***	-0.013***	-0.001*	-0.010***	-0.012***	-0.013***
	(-12.26)	(-16.42)	(-1.77)	(-11.16)	(-13.27)	(-12.00)
Bachelor	0.062***	0.020	-0.005	0.087***	0.091***	0.080***
	(4.76)	(1.22)	(-0.33)	(5.46)	(6.20)	(4.80)
Master (MBA)	0.055***	-0.025	-0.078***	0.147***	0.102***	0.111***
	(3.50)	(-1.25)	(-4.15)	(6.75)	(5.65)	(5.42)
PhD	0.010	-0.027	-0.052	0.096	0.028	0.023
	(0.24)	(-0.58)	(-1.15)	(1.47)	(0.56)	(0.37)
Manager	0.067***	0.215***	0.155***	-0.127***	0.051***	0.060***
	(5.00)	(10.86)	(7.12)	(-6.15)	(3.68)	(3.79)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	96,983	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.154	0.117	0.171	0.129	0.119	0.145

Panel B. Gender differences in job attribute preferences after replacing the education variable with education dummies

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	0.026	0.028	-0.114***	-0.065***	-0.073***
	(1.20)	(1.12)	(-4.72)	(-3.33)	(-2.91)
Career	0.656***				
	(128.01)				
Career × Female	-0.013**				
	(-2.15)				
Compensation		0.578***			
		(103.66)			
Compensation × Female		-0.019***			
		(-2.70)			
Work-life			0.510***		
			(71.44)		
Work-life × Female			0.033***		
			(5.13)		
Leadership				0.630***	
				(123.79)	
Leadership × Female				0.015***	
				(2.74)	
Culture					0.627***
					(96.14)
Culture × Female					0.014**
					(2.06)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.554	0.413	0.419	0.580	0.572

Panel C. Gender gaps in workplace preferences among mid-level managers after replacing the education variable with education dummies

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Manager	-0.133***	-0.082**	0.133***	-0.058*	-0.055*
	(-4.29)	(-2.15)	(3.24)	(-1.90)	(-1.66)
Female	0.032	0.039	-0.158***	-0.075***	-0.089***
	(1.29)	(1.39)	(-5.28)	(-3.13)	(-2.82)
Female × Manager	-0.032	-0.054	0.147***	0.032	0.055
	(-0.68)	(-1.01)	(2.87)	(0.73)	(1.12)
Career	0.650***				
	(117.81)				
Career × Female	-0.012*				
	(-1.69)				
Career × Manager	0.023***				
	(3.06)				
Career × Female × Manager	-0.003				
	(-0.23)				
Benefit		0.572***			
		(95.48)			
Benefit × Female		-0.019**			
		(-2.35)			
Benefit × Manager		0.022**			
		(2.27)			
Benefit × Female × Manager		0.004			
		(0.30)			
Work-life			0.510***		
			(65.08)		
Work-life × Female			0.045***		
			(5.80)		
Work-life × Manager			-0.001		
			(-0.10)		
Work-life × Female × Manager			-0.041***		
			(-2.96)		
Leadership				0.621***	
				(109.75)	
Leadership × Female				0.017***	
				(2.58)	
Leadership × Manager				0.030***	
				(3.73)	
Leadership × Female × Manager				-0.009	
				(-0.71)	
Culture					0.620***
					(87.54)
Culture × Female					0.019**
					(2.22)
Culture × Manager					0.024***
					(2.75)
Culture × Female × Manager					-0.017
					(-1.36)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.554	0.414	0.419	0.580	0.573

Appendix 2-A4. Robustness tests: Excluding observations between 2008 and 2010

This table reproduces my main results (Tables 3, 4, and 6) after excluding observations between 2008 and 2010. The dependent variables include the overall job satisfaction rating, *Overall Rating*, and the five subcomponent ratings, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively in Panel A. The variable of interest, *Female*, is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Gender differences in job satisfaction after excluding observations between 2008 and 2010

	Overall rating	Career	Compensation	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Female	**-0.045*** **	**-0.034*** **	**-0.012**	**-0.074*** **	**-0.037*** **	**-0.039*** **
	(-3.95)	**(-2.90)**	**(-1.00)**	**(-5.74)**	**(-3.03)**	**(-3.12)**
Age	-0.011***	-0.013***	-0.002***	-0.011***	-0.013***	-0.013***
	(-12.21)	(-15.73)	(-2.92)	(-11.26)	(-13.28)	(-12.28)
Education	0.028***	-0.007	-0.039***	0.065***	0.038***	0.047***
	(3.32)	(-0.72)	(-4.22)	(5.70)	(3.87)	(4.78)
Manager	0.068***	0.217***	0.165***	-0.151***	0.047***	0.060***
	(4.77)	(10.04)	(7.55)	(-7.08)	(3.21)	(3.81)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	79,822	77,833	77,746	77,718	77,309	71,100
Adjusted R-sq	0.147	0.114	0.171	0.133	0.119	0.145

Panel B. Gender differences in job attribute preferences after excluding observations between 2008 and 2010

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	0.026	0.034	-0.126***	-0.055***	-0.074***
	(1.10)	(1.35)	(-4.78)	(-2.61)	(-2.92)
Career	0.643***				
	(113.99)				
Career × Female	-0.015**				
	(-2.22)				
Compensation		0.569***			
		(99.47)			
Compensation × Female		-0.022***			
		(-3.10)			
Work-life			0.498***		
			(63.37)		
Work-life × Female			0.035***		
			(4.95)		
Leadership				0.627***	
				(110.72)	
Leadership × Female				0.011*	
				(1.89)	
Culture					0.627***
					(96.05)
Culture × Female					0.014**
					(2.07)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	77,833	77,746	77,718	77,309	71,100
Adjusted R-sq	0.542	0.412	0.409	0.575	0.572

Panel C. Gender gaps in workplace preferences among mid-level managers after excluding observations between 2008 and 2010

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Manager	-0.149***	-0.107***	0.140***	-0.066**	-0.055*
	(-4.21)	(-2.63)	(3.21)	(-1.99)	(-1.65)
Female	0.024	0.040	-0.176***	-0.065**	-0.089***
	(0.86)	(1.36)	(-5.24)	(-2.45)	(-2.83)
Female × Manager	-0.001	-0.032	0.164***	0.031	0.055
	(-0.02)	(-0.57)	(2.93)	(0.66)	(1.13)
Career	0.635***				
	(103.00)				
Career × Female	-0.011				
	(-1.41)				
Career × Manager	0.028***				
	(3.33)				
Career × Female × Manager	-0.012				
	(-0.90)				
Benefit		0.562***			
		(90.53)			
Benefit × Female		-0.021**			
		(-2.46)			
Benefit × Manager		0.029***			
		(2.70)			
Benefit × Female × Manager		-0.002			
		(-0.15)			
Work-life			0.498***		
			(57.81)		
Work-life × Female			0.049***		
			(5.55)		
Work-life × Manager			0.000		
			(0.01)		
Work-life × Female × Manager			-0.047***		
			(-3.07)		
Leadership				0.618***	
				(98.19)	
Leadership × Female				0.014*	
				(1.86)	
Leadership × Manager				0.034***	
				(3.96)	
Leadership × Female × Manager				-0.009	
				(-0.67)	
Culture					0.621***
					(87.40)
Culture × Female					0.019**
					(2.23)
Culture × Manager					0.024***
					(2.73)
Culture × Female × Manager					-0.018
					(-1.37)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	77,833	77,746	77,718	77,309	71,100
Adjusted R-sq	0.543	0.412	0.409	0.575	0.572

Appendix 2-A5. Robustness tests: Using reviews by both current and former employees and excluding controls for employee characteristics

This table reproduces my main results (Tables 3, 4, and 6) after adding back reviews by former employees and excluding the controls for employee characteristics. The dependent variables include the overall job satisfaction rating, *Overall Rating*, and the five subcomponent ratings, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively in Panel A. The variable of interest, *Female*, is an indicator variable that equals one if the review is posted by female employee, and zero otherwise. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Gender differences in job satisfaction after adding back reviews by former employees and excluding controls for employee characteristics

	Overall rating	Career	Compensation	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Former	-0.307***	-0.267***	-0.072***	-0.243***	-0.320***	-0.342***
	(-26.32)	(-24.23)	(-6.00)	(-30.78)	(-26.56)	(-28.20)
Female	**-0.046*** **	**-0.043*** **	**-0.005**	**-0.085*** **	**-0.033*** **	**-0.043*** **
	(-7.34)	**(-6.72)**	**(-0.63)**	**(-10.76)**	**(-4.52)**	**(-5.78)**
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	319,279	299,116	298,854	298,805	296,853	232,072
Adjusted R-sq	0.140	0.102	0.165	0.114	0.108	0.141

Panel B. Gender differences in job attribute preferences after adding back reviews by former employees and excluding controls for employee characteristics

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Former	-0.134***	-0.269***	-0.180***	-0.101***	-0.110***
	(-21.07)	(-32.06)	(-20.69)	(-19.08)	(-20.49)
Female	0.045***	0.017	-0.068***	-0.047***	-0.032**
	(3.73)	(1.16)	(-5.15)	(-4.09)	(-2.51)
Career	0.670***				
	(166.02)				
Career × Female	-0.019***				
	(-5.35)				
Compensation		0.580***			
		(136.01)			
Compensation × Female		-0.017***			
		(-4.03)			
Work-life			0.530***		
			(111.64)		
Work-life × Female			0.023***		
			(5.83)		
Leadership				0.652***	
				(155.77)	
Leadership × Female				0.010***	
				(2.71)	
Culture					0.647***
					(148.23)
Culture × Female					0.004
					(1.18)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	299,116	298,854	298,805	296,853	232,072
Adjusted R-sq	0.546	0.395	0.421	0.585	0.590

