ESSAYS ON CORPORATE INTANGIBLES AND MISCONDUCT

SHIU-YIK AU

A DISSERTATION SUBMITTED TO
THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULLFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

GRADUATE PROGRAM IN BUSINESS ADMINISTRATION
YORK UNIVERSITY
TORONTO, ONTARIO

April, 2018

Abstract

This dissertation examines three different aspects of corporate intangibles or misconduct and their impact on firms. The first essay examines the impact of employee flexibility on firm value, the second essay examines whether the SEC can deter financial misconduct through its enforcement, and the third essay examines the impact of mandating risk disclosure on firm innovation.

In the first essay, I hypothesize that employee flexibility enhances firm value because a flexible and empowered workforce helps the firm to respond to exogenous shocks. I estimate employee flexibility scores through textual analysis of online job reviews and I find that a high employee flexibility score leads to superior stock returns, especially for firms with high exposure to exogenous risk.

In the second essay, I examine whether the Securities and Exchange Commission's (SEC) enforcement actions, and who these actions target, deter future financial misconduct. An enforcement action reduces the incidence of misconduct in other firms in the same industry and metropolitan statistical area (MSA) in the future. Furthermore, an enforcement that punishes a guilty company has a larger deterrence effect on future misconduct than punishing an officer, auditor, attorney, or other entity.

Finally, in the third essay, I test whether mandatory risk disclosure reduces firm innovation. Based on text analysis of risk disclosure in 10-K filings for over 44,000 firm-years, I find that an increase in disclosed risk is linked to a decline in research and development, patents filed, and citation-weighted value of patents. Furthermore, by exploiting two natural experiments and a regression discontinuity design, I am able to show that mandatory disclosure of risk in the 10-K exacerbates the effect. The mechanism for this negative association with innovation

appears to be linked to firms' financial constraints; firms with financial constraints experience even larger declines in innovation when risk disclosure is high than other firms. These results show that increased disclosure requirements can have a negative impact on some firms.

Dedication

This dissertation is dedicated to my wife Ria; her support gave me the perseverance to finish this long labour. I also wish to thank my parents and brother for helping encourage me through the entire PhD process. Finally, I wish to acknowledge Duffy, whose paws often accidentally typed things that were more coherent than my own ramblings.

Acknowledgements

I want to thank my advisor, Ming Dong, for all of his guidance and help during the entire dissertation process. He helped me complete what seemed a Sisyphean task with gentle advice and constant encouragement. This thesis would also not have been possible without my other committee members, Mark Kamstra and Douglas Cumming. Mark was instrumental in teaching me the finer points of empirical analysis and Doug was key to sparking my imagination for new topics. I also want to thank Hongping Tan for challenging me along the way and showing me a methodical way to execute great research. I want to acknowledge the great questions and ideas my examiners, George Georgopoulos and Jianping Qiu, discussed during my defense. Finally, I want to thank Gordon Roberts—I will miss our meandering conversations in his office.

For chapter 2, *Employee Flexibility, Exogenous Risk, and Firm Value*, I wish to thank a long list of individuals and groups that provided feedback and advice including Kee-Hong Bae, Frederick Bereskin, Nathan Dong, Marie Dutordoir, Mariassunta Giannetti, Campbell Harvey, David Hirshleifer, Marc Idelson, Mark Kamstra, Jisok Kang, Jongsub Lee, Tingting Liu, Tim Loughran, Ron Masulis, Lilian Ng, Jong-Min Oh, Jillian Popadak (Grennan), Gordon Roberts, Zheng Sun, Chris Veld, Jing Yang, Xiaoyun Yu, and seminar participants at the 2017 FMA Annual Meeting, 2017 Paris Financial Management conference and York University for helpful comments.

For chapter 3, *The Effectiveness of SEC Enforcement in Deterring Financial Misconduct*, I wish to thank Douglas Cumming, Ming Dong, Mark Kamstra, Timothy Lane, Gordon Roberts, and Hongping Tan for helpful comments and ideas.

For chapter 4, *Too Much of a Good Thing? Mandatory Risk Disclosure and its Impact on Corporate Innovation*, we want to thank Douglas Cumming, Ming Dong, Paolo Fulghieri, Johan

Hombert, Mark Kamstra, Laurie Krigman, Lilian Ng, Jerome Taillard, Yelin Zhang, and seminar participants at the University of Manitoba, University of Saskatchewan, and York University for helpful comments.

Finally, I want to thank the faculty, students and staff at York for their help. The faculty were invaluable resources for ideas and feedback, the students helped keep my spirits up when times were tough, and the staff kept my head above a steadily rising tide of work.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

In this dissertation, I investigate three aspects of corporate intangibles and ethics. While not measured on a firm's financial statements, intangibles are a critical portion of firm value. For example, emerging studies have shown the importance of corporate culture on firm value and performance, the importance of integrity and financial misconduct on improving or damaging firm reputation, the effect of qualitative risk disclosures on traditional measures of firm risk, and the impact of innovation on helping the economy grow and firms to thrive.

However, due to the insubstantial nature of intangibles, they are difficult to measure and study—there are no inventories to count nor are there any factories to visit. This dissertation attempts to bridge that gap by using the emerging technique of text analysis. Text analysis can glean qualitative information from thousands of firms over many years—an impossible task by hand—allowing the incorporation of data previously unavailable to researchers. By using text analysis, I am able to measure intangibles on a large cross-sectional sample of firms over time and empirically test for the impact of these intangibles with a sample size impossible with hand coded responses.

Chapter 2 uses this textual analysis technique to analyze the impact of employee empowerment or flexibility on firm performance when exposed to risk. Chapter 4, in turn, examines the interplay of two different intangibles by identifying the relationship between risk disclosed by a firm and the amount of innovation the firm produces. Finally, Chapter 3, though it does