Panel C. Gender gaps in workplace preferences among mid-level managers after adding back reviews by former employees and excluding controls for employee characteristics

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Former	-0.133***	-0.266***	-0.178***	-0.101***	-0.109***
	(-18.54)	(-30.34)	(-19.20)	(-16.65)	(-17.73)
Manager	-0.167***	-0.141***	0.128***	-0.041**	-0.045**
	(-7.31)	(-4.75)	(4.31)	(-2.10)	(-2.11)
Female	0.054***	0.023	-0.099***	-0.042***	-0.027
	(2.96)	(1.06)	(-5.05)	(-2.76)	(-1.43)
Female × Manager	-0.014	0.002	0.101***	0.013	0.032
	(-0.43)	(0.06)	(3.19)	(0.54)	(1.09)
Career	0.660***				
	(135.37)				
Career × Female	-0.018***				
	(-3.54)				
Career × Manager	0.024***				
	(4.31)				
Career × Female × Manager	-0.007				
	(-0.86)				
Benefit		0.573***			
		(110.47)			
Benefit × Female		-0.013**			
		(-2.07)			
Benefit × Manager		0.016**			
		(2.08)			
Benefit × Female × Manager		-0.011			
		(-1.04)			
Work-life			0.529***		
			(89.98)		
Work-life × Female			0.036***		
			(6.30)		
Work-life × Manager			-0.009		
			(-1.13)		
Work-life × Female × Manager			-0.029***		
			(-3.17)		
Leadership				0.640***	
				(139.97)	
Leadership × Female				0.010**	
				(2.20)	
Leadership × Manager				0.024***	
				(4.49)	
Leadership × Female × Manager				-0.003	
				(-0.36)	
Culture					0.640***
					(132.83)
Culture × Female					0.006
					(1.03)
Culture × Manager					0.018***
					(3.16)
Culture × Female × Manager					-0.011
					(-1.41)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	188,518	188,395	188,359	187,386	146,936
Adjusted R-sq	0.542	0.396	0.421	0.580	0.588

Appendix 2-A6. Robustness tests: Excluding extreme reviewers

This table reproduces my main results (Tables 3, 4, and 6) after dropping extreme reviews with a 1 or 5 overall rating. The dependent variables include the overall job satisfaction rating, *Overall Rating*, and the five subcomponent ratings, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively in Panel A. The variable of interest, *Female*, is an indicator variable that equals one if the review is posted by a female employee, and zero otherwise. *Manager* is an indicator variable that equals to one if the review is posted by a mid-level manager, and zero otherwise. All other variables are defined in Appendix 2-A1. Firm-Year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A. Gender differences in job satisfaction after dropping extreme reviews with 1 or 5 overall rating

	Overall rating	Career	Benefit	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Female	**-0.035*** **	**-0.026** **	**-0.011**	**-0.086*** **	**-0.031** **	**-0.047*** **
	(-4.65)	**(-2.28)**	**(-0.90)**	**(-7.04)**	**(-2.48)**	**(-3.80)**
Age	-0.006***	-0.010***	0.002**	-0.009***	-0.011***	-0.010***
	(-10.98)	(-14.83)	(2.27)	(-8.84)	(-11.89)	(-10.49)
Education	0.030***	-0.008	-0.034***	0.088***	0.057***	0.064***
	(5.22)	(-0.83)	(-3.59)	(7.71)	(6.23)	(5.93)
Manager	0.019**	0.189***	0.138***	-0.174***	0.004	0.015
	(2.00)	(9.66)	(6.14)	(-7.27)	(0.29)	(0.99)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	70,698	69,157	69,105	69,093	68,796	50,708
Adjusted R-sq	0.085	0.068	0.137	0.119	0.061	0.092

Panel B. Gender differences in job attribute preferences after dropping extreme reviews with 1 or 5 overall rating

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	0.088***	0.045*	-0.064***	-0.025	-0.052***
	(4.18)	(1.86)	(-3.28)	(-1.45)	(-2.60)
Career	0.398***				
	(82.11)				
Career × Female	-0.037***				
	(-6.02)				
Benefit		0.309***			
		(59.60)			
Benefit × Female		-0.025***			
		(-3.54)			
Work-life			0.264***		
			(69.27)		
Work-life × Female			0.016***		
			(3.04)		
Leadership				0.384***	
				(95.89)	
Leadership × Female				0.000	
				(0.01)	
Culture					0.360***
					(93.68)
Culture × Female					0.006
					(1.11)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	69,157	69,105	69,093	68,796	50,708
Adjusted R-sq	0.340	0.226	0.228	0.377	0.364

Panel C. Gender gaps in workplace preferences among mid-level managers after dropping extreme reviews with 1 or 5 overall rating

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Manager	-0.088***	-0.020	0.095***	-0.091***	-0.035
	(-3.28)	(-0.54)	(3.30)	(-4.04)	(-1.21)
Female	0.097***	0.053*	-0.088***	-0.035*	-0.055**
	(3.89)	(1.87)	(-3.78)	(-1.75)	(-2.17)
Female × Manager	-0.038	-0.034	0.072*	0.033	0.008
	(-0.88)	(-0.65)	(1.80)	(0.92)	(0.18)
Career	0.395***				
	(70.63)				
Career × Female	-0.039***				
	(-5.33)				
Career × Manager	0.012*				
	(1.73)				
Career × Female × Manager	0.008				
	(0.63)				
Benefit		0.309***			
		(49.06)			
Benefit × Female		-0.027***			
		(-3.23)			
Benefit × Manager		-0.000			
		(-0.00)			
Benefit × Female × Manager		0.009			
		(0.58)			
Work-life			0.267***		
			(63.52)		
Work-life × Female			0.021***		
			(3.41)		
Work-life × Manager			-0.012		
			(-1.59)		
Work-life × Female × Manager			-0.016		
			(-1.34)		
Leadership				0.374***	
				(83.43)	
Leadership × Female				0.002	
				(0.26)	
Leadership × Manager				0.036***	
				(5.56)	
Leadership × Female × Manager				-0.005	
				(-0.43)	
Culture					0.357***
					(87.50)
Culture × Female					0.005
					(0.76)
Culture × Manager					0.012
					(1.60)
Culture × Female × Manager					0.004
					(0.31)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
N	69,157	69,105	69,093	68,796	50,708
Adjusted R-sq	0.340	0.226	0.228	0.378	0.364

Appendix 2-A7. Robustness tests: Introducing firm-position-year fixed effects

In this table, I reproduce the main results for my employee-level analyses after introducing firm-position-year fixed effects. The dependent variables include the overall job satisfaction rating, *Overall Rating*, and the five subcomponent ratings, *Career*, *Compensation*, *Work-life*, *Leadership*, and *Culture*, respectively. The variable of interest, *Female*, is a dummy variable taking a value of one if female, and zero otherwise. All other variables are defined in Appendix 2-A1. Statistical significance is based on the heteroscedasticity robust firm-clustered standard errors reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Panel A. Gender differences in job satisfaction with firm-position-year fixed effects

	Overall rating	Career	Compensation	Work-life	Leadership	Culture
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.045***	-0.027**	-0.009	-0.072***	-0.037**	-0.042***
	(-3.59)	(-2.14)	(-0.66)	(-5.52)	(-2.55)	(-2.80)
Age	-0.010***	-0.013***	-0.002***	-0.011***	-0.013***	-0.013***
	(-10.10)	(-13.96)	(-2.71)	(-10.43)	(-10.80)	(-10.09)
Education	0.012	-0.028***	-0.041***	0.043***	0.029***	0.040***
	(1.51)	(-2.84)	(-4.24)	(4.10)	(3.21)	(3.70)
Firm-Position-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	96,983	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.173	0.136	0.183	0.152	0.133	0.157

Panel B. Gender differences in job attribute preferences with firm-position-year fixed effects

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	0.002	-0.001	-0.136***	-0.072***	-0.078**
	(0.10)	(-0.02)	(-4.78)	(-3.23)	(-2.54)
Career	0.650***				
	(111.51)				
Career × Female	-0.009				
	(-1.28)				
Compensation		0.574***			
		(91.04)			
Compensation × Female		-0.012			
		(-1.54)			
Work-life			0.505***		
			(60.03)		
Work-life × Female			0.038***		
			(5.01)		
Leadership				0.621***	
				(106.31)	
Leadership × Female				0.017***	
				(2.67)	
Culture					0.618***
					(86.12)
Culture × Female					0.014*
					(1.77)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Position-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.559	0.427	0.428	0.581	0.576

Panel C. Gender gaps in workplace preferences among mid-level managers with firm-position-year fixed effects

	Overall rating				
	(1)	(2)	(3)	(4)	(5)
Female	-0.012	-0.002	-0.180***	-0.090***	-0.100**
	(-0.42)	(-0.06)	(-4.98)	(-3.20)	(-2.58)
Female × Manager	0.052	0.003	0.136**	0.058	0.076
	(0.94)	(0.05)	(2.26)	(1.16)	(1.36)
Career	0.644***				
	(99.59)				
Career × Female	-0.005				
	(-0.59)				
Career × Manager	0.022**				
	(2.35)				
Career × Female × Manager	-0.015				
	(-1.08)				
Compensation		0.568***			
		(82.45)			
Compensation × Female		-0.011			
		(-1.23)			
Compensation × Manager		0.022*			
		(1.85)			
Compensation × Female × Manager		-0.002			
		(-0.14)			
Work-life			0.500***		
			(55.00)		
Work-life × Female			0.051***		
			(5.45)		
Work-life × Manager			0.017		
			(1.44)		
Work-life × Female × Manager			-0.044***		
			(-2.66)		
Leadership				0.609***	
				(93.34)	
Leadership × Female				0.023***	
				(2.84)	
Leadership × Manager				0.041***	
				(4.03)	
Leadership × Female × Manager				-0.019	
				(-1.39)	
Culture					0.609***
					(78.00)
Culture × Female					0.021**
					(2.05)
Culture × Manager					0.029***
					(2.71)
Culture × Female × Manager					-0.022
					(-1.54)
Controls	Yes	Yes	Yes	Yes	Yes
Firm-Position-Year FE	Yes	Yes	Yes	Yes	Yes
N	94,994	94,907	94,879	94,470	71,100
Adjusted R-sq	0.559	0.427	0.428	0.582	0.576

Appendix 2-A8. Gender gap in overall rating and firm value

This table examines the relation between the gender gap in overall rating and firm value. The dependent variable is *Tobin's q*, defined as the market value of equity plus total assets minus the book value of equity, all divided by total assets. For each firm in a particular year, I compute *Gender gap_Overall* as the average overall rating of male employees minus the average overall rating of female employees. I include a rich set of firm, governance, and CEO controls. *Average overall rating* is the average overall rating of all employees in a firm. *Best100* is an indicator that equals one if a firm is included in the "100 Best Companies to Work For in America" list, and zero otherwise. *R&D* is the ratio of R&D expenditures to total assets. *Ln(Sales)* is the natural logarithm of sales. *Cash* is cash and short-term investments divided by total assets. *Leverage* is total debt divided by total assets, where total debt is defined as current liabilities plus long-term debt. *Return* is the annual stock return. *Ln(Employee)* is the natural logarithm of the total number of employees. *% of Female director* is the fraction of female directors on the board. *Board size* is the number of directors on the board. *CEO chair* is an indicator variable that equals one if the CEO also chairs the board, and zero otherwise. *Female CEO* is an indicator that equals one if the CEO is female, and zero otherwise. *Ln(CEO tenure)* is the natural logarithm of the number of years the CEO has been in office. *Ln(CEO age)* is the natural logarithm of CEO age in years. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Tobin's Q	
	(1)	(2)
Gender gap_Overall	**-0.030****	**-0.030****
	(-2.27)	**(-2.28)**
Average overall rating	0.133***	0.132***
	(3.77)	(3.78)
Best100		0.100
		(0.75)
R&D	3.597	3.623
	(0.63)	(0.64)
Ln(Sales)	0.608**	0.609**
	(2.38)	(2.39)
Cash	0.656**	0.665**
	(1.97)	(2.02)
Leverage	-0.217	-0.208
	(-0.73)	(-0.71)
Return	0.595***	0.595***
	(10.12)	(10.14)
Ln(Employee)	-0.255	-0.258
	(-1.40)	(-1.42)
% Female director	-0.309	-0.311
	(-0.97)	(-0.98)
Board size	-0.001	-0.002
	(-0.12)	(-0.13)
CEO chair	-0.011	-0.012
	(-0.17)	(-0.18)
Female CEO	0.015	0.015
	(0.13)	(0.13)
Ln(CEO tenure)	0.064*	0.064*
	(1.88)	(1.89)
Ln(CEO age)	-0.626**	-0.628**
	(-2.45)	(-2.45)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	3,758	3,758
Adjusted R-sq	0.217	0.218

Appendix 2-A9. Instrumental variable approach

This table presents the results of the instrumental variable method using two-stage least squares (2SLS) panel regressions. The dependent variables are *Gender gap_WL* and *Tobin's q* for the first-stage and second-stage regressions, respectively. *Tobin's q* is defined as the market value of equity plus total assets minus the book value of equity, all divided by total assets. For each firm-year observation, I calculate *Gender gap_WL* as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. The instrumental variable, *Average cost childcare*, is the average employee-specific *Cost childcare under 3* in a firm in a year, based on the employee's work location. I add the same set of firm, governance, and CEO controls as in Table 9 including *Average overall rating*, *Best100*, *R&D*, *Ln*(*Sales*), *Cash*, *Leverage*, *Return*, *Ln(Employee)*, *% Female directors*, *Board size*, *CEO chair*, *Female CEO*, *Ln(CEO tenure)*, and *Ln(CEO age)*. All other variables are defined in Appendix 2-A1. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	2SLS	
	Gender gap_WL First stage	Tobin's Q Second stage
	(1)	(3)
Gender gap_WL		-0.665*
		(-1.65)
Average cost childcare	3.046**	
	(2.11)	
Controls	Yes	Yes
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
N	2,798	2,798

Appendix 2-A10. Alternative explanations for the value effect of gender satisfaction gap

This table reports the results of regressing employee turnover and corporate innovation on the gender gap of work-life balance. *Employee turnover* is the number of forfeited employee stock options in the previous year divided by the total number of outstanding stock options, following Carter and Lynch (2004) and Babenko and Sen (2014). *Ln(Patent)* is the natural logarithm of the number of patents. For each fir-year, I compute *Gender gap_WL* as the average work-life balance rating of male employees minus the average work-life balance rating of female employees. All other variables are defined in Appendix 2-A1. Firm and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Employee turnover	Ln(Patent)
	(1)	(2)
Gender gap_WL	**-0.001**	**0.001**
	(-0.28)	**(0.17)**
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	3,547	3,758
Adjusted R-sq	0.040	0.308

3 Financial Constraints and Employee Satisfaction

3.1 Introduction

Employees, as a key ingredient of human capital, play a pivotal role in the modern corporation. Most firms face the challenge of recruiting and retaining talented and skilled employees and improving employee engagement in today's competitive labor market. Prior literature highlights the satisfaction of employees can enhance employee motivation and retention (Maslow, 1943; Hertzberg, 1959; McGregor, 1960; Becker and Gerhart, 1996), which in turn have a favorable impact on firm performance (Edmans, 2011; Green et al., 2019). To increase employee satisfaction, many firms spend considerable resources not only on employee compensation but also on the construction of employee-friendly workplaces with flexible working schedules and supportive management styles. For instance, Google provides various benefits for employees, including free food, onsite childcare facilities, flexible holiday and leave policies, 20% Creative Time Program, and employee stock options.[69]

Investments in employee satisfaction, however, depend on a firm's access to finance. As with other forms of investments in intangible assets such as research and development (R&D), spending on employee wellbeing must be financed by firms, while the payoffs of such investments generally accrue slowly and are difficult to be evaluated by capital markets. In the face of financing constraints, managers have strong incentives to preserve internal cash flows by reducing investments in long-term projects (Savignac, 2008; Cohn and Wardlaw, 2016; Xu and Kim, 2020). Hence, financially constrained firms can see the reduction in investments in employee wellbeing and deteriorating workplace culture. For example, employees in financially

[69] 20% Creative Time Program is that employees are allowed to use twenty percent of their paid work time in the project they are interested in.

constrained firms are likely to work overtime, face greater performance pressure, and have more uncertain career prospects. As a result, such employees are significantly less satisfied with their jobs. In this chapter, I investigate the effect of financial constraints on employee satisfaction using 120,610 Glassdoor employee reviews from 848 U.S. public firms between 2008 and 2015. I hypothesize financial constraints have an adverse impact on employee satisfaction.

Glassdoor is an employer review platform where employees can voluntarily and anonymously review their companies and share working experiences. Each company review contains the rating of employee overall satisfaction, as well as other workplace attributes such as work-life balance, senior leadership, career opportunity, and recommendation. In addition, Glassdoor provides a rich set of employee information, including employee gender, highest education level, and age. Using this novel dataset, I examine the influence of corporate financing conditions on employee satisfaction at the individual level after controlling for various employee and firm characteristics.

Using several proxies and empirical strategies to capture corporate financial constraints, I find that employee satisfaction is substantially lower in financially constrained firms. This effect is not only statistically but also economically significant. On average, a one-standard-deviation increase in the degree of financial constraints reduces employee overall satisfaction by roughly 3.3%. The results are robust to controls for a battery of employee and firm characteristics, various models, and different subsamples. In addition, I find male, high-educated, and young employees are on average more satisfied with their working environment.

To sharpen my evidence, I further explore the moderating effect of exogenous state-level corporate tax increases on financially constrained firms (Heider and

Ljungqvist, 2015). The increases in corporate tax result in firms having a greater demand for debt financing due to an enlarged tax shield (Modigliani and Miller, 1963), while it is hard for financially constrained firms to adjust their leverage to seize the benefits (Farre-Mensa and Ljungqvist, 2016). If employee-friendly policies are significantly shaped by financial constraints, I expect the effect to be amplified when increasing debt level is optimal. The estimation results are consistent with my conjecture that the adverse impact of financial constraints on employee satisfaction is more pronounced in firms incorporated in the states with exogenous increases in state-level corporate tax.

In addition to employee overall satisfaction, I further explore which specific aspect of workplace attributes is influenced more by financial constraints. By decomposing the overall rating, I find the lower employee satisfaction in financially constrained firms is mainly driven by decreasing employee assessments of work-life balance, lower confidence in senior leadership, and worse career opportunities. Career opportunity is the workplace attribute most sensitive to the degree of financial constraints, suggesting employees in financially constrained firms have more pessimistic expectations about their career prospects. Consequently, such employees are less likely to recommend their employer in the job market, impeding the recruitment of talent.

Finally, I explore the value implications of employee satisfaction. Employees are widely recognized as the critical organizational assets, who can create value for firms through fostering product innovation or building customer relationships (Maslow, 1943; Hertzberg, 1959; McGregor, 1960). Satisfied employees are more motivated, productive, and loyal and consequently improve firm performance (Edmans, 2011). In this chapter, I find that employee overall satisfaction, as well as the satisfaction on various workplace attributes such as work-life balance, senior leadership, career opportunity, and recommendation, is positively associated with firm performance. This is consistent with Edmans (2011) and Green et al. (2019) that employee-friendly policies are beneficial for firm value and shareholder wealth. More importantly, my results highlight employee satisfaction is a plausible channel through which financial constraints influence firm performance.

This chapter contributes to several strands of the literature. First, this chapter is related to the literature on the real effects of financial constraints on corporate social and environmental performance. The investments in social and environmental performance are costly but the benefits accrue slowly over time. Therefore, financially constrained firms are incentivized to underinvest in such projects to preserve internal cash flows (Savignac, 2008; Cohn and Wardlaw, 2016; Xu and Kim, 2020). For instance, Hong et al. (2012) report a negative impact of financial constraints on corporate social responsibility. Xu and Kim (2020) find the relaxation of financial constraints encourages managers to invest more in pollution abatement and thus reduce corporate pollution. With respect to employee wellbeing, Cohn and Wardlaw (2016) suggest financing frictions reduce corporate investments in workplace safety, leading to higher workplace injury rates. Using bankruptcy filings by U.S. public firms, Graham et al. (2013) show employee compensation in financially distressed firms significantly decreases around bankruptcy. Benmelech et al. (2019) uncover a negative effect of financial frictions on employment during the Great Depression. Using Glassdoor reviews, this chapter studies the effect of financial constraints on employee satisfaction which is an important aspect of social and environmental performance. Consistent with previous studies, I find that financial constraints may result in underinvestment in employee-friendly workplaces, leading to lower employee satisfaction.

Second, this chapter contributes to the literature on the determinants of employee-friendly policies. Over recent years, extensive literature explores the implications of employee satisfaction on innovation (Chen et al., 2016), capital structure (Bae et al., 2011), cash holding (Ghaly et al., 2015), financial misconduct (Zhou and Makridis, 2019), corporate disclosure (Ji et al., 2017), and firm performance (Edmans, 2011, 2012; Guiso et al., 2015; Hales et al., 2018; Green et al., 2019). However, the drivers of employee satisfaction remain largely unexplored.[70] In this chapter, I find that financial constraints are the key determinant of employee-friendly policies. Employees may be less satisfied with their employer in the face of financing constraints. To the best of my knowledge, this chapter is the first study to provide empirical evidence on how corporate financing conditions influence employee satisfaction at the individual level.

Lastly, this chapter finds employee overall rating, as well as various workplace attributes such as work-life balance, senior leadership, career opportunity, and recommendation, is positively associated with firm performance. My results complement previous studies using similar data. For instance, Green et al. (2019) suggest a positive effect of the change in employee overall satisfaction on stock returns, while Hales et al. (2018) and Sheng (2019) find employees' assessment of company's business outlook can predict future performance. More importantly, this chapter suggests the underinvestment in intangible assets (i.e., employee satisfaction) can be a potential channel through which financial constraints reduce firm value, particularly in the long run, which echoes the findings by Cohn and Wardlaw (2016) that the increased workplace injury rates caused by financial constraints substantially

[70] There is a small contemporary literature on how employee satisfaction is determined by corporate governance (Menner and Menninger, 2018), relative compensation (Leah-Martin, 2017), and organization form (Huang et al., 2015).

reduce firm value. The results caution against reducing investments in intangible assets when financing is tight. Moreover, given the importance of employee satisfaction for firm performance, the results imply that firms should be prudent in their financing choice. Maintaining financial slack (i.e., spare debt capacity and cash reserve) could play a pivotal role in sustaining employee satisfaction.

3.2 Data and Summary Statistics

3.2.1 Glassdoor data

Glassdoor (www.glassdoor.com) is an employee review website with 60 million monthly visits where employees can review their companies, interview experience, compensation and benefits, and other workplace practices.[71] The platform was founded in 2008 and contains approximately three million reviews from 280,000 firms (including public and private firms) in 2015.

For each employee review, I extract information of employees' overall rating for their employer (*Overall rating*), as well as sub-category ratings regarding work-life balance (*Work-life*), senior leadership (*Leadership*), and career opportunity (*Career*), ranging from 1 (least satisfied) to 5 (most satisfied). In addition to these ratings, Glassdoor provides an assessment of recommendation (*Recommend*) that is an indicator variable that equals to one if the employee is willing to recommend this company to others, and zero otherwise. Moreover, each review contains a set of employee characteristics such as employee gender (*Gender)*, the highest education level (*Education*), and age (*Age*). *Gender* is an indicator variable that equals one for male employee, and zero for female employee. *Education* is an indicator variable set to one if the employee owns a bachelor or higher degree and zero otherwise. *Age* is employees' age in the years.

[71] Source: https://www.glassdoor.com/about-us/

3.2.2 Measures of financial constraints

There are various measures for financial constraints in previous studies (e.g., Kaplan and Zingales, 1997; Whited and Wu, 2006; Hadlock and Pierce, 2010; Hoberg and Maksimovic, 2015; Farre-Mensa and Ljungqvist, 2015). In this chapter, I use several proxies prevalent in the literature, including the Whited-Wu (WW) index (Whited and Wu, 2006) and the text-based equity and debt constraints (Hoberg and Maksimovic, 2015).

The main measure for financial constraints is the WW index (Whited and Wu, 2006) that is an accounting-based measure constructed by the coefficients of a structural model. As compared to other widely used accounting-based financial constraints measures such as the KZ index (Kaplan and Zingales, 1997) and the HP index (Hadlock and Pierce, 2010), the WW index can more accurately identify firm characteristics related to financial constraints and avoid the problems of sample selection, simultaneity, and measurement-error (Whited and Wu, 2006). In addition, the WW index can provide "sufficient" time-series variation and thus I can include firm fixed effects in the estimation to control for firm-level time-invariant and unobservable characteristics. The construction of the WW index loads on six accounting variables, including cash flow to total assets (negative), an indicator variable of dividend policy (negative), long-term debt to total assets (positive), firm size (negative), sales growth (negative), and industry sales growth (positive). The less profitable, highly leveraged, smaller, and lower growth firms will have a larger WW index, representing a higher degree of financial constraints. The linear combination of the WW index is presented as follows:

$$\begin{aligned} WW\ index = & -0.091CF_{it} - 0.062PayDiv_{it} + 0.021LTD_{it} \\ & - 0.044SIZE_{it} + 0.102IndustrySG_{it} - 0.035SG_{it} \end{aligned} \tag{3-1}$$

Where i indexes firm and t indexes year. *CF* is the sum of income before extraordinary items and depreciation and amortization, divided by total assets. *PayDiv* is an indicator variable set to one if firms pay dividends and zero otherwise. *LTD* is the ratio of long-term debts to total assets. *SIZE* is the logarithm of total assets. *IndustrySG* is the average industry sales growth by the SIC three-digit industry code. *SG* is the firm sales growth.

In addition to the WW index, I employ two text-based financial constraints measures, developed by Hoberg and Maksimovic (2015).[72] Through analysing the mandatory disclosure of liquidity in the Management Discussion and Analysis (MD&A) section in the 10-K file, Hoberg and Maksimovic (2015) evaluate corporate financing constraints using the objective algorithm, with higher values indicating that firms are more at risk of delaying their investments due to issues with liquidity. The merit of this measure is not relying on corporate accounting information that may be associated with employee satisfaction. Indeed, I find the text-based financial constraints measures are weakly correlated with accounting-based financial measures (i.e., KZ, WW, and HP index). Specifically, I focus on two text-based variables, *equity constraints* and *debt constraints*, to capture financial constraints in the equity and debt market, respectively. The higher score indicates firms are more constrained in the equity and debt market. The definitions of all variables are presented in Table 3-1.

[Insert Table 3-1 here]

3.2.3 Sample construction and summary statistics

To construct my sample, I begin with Glassdoor employee reviews for public firms listed on NYSE, AMEX, or NASDAQ from 2008 to 2015. I exclude financial (SIC code 6000-6999) and utility firms (SIC code 4900-4999) because their firm

[72] Data source: http://faculty.marshall.usc.edu/Gerard-Hoberg/MaxDataSite/index.html

characteristics (e.g., capital structure) are affected by regulatory requirements. To ensure the informativeness of the ratings, I first remove the reviews posted by "former" employees since the exact departure date of former employees is not presented in Glassdoor.[73] In addition to timeliness, the former employees, especially the dismissed employees, are more likely to post irrational reviews on their employer.[74] To alleviate the concern that the results are manipulated by the firms with few reviews, I then require firms to have at least 50 reviews during the sample period (Hales et al., 2018).[75] Further, I delete all the incomplete reviews with missing employee characteristics (i.e., employee gender, highest education level, and age).

I then merge Glassdoor data with the Compustat database to obtain financial information. As Glassdoor data have no common identifier with Compustat, I manually match Glassdoor company names with those from the Compustat database. To ensure the accuracy of the match, I manually check my sample firms on several identifiers such as CEO name, company headquarter, founding year, and short business description provided by Glassdoor and delete incorrect matches. Finally, my sample consists of 12,610 employee reviews from 848 U.S. public firms listed on NASDAQ, NYSE, and AMEX between 2008 and 2015. Panel A of Table 3-2 presents summary statistics for Glassdoor variables. The number of reviews in sub-category ratings is slightly less than that in the overall rating because the filling of such reviews is not compulsory.

[Insert Table 3-2 here]

[73] Employees are required by Glassdoor to claim the employee status (current or previous employee) when they post a company review.
[74] Indeed, I find that former employees are significantly less satisfied with all workplace attributes than current employees.
[75] I also set the threshed as at least 40, 60, 80, and 100 reviews, the results are not materially changed.

On average, employee overall satisfaction (*Overall Rating)* is 3.440. The sub-category ratings vary from 3.038 (*Leadership*) to 3.413 (*Work-life*), suggesting employees tend to post a positive rating for their companies. To mitigate the concern of selection bias that only most and least satisfied employees could post reviews, I calculate the mode of each employee rating. The mode is 4.00 for *Overall Rating* and *Work-life,* and 3.00 for *Leadership* and *Career,* indicating reviews on Glassdoor platform are mainly posted by moderate employees.[76] Unlike the 5-star scale of other ratings, the *Recommend* is a dummy variable that equals to one if reviewers are willing to recommend this company to their friends, and zero otherwise. The mean *Recommend* is 0.68, suggesting considerable employees regard their current company as a good place to work. In terms of employee characteristics, 84.4% of employees in my sample have a bachelor or higher degree, 66.7% of employees are male, and the average age of employees is 33.08.

Panel B of Table 3-2 presents the correlation matrix for Glassdoor ratings. Unsurprisingly, all sub-category ratings are highly correlated with *Overall Rating.* In particular, *Overall Rating* is least correlated with *Work-life Balance* (0.575) and most correlated with *Recommend* (0.748). The correlations among sub-category ratings vary from 0.426 (*Work-life Balance & Career Opportunity*) to 0.638 (*Senior Leadership & Recommend*).

Panel C of Table 3-2 reports a univariate analysis for differences in Glassdoor variables between financially constrained and unconstrained firms. Following Farre-Mensa and Ljungqvist (2016), I define firms as “constrained” if the WW index is in the top tercile of the sample and as “unconstrained” in the bottom tercile. Employee

[76] To further mitigate this concern, I replicate my main results after excluding extreme review (1 or 5 rating). The results main robust.

satisfaction is substantially lower in financially constrained firms than that in unconstrained firms. For instance, the mean value of *Overall Rating* in unconstrained firms is 3.586, while that is only 3.294 in constrained firms, leading to a 0.292 unconditional gap.

3.3 Main Results

3.3.1 Financial constraints and employee overall rating

In this section, I employ the ordinary least square (OLS) regressions to investigate the effect of financial constraints on employee overall rating.[77] The regression specification is as follows:

$$Y_{ijt} = \alpha + \beta FC_{jt} + \gamma X_{ijt} + \delta Z_{jt} + \varepsilon_{ijt} \tag{3-2}$$

Where i indexes the individual review, j indexes the firm, and t indexes the year respectively. The dependent variable is employee overall rating (*Overall rating*). The variable of interest, FC_{jt}, measures financial constraints using the Whited and Wu (2006) index (WW index) and text-based financial constraints measures in the equity and debt markets (Hoberg and Maksimovic, 2015). X_{ijt} is a vector of employee characteristics including *employee gender*, *employee education*, and *employee age*. Z_{jt} is a vector of firm characteristics such as return on asset (*ROA*), firm size (*Size*), capital structure (*Leverage*), and market-to-book ratio (*Market-to-Book*). The definitions of variables are presented in Table 3-1. Firm and year fixed effects are included in all specifications to control for time-invariant firm and year characteristics. I cluster the standard errors at the firm level.

The estimation results are presented in Table 3-3. *FC* stands for *WW index* in Columns (1), (2), and (5), *equity constraints* in Column (3), and *debt constraints* in

[77] As Glassdoor employee rating ranges from 0 to 5, I also employ the ordered probit model to replicate the main results and obtain similar results.

Column (4), respectively. I start with a model without control variables in Column (1). The coefficient on *FC* is negative and statistically significant at the 1% level, suggesting employees are less satisfied in financially constrained firms. The coefficient on *FC* remains negative and statistically significant when controlling for employee and firm characteristics in Column (2). This effect is also economically significant. As shown in Column (2), a one-standard-deviation increase in financial constraints is associated with approximately a 3.3% decrease in employee overall satisfaction. Columns (3) and (4) use *equity constraints* and *debt constraints* as alternative measures for financial constraints in the equity and debt markets (Hoberg and Maksimovic, 2015). In both columns, the results continue to show a negative effect of financial constraints on employee satisfaction, suggesting firms subject to difficulty in raising funds through equity or debt markets have significantly lower employee satisfaction. Taken together, regardless of the financial constraints proxy, this chapter reports a significant and negative effect of financial constraints on employee satisfaction. In addition, the coefficients on employee characteristics imply that male, highly educated, and young employees are more satisfied at work with their employer.

[Insert Table 3-3 here]

I then explore the moderating effect of corporate tax increases on constrained firms (Heider and Ljungqvist, 2015). Trade-off theory predicts the optimal capital structure is determined by the trade-off between tax-saving and bankruptcy cost (Scott, 1977). As debt confers tax benefits on firms when interests are tax-deductible, increases in tax rates may raise the value of tax shields, thereby motivating firms to improve the use of debt financing (Modigliani and Miller, 1963). Indeed, Heider and Ljungqvist (2015) find firms are incentivized to increase firm leverage and borrowing to take advantage of tax shields, in response to an increase in state corporate tax. However, financially constrained firms may have difficulties increasing their leverage to seize the benefits of a larger tax shield after tax increases, thereby becoming more constrained (Farre-Mensa and Ljungqvist, 2016). Thus, if financial constraints indeed decrease employee satisfaction, I conjecture this relation could be more pronounced in periods of corporate tax increases.

To test this conjecture, I exploit state corporate income tax increases during my sample period.[78] I define *Tax Shock* as an indicator variable that equals one if a state experiences an increase in corporate income tax in the given year, and zero otherwise. In Column (5) of Table 3-3, I explore how the WW index interacts with state-level corporate tax increases to influence employee satisfaction. As expected, I find that the coefficient on the interaction term *FC*Tax Shock* is negative and statistically significant at the 1% level. It suggests that financially constrained firms become more constrained in the period of corporate tax increases, thereby amplifying the negative effect of financial constraints on employee satisfaction.

3.3.2 Robustness tests

In this section, I perform a battery of robustness tests to confirm the validity of the results. I start with the major concern of over/under-sampling due to the distribution of employee reviews. As my sample consists of 120,610 reviews from only 848 unique public firms, the number of reviews per firm may vary largely within and across the sample. Appendix 3-A1 reports the average number of reviews per firm across years at the different percentiles of the distribution (5^{th}-95^{th}). Indeed, there is substantial variation both across years and across firms. For example, the median

[78] The list of state corporate income tax increases is collected from Heider and Ljungqvist (2015), the *Book of the States*, and the Tax Foundation website (http://www.taxfoundation.org).

number of reviews is only 7 in 2008, while it significantly increases to 26 reviews in 2015. Also, there is a cross-sectional variation in the same year. The number of reviews per firm at the 5th and 95th percentile is 40 and 228 respectively in 2015. Moreover, I find the reviews in my sample are concentrated in a few firms. The number of reviews in the top 10 firms (with most reviews) accounts for approximately 20% (24,616 reviews) of sample observations.

I conduct two tests to alleviate this concern. First, I replicate my main results with Weighted Least Squares (WLS) regression, weighting by the number of reviews per firm scaled by total reviews. The results are presented in Appendix 3-A2 and are robust to this alternative estimated model. Second, I drop reviews (25,116) from the top 10 firms with the most (least) reviews and re-estimate the regressions.[79] As shown in Appendix 3-A3, my main findings are not materially changed after excluding firms with the most (least) reviews. Overall, the over/under-sampling issue is unlikely to influence the validity of the results.

Second, a common concern with online reviews is the sample selection bias; that is, the extremely satisfied or unsatisfied employees are more likely to post an online review compared with moderate ones. To address this concern, I first calculate the mode of each rating. The mode for overall satisfaction (*Overall Rating*) and work-life balance (*Work-life*) is 4 and for senior leadership (*Leadershi*p) and career opportunity (*Career*) it is 3, suggesting most reviews are posted by moderate employees. In addition, I exclude the extreme reviews with 1 or 5 ratings and re-run the estimations. The results reported in Appendix 3-A4 demonstrate that my main findings remain robust after excluding the extreme reviews.

[79] In untabulated tables, I also try to exclude the top 5 and 20 firms with the most/least reviews, respectively and find qualitatively similar results

Third, financially constrained firms are less likely to attract new employees (Garmaise, 2008) and more likely to reduce employment (Siemer, 2019), hindering the retaining and recruitment of talent in the labor market. The changes in employment may be associated with the number of reviews and ratings for the employer (Huang et al., 2015). As such, in Appendix 3-A5 I obtain an additional control variable, *employee turnover*, to control for the annual percentage change in employees. The results are quantitatively similar.

3.3.3 Financial constraints and employee sub-category ratings

Next, I explore which specific aspects of workplace practices are influenced more by financial conditions. Employees in financially constrained firms are likely to work overtime, face greater performance pressure from senior management, and have more uncertain career prospects. From this perspective, I investigate the effect of financial constraints on employee rating of work-life balance, senior leadership, and career opportunity. The results are presented in Table 3-4. Columns (1) to (3) report the estimation results for the effects of financial constraints on work-life balance (*Work-life*), senior leadership (*Leadershi*p), and career opportunity (*Career*), respectively. The variable of interest is financial constraints *FC* measured by the WW index.[80] The regression specifications are the same as those in Table 3-3.

[Insert Table 3-4 here]

Consistent with results for overall satisfaction, the coefficient on *FC* in Columns (1) to (3) is negative and statistically significant at the 1% level, indicating that the lower satisfaction in financially constrained firms is mainly driven by decreasing employee assessments of work-life balance, lower confidence in senior

[80] I obtain similar results when two text-based measures (i.e., Equity and debt constraints) are employed as proxies for financial constraints.

leadership and more pessimistic expectations about career prospects. Career opportunity is most sensitive to corporate financial conditions. The magnitude of coefficient for *Career* is -1.357 which is considerably larger than those for *Work-life* (-0.903) and *Leadership* (-1.073).

Finally, I explore whether lower employee satisfaction with work-life balance, senior leadership, and career opportunity consequently lead to challenges in the recruitment of talent. In Column (4) of Table 3-4, I find employees in firms with financial constraints are less likely to recommend their employer to others, suggesting financial constraints result in difficulty in recruiting new talent. This finding complements Brown and Matsa (2016), that a deterioration in financial condition reduces a firm’s attractiveness in the job market.

3.4 Employee Satisfaction and Firm Value

While my results so far indicate an adverse effect of financial constraints on employee satisfaction, one important question remains unanswered: Whether the reduced employee satisfaction sufficiently matters for firms? To address this question, I explore the consequences of the reduction in employee satisfaction on firm value in this section.

Previous literature indicates employee satisfaction benefits firms in several ways. First, high employee satisfaction can enhance the motivation of employees. Human relations theories view employees as the key source of human capital assets that can create substantial value for companies through building client relationships or inventing new products and patents (Maslow, 1943; McGregor, 1960; Becker and Gerhart, 1996). Employee-friendly workplaces can motivate employees to enhance efforts due to the increasing costs of losing a satisfying job (Shapiro and Stiglitz, 1984). Accordingly, satisfied employees are motivated to complete, even go beyond the formal requirements of the job, whereby producing additional values for companies (Edmans, 2012). Second, maintaining employee satisfaction benefits the recruitment and retention of talented employees who are becoming increasingly valuable for modern firms; to the extent that compensation is not the only deciding factor in terms of which company they working for. Instead, the “soft” factors such as a pleasant and flexible working environment, employee-friendly corporate culture, and potential career opportunities are more likely to attract employees (Mitchell et al., 2001). In contrast, firms with a bad reputation may suffer a higher turnover rate and challenges in the recruitment of talent (Shapiro and Titman, 1986), leading to a lower firm valuation. Indeed, recent studies (Edmans, 2011; Green et al., 2019) find a significant positive relation between employee satisfaction and firm performance.

In this section, I attempt to investigate the value implications of employee satisfaction using Glassdoor reviews. Specifically, I estimate the model as follows:

$$Firm\ value_{jt} = \alpha + \beta Average\ employee\ satisfaction_{jt} + \delta Z_{jt} + \varepsilon_{jt} \qquad (3\text{-}3)$$

Where j indexes the firm and t indexes the year. The dependent variable is one of two measures for firm value, *Tobin’s Q* and *ROA*. *Tobin’s Q* is defined as the market value of equity plus total assets minus the book value of equity, divided by total assets. *ROA* is the return on assets calculated as the operating income divided by total assets. To capture the employee satisfaction at the firm level, I calculate *Average employee satisfaction* as the average employee rating of overall satisfaction, as well as each workplace practice, submitted by all employees for each firm-year observation. Z is a vector of firm characteristics including firm size, leverage ratio, and market-to-book ratio. I control for firm and year fixed effects in my analysis and cluster standard errors at the firm level.

The estimation results are shown in Table 3-5. The dependent variable is *Tobin's Q* in Panel A and *ROA* in Panel B. I start by regressing the average overall rating on *Tobin's Q* in Column (1) of Panel A. The coefficient on *average employee satisfaction* is positively related to *Tobin's Q*, suggesting higher employee overall satisfaction can significantly improve firm value. In Columns (2) to (5), I explore how *Tobin's Q* is influenced by average employee satisfaction of *Work-life balance*, *Career*, *Leadership*, and *Recommend*, respectively. Across all columns, the coefficient on *average employee satisfaction* remains positive and statistically significant at the 5% level or better.

[Insert Table 3-5 here]

I then replicate the same regressions as those employed in Panel A with the dependent variable of ROA. The results are shown in Panel B. Similarly, the coefficient on *average employee satisfaction* remains positive and statistically significant in the specifications of overall rating, career opportunity, senior leadership, and recommend, while the regression of average work-life balance rating becomes insignificant.

To summarize, Table 3-5 provides strong evidence in support of the value implications of employee satisfaction. My results are consistent with Edmans (2011) and Green et al. (2019) that employee satisfaction is positively associated with firm performance. More importantly, combined with the finding that financial constraints may reduce employee satisfaction, my study implies that employee satisfaction could be an important channel through which financial constraints reduce firm value. Given the importance of employee-friendly workplaces for firm performance, my results suggest firms should be prudent in their financing choice. Maintaining financial slack (i.e., spare debt capacity and cash reserve) could play an important role in sustaining employee satisfaction and consequently influence the firm valuation.

3.5 Conclusions

This chapter investigates the effect of financial conditions on employee satisfaction. Using over 120,000 employee reviews from Glassdoor, I find an adverse impact of financial constraints on employee satisfaction. Decomposing employee overall rating, I find lower overall employee satisfaction is mainly driven by worse assessments of work-life balance, senior leadership, and career prospects. Consequently, unsatisfied employees are less likely to recommend their employer, impeding the recruitment of talent in the labor market. Finally, I explore the value implications of employee-friendly workplaces. The average overall employee rating, as well as various sub-category ratings, is positively associated with firm performance, which supports the findings of Edmans (2011) and Green et al. (2019).

This chapter highlights employee satisfaction is an important channel through which financial constraints reduce firm value. Given the pivotal role employee satisfaction plays in improving firm performance, my results caution against underinvestment in employee-friendly workplaces when financing is tight. By contrast, managers should be prudent in their financing choice and hold more financial slack (i.e., spare debt capacity and cash reserve) to maintain employee satisfaction.

Table 3-1. Variable definitions

Variable	Definition	Data Source
Glassdoor Rating		
Overall	Employee's overall rating of employer scaled on 1-5 star: five (one) is most favorable (unfavorable).	Glassdoor
Work-life	Employee's evaluation of his or her work-life balance in this company scared on a 1-5 star: five (one) is most favorable (unfavorable).	Glassdoor
Leadership	Employee's evaluation of employee's senior management scaled on a 1-5 star: five (one) is most favorable (unfavorable).	Glassdoor
Career	Employee's evaluation of career development in this company scaled on a 1-5 star: five (one) is most favorable (unfavorable).	Glassdoor
Recommend	Would you recommend your company to a friend? 1-No, 2-Yes	Glassdoor
Employee Characteristics		
Age	Employees' age in years	Glassdoor
Education	An indicator variable set to one if employees' highest education degree is a bachelor or higher, and zero otherwise.	Glassdoor
Gender	An indicator variable set to one if an employee is male, and zero otherwise.	Glassdoor
Financial Constraints		
WW index	Constructed following Whited and Wu (2006), as –0.091*[(*ib* + *dp*)/*at*] – 0.062*[indicator set to one if *dvc* + *dvp* is positive, and zero otherwise] + 0.021*[*dltt/at*]– 0.044*[log(*at*)] + 0.102*[average SIC 3-digit industry sales growth] – 0.035*[firm sales growth]	Compustat
Equity Constraints	Text-based measure of equity financing constraints	Hoberg and Maksimovic (2015)
Debt Constraints	Text-based measure of debt financing constraints	Hoberg and Maksimovic (2015)
Tax Shock	An indicator variable set to one if one state experiences the shock of corporate tax rate increase, and zero otherwise.	Heider and Ljungqvist (2015)
Firm Characteristics		
Leverage	Total debt over total assets	Compustat
Size	The natural logarithm of total sales	Compustat
Market-to-Book	Market value of equity over the book value of equity	Compustat
ROA	Net income over the total sales	Compustat
Tobin Q	Market value of equity plus total assets minus the book value of equity, over the total assets	Compustat
Employee turnover	Percentage annual change in the number of employees.	Compustat

Table 3-2. Descriptive statistics

This table reports summary statistics of the main variables. Panel A presents the distribution and the number of observations of Glassdoor variables for my sample. Panel B shows the correlation matrix. Panel C reports the univariate analysis results by constrained (unconstrained). I identify the firms with the top (bottom) tercile of the WW index as the constrained (non-constrained) firms. All variables are defined in Table 3-1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Descriptive Statistics

Variable	Obs	Mean	Std.	25th	Median	75th
Overall	120,610	3.440	1.162	3.000	4.000	4.000
Work-life	113,465	3.413	1.236	3.000	4.000	4.000
Leadership	112,832	3.038	1.275	2.000	3.000	4.000
Career	113,660	3.254	1.207	2.000	3.000	4.000
Recommend	101,857	1.680	0.467	1.000	2.000	2.000
Education	120,610	0.844	0.363	1.000	1.000	1.000
Age	120,610	33.080	9.728	25.000	31.000	39.000
Gender	120,610	0.667	0.471	0.000	1.000	1.000

Panel B: Correlation Matrix

	Overall Rating	Work-life	Leadership	Career	Recommend
Overall	1.000				
Work-life	0.575***	1.000			
Leadership	0.738***	0.536***	1.000		
Career	0.715***	0.426***	0.629***	1.000	
Recommend	0.748***	0.494***	0.638***	0.606***	1.000

Panel C. Univariate analysis by constrained (unconstrained) defined by WW index

	Unconstrained		Constrained		Difference	
	Mean	Median	Mean	Median	Mean	Median
Overall	3.586	4.000	3.294	3.000	0.292***	1.000***
Work-life	3.632	4.000	3.176	3.000	0.456***	1.000***
Leadership	3.153	3.000	2.931	3.000	0.222***	0.000***
Career	3.358	3.000	3.157	3.000	0.201***	0.000***
Recommend	1.740	2.000	1.618	2.000	0.122***	0.000***
Education	0.910	1.000	0.761	1.000	0.148***	0.000***
Age	33.786	32.000	32.672	30.000	1.114***	2.000***
Gender	0.729	1.000	0.582	1.000	0.147***	0.000***

Table 3-3. Financial constraints and employee overall rating

This table reports the panel regression on the effect of financial constraints on employee overall satisfaction. The dependent variable is *Overall Rating*. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by WW index in Columns (1), (2), and (5), Equity Constraints in Column (3), and Debt Constraints in Column (4). *Tax Shock* is an indicator variable that equals to one if the state of a company incorporated experiences a corporate tax increase in the given year, and zero otherwise. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall Rating				
	WW Index	WW Index	Equity Constraints	Debt Constraints	WW index* Tax shock
	(1)	(2)	(3)	(4)	(5)
FC	**-1.475*** **	**-1.333*** **	**-0.730** **	**-0.599*** **	**-1.435*** **
	(-4.13)	**(-3.51)**	**(-2.25)**	**(-2.70)**	**(-2.85)**
FC*Tax shock					**-0.286*** **
					(-2.87)
Tax shock					-0.003
					(-0.05)
Gender		0.047***	0.037***	0.038***	0.037***
		(5.06)	(3.13)	(3.18)	(3.06)
Education		0.057***	0.059***	0.059***	0.022
		(4.39)	(3.51)	(3.51)	(1.30)
Age		-0.011***	-0.010***	-0.010***	-0.011***
		(-10.90)	(-7.86)	(-7.81)	(-9.07)
ROA		0.056	-0.018	-0.034	-0.330
		(0.29)	(-0.06)	(-0.13)	(-0.98)
Size		0.034	0.122	0.145*	0.101
		(0.55)	(1.46)	(1.79)	(1.06)
Leverage		0.000	-0.090	-0.071	0.145
		(0.00)	(-0.66)	(-0.49)	(0.95)
Market-to-Book		-0.001	-0.002	-0.001	-0.001
		(-0.51)	(-0.89)	(-0.44)	(-0.43)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	120,610	120,610	77,129	77,129	67,956
R-sq	0.014	0.023	0.022	0.022	0.031

Table 3-4. Financial constraints and employee sub-category ratings

This table reports the panel regression on the effect of financial constraints on employee sub-categories ratings. The dependent variables include *Work-life*, *Leadership*, *Career*, and *Recommend* in Columns (1) to (4), respectively. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by the WW index. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Sub-category ratings			
	Work-life	Leadership	Career	Recommend
	(1)	(2)	(3)	(4)
FC	**-0.907*** **	**-1.074*** **	**-1.361*** **	**-0.316***
	(-2.81)	**(-2.74)**	**(-3.60)**	**(-1.73)**
Gender	0.069***	0.024**	0.044***	0.015***
	(6.14)	(2.34)	(4.58)	(3.97)
Education	0.076***	0.100***	0.026	0.029***
	(4.20)	(6.87)	(1.61)	(4.92)
Age	-0.013***	-0.013***	-0.012***	-0.005***
	(-13.13)	(-12.82)	(-12.61)	(-9.68)
ROA	-0.174	0.328*	0.052	0.084
	(-1.29)	(1.94)	(0.29)	(0.93)
Size	0.062	0.032	0.089	0.016
	(1.15)	(0.50)	(1.56)	(0.58)
Leverage	-0.089	-0.075	0.010	0.020
	(-0.70)	(-0.60)	(0.09)	(0.42)
Market-to-Book	-0.001	0.000	-0.000	-0.000
	(-0.56)	(0.05)	(-0.02)	(-0.65)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	113,465	112,832	113,660	101,857
R-sq	0.015	0.014	0.016	0.019

Table 3-5. Employee satisfaction and firm performance

This table reports the panel regression on the implication of employee satisfaction on firm performance at the firm level. The dependent variable is *Tobin Q* in Panel A and *ROA* in Panel B, as proxies for firm performance. *Employee Rating* is the firm-year average rating of employee overall satisfaction in Column (1), work-life balance in Column (2), senior leadership in Column (3), career opportunity in Column (4), and recommend in Column (5). The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

Panel A: Tobin Q

	Tobin Q				
	Overall Rating	Work-life	Leadership	Career	Recommend
	(1)	(2)	(3)	(4)	(5)
Employee Rating	**0.144*** **	**0.087** **	**0.136*** **	**0.108*** **	**0.201** **
	(3.28)	**(2.37)**	**(3.77)**	**(2.62)**	**(2.11)**
Size	-0.323**	-0.311**	-0.322**	-0.323**	-0.318**
	(-2.45)	(-2.34)	(-2.43)	(-2.45)	(-2.36)
Leverage	-0.790**	-0.792**	-0.771**	-0.790**	-0.791**
	(-2.55)	(-2.56)	(-2.49)	(-2.55)	(-2.53)
Market-to-Book	0.034***	0.034***	0.033***	0.033***	0.033***
	(4.69)	(4.65)	(4.63)	(4.67)	(4.65)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3,235	3,235	3,235	3,235	3,222
R-sq	0.144	0.140	0.145	0.142	0.140

Panel B: ROA

	ROA				
	Overall Rating	Work-life	Leadership	Career	Recommend
	(1)	(2)	(3)	(4)	(5)
Employee Rating	**0.015*** **	**0.008**	**0.015*** **	**0.010*** **	**0.035*** **
	(3.06)	**(1.62)**	**(3.45)**	**(2.67)**	**(3.63)**
Size	0.029**	0.031**	0.029**	0.030**	0.029**
	(2.24)	(2.33)	(2.23)	(2.23)	(2.21)
Leverage	-0.209***	-0.210***	-0.207***	-0.209***	-0.212***
	(-6.98)	(-6.92)	(-6.96)	(-6.92)	(-7.02)
Market-to-Book	0.001**	0.001**	0.001**	0.001**	0.001**
	(2.52)	(2.48)	(2.40)	(2.50)	(2.46)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	3,235	3,235	3,235	3,235	3,222
R-sq	0.094	0.090	0.097	0.091	0.097

Appendix 3-A1. Average number of reviews per firm and year for the n^{th} percentile

This table reports the average number of reviews per firm across years at the different percentile of the distribution (5^{th}-95^{th}).

Year	Percentile				
	5%	25%	50%	75%	95%
2008	1	4	7	12.5	40
2009	9	13	22	40	106
2010	8	13	19	44	147
2011	2	5	8	14	49
2012	8	14	25.5	48	182
2013	11	21	31	61	237
2014	14	25	37	72	316
2015	9	16	26	47.5	228

Appendix 3-A2. Robustness tests: WLS Regression

This table replicates the baseline results with WLS regression, weighting by the number of reviews per firm dividend by the total number of reviews. The dependent variable is *Overall Rating*. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by WW index in Columns (1), (2), and (5), Equity Constraints in Column (3), and Debt Constraints in Column (4). *Tax Shock* is an indicator variable that equals to one if the state of a company incorporated experiences a corporate tax increase in the given year, and zero otherwise. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall Rating				
	WW Index	WW Index	Equity Constraints	Debt Constraints	WW index* Tax shock
	(1)	(2)	(3)	(4)	(5)
FC	**-1.732*** **	**-2.108** **	**-1.891** **	**-1.146*** **	**-1.586** **
	(-2.83)	**(-2.48)**	**(-2.17)**	**(-3.78)**	**(-2.01)**
FC*Tax shock					**-0.461*** **
					(-3.18)
Tax shock					-0.031
					(-0.31)
Gender		0.041**	0.033	0.034	0.031
		(2.57)	(1.58)	(1.62)	(1.60)
Education		0.034**	0.020	0.019	-0.019
		(2.07)	(0.90)	(0.85)	(-0.95)
Age		-0.013***	-0.013***	-0.013***	-0.012***
		(-5.30)	(-4.86)	(-4.71)	(-4.99)
ROA		-0.417	-0.511	-0.282	-0.676
		(-1.12)	(-0.89)	(-0.73)	(-1.26)
Size		-0.053	0.082	0.147	-0.036
		(-0.39)	(0.70)	(1.04)	(-0.20)
Leverage		0.123	0.031	0.181	0.499
		(0.47)	(0.08)	(0.37)	(1.40)
Market-to-Book		-0.004	-0.008*	-0.008	-0.007
		(-1.31)	(-1.69)	(-1.44)	(-0.98)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	120,610	120,610	77,129	77,129	67,956
R-sq	0.096	0.108	0.094	0.094	0.113

Appendix 3-A3. Robustness tests: Exclude firms with most/least reviews

This table replicates the baseline results after excluding the top 10 firms with the most and least reviews. The dependent variable is *Overall Rating*. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by WW index in Columns (1), (2), and (5), Equity Constraints in Column (3), and Debt Constraints in Column (4). *Tax Shock* is an indicator variable that equals to one if the state of a company incorporated experiences a corporate tax increase in the given year, and zero otherwise. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall Rating				
	WW Index	WW Index	Equity Constraints	Debt Constraints	WW index* Tax shock
	(1)	(2)	(3)	(4)	(5)
FC	**-1.476*** **	**-1.369*** **	**-0.920** **	**-0.485* **	**-1.397** **
	(-3.29)	**(-3.03)**	**(-2.38)**	**(-1.75)**	**(-2.51)**
FC*Tax shock					**-0.299*** **
					(-2.98)
Tax shock					-0.002
					(-0.03)
Gender		0.044***	0.037***	0.038***	0.038***
		(4.10)	(2.66)	(2.69)	(2.78)
Education		0.050***	0.054***	0.054***	0.019
		(3.39)	(2.78)	(2.75)	(1.00)
Age		-0.011***	-0.010***	-0.010***	-0.010***
		(-8.74)	(-6.16)	(-6.10)	(-7.41)
ROA		-0.116	-0.284	-0.282	-0.427
		(-0.47)	(-0.79)	(-0.87)	(-1.07)
Size		0.059	0.152	0.177*	0.122
		(0.77)	(1.39)	(1.65)	(1.12)
Leverage		-0.020	-0.172	-0.140	0.080
		(-0.16)	(-1.06)	(-0.80)	(0.48)
Market-to-Book		0.000	-0.001	-0.000	-0.002
		(0.08)	(-0.59)	(-0.06)	(-0.64)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	95,496	95,496	59,379	59,379	55,713
R-sq	0.015	0.024	0.023	0.023	0.031

Appendix 3-A4. Robustness tests: Exclude extreme reviews

This table replicates the baseline results after excluding the reviews with 1 or 5 overall ratings. The dependent variable is *Overall Rating*. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by WW index in Columns (1), (2), and (5), Equity Constraints in Column (3), and Debt Constraints in Column (4). *Tax Shock* is an indicator variable that equals to one if the state of a company incorporated experiences a corporate tax increase in the given year, and zero otherwise. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall Rating				
	WW Index	WW Index	Equity Constraints	Debt Constraints	WW index* Tax shock
	(1)	(2)	(3)	(4)	(5)
FC	**-0.693*** **	**-0.614** **	**-0.528*** **	**-0.418*** **	**-0.586**
	(-3.18)	**(-2.49)**	**(-2.91)**	**(-4.15)**	**(-1.60)**
FC*Tax shock					**-0.045**
					(-0.67)
Tax shock					0.005
					(0.14)
Gender		0.037***	0.036***	0.036***	0.029***
		(5.65)	(4.56)	(4.60)	(3.19)
Education		0.048***	0.047***	0.047***	0.028**
		(4.69)	(3.65)	(3.65)	(2.24)
Age		-0.006***	-0.006***	-0.006***	-0.007***
		(-11.29)	(-8.71)	(-8.64)	(-9.21)
ROA		0.037	0.045	0.040	-0.112
		(0.34)	(0.29)	(0.30)	(-0.60)
Size		0.019	0.062	0.080*	0.086
		(0.55)	(1.36)	(1.74)	(1.60)
Leverage		-0.012	-0.014	0.003	0.099
		(-0.19)	(-0.17)	(0.04)	(0.98)
Market-to-Book		-0.001	-0.002	-0.001	-0.001
		(-0.84)	(-1.60)	(-1.13)	(-0.81)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	87,885	87,885	57,080	57,080	50,672
R-sq	0.011	0.019	0.018	0.018	0.025

Appendix 3-A5. Robustness tests: Control for employee turnover

This table replicates the baseline results after controlling for employee turnover. The dependent variable is *Overall Rating*. The variable of interest is *FC* that is the abbreviation of Financial Constraints, measured by WW index in Columns (1), (2), and (5), Equity Constraints in Column (3), and Debt Constraints in Column (4). *Tax Shock* is an indicator variable that equals to one if the state of a company incorporated experiences a corporate tax increase in the given fiscal year, and zero otherwise. *Employee turnover* is the percentage annual change in the number of employees. The detailed definitions of all variables are presented in Table 3-1. Standard errors are clustered at the firm level. t-values are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

	Overall Rating				
	WW Index	WW Index	Equity Constraints	Debt Constraints	WW index* Tax shock
	(1)	(2)	(3)	(4)	(5)
FC	**-1.382*****	**-1.272*****	**-0.752****	**-0.593*****	**-1.436*****
	(-3.75)	**(-3.21)**	**(-2.32)**	**(-2.66)**	**(-2.85)**
FC*Tax shock					-0.277***
					(-2.75)
Tax shock					-0.002
					(-0.04)
Gender		0.047***	0.037***	0.038***	0.037***
		(5.04)	(3.16)	(3.20)	(3.05)
Education		0.057***	0.060***	0.060***	0.023
		(4.42)	(3.55)	(3.55)	(1.36)
Age		-0.011***	-0.010***	-0.010***	-0.011***
		(-10.89)	(-7.87)	(-7.82)	(-9.12)
ROA		0.048	-0.048	-0.059	-0.329
		(0.24)	(-0.17)	(-0.23)	(-0.98)
Size		0.028	0.091	0.118	0.090
		(0.44)	(1.04)	(1.39)	(0.90)
Leverage		-0.019	-0.115	-0.094	0.155
		(-0.18)	(-0.83)	(-0.65)	(0.99)
Market-to-Book		-0.001	-0.002	-0.001	-0.002
		(-0.64)	(-0.94)	(-0.51)	(-0.69)
Emp. turnover	0.048	0.041	0.068	0.062	-0.035
	(0.95)	(0.85)	(0.99)	(0.89)	(-0.42)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	120,050	120,050	76,784	76,784	67,570
R-sq	0.014	0.023	0.022	0.022	0.031

Conclusions

This thesis contains three essays that explore the determinants and implications of corporate social and environmental performance. In Chapter 1, I focus on a key driver of corporate environmental policies—financial analysts. Using two quasi-natural experiments (i.e., brokerage closures and mergers) to capture an exogenous decrease in analyst coverage, I find firms are likely to release more toxic pollution after analyst loss. This effect is more pronounced for firms with weak corporate governance, with less regulatory scrutiny, and incorporated in states where stakeholder orientation laws are not enacted. Further analyses show that underinvestment in pollution abatement and green innovation, deterioration of internal environmental governance mechanisms, and less environmental pressure imposed by institutional investors are three potential channels through which financial analysts shape corporate environmental policies.

My evidence is consistent with the *external monitoring hypothesis* that financial analysts play a pivotal role in the monitoring of environmentally harmful behavior. Given the negative externalities involved with toxic emissions, my findings suggest that increased oversight of corporate environmental policies can generate welfare gains for society.

In Chapter 2, I explore the gender differences in job satisfaction and workplace preferences and the implications of such gender gaps. Using Glassdoor employer reviews, I find females, on average, are less satisfied at work than males. It is worth noting that work-life balance is the most important workplace attribute responsible for gender gaps in job satisfaction. Moreover, female and male employees differ systematically in workplace preferences. In particular, females care more about work-life balance relative to males. However, this preference vanishes when they become a mid-level manager. Lastly, I find family-friendly workplaces with lower gender satisfaction gaps in work-life balance are beneficial for firm valuation.

This chapter highlights the gender differences in job satisfaction and workplace preferences between males and females, particularly those regarding work-life balance. Interestingly, this gender difference vanishes at the manager level, illustrating the role of selection. This evidence shows that female career progression is likely to be constrained if they have to sacrifice their balance between work and family, given the fact that females tend to pay more attention to family responsibilities as compared to males. As such, I suggest a crucially important role family-friendlessness plays in female career advancement.

Chapter 3 documents an adverse impact of financial constraints on employee satisfaction. By decomposing employee overall rating, I find the lower employee satisfaction in financially constrained firms is largely due to the decreasing employee assessments of work-life balance, lower confidence in senior leadership, and worse career opportunity. As a result, unsatisfied employees are reluctant to recommend their employer to others, reducing the firms' competitiveness in the labor market. Finally, I uncover a positive effect of employee-friendly workplaces on firm performance, as satisfied employees are more motivated, productive, and loyal.

My findings suggest employee satisfaction is an important channel through which financial constraints reduce firm value. Firms should be prudent in reducing the investments in employee wellbeing in the face of financial constraints, given the importance of employee satisfaction for firm value.

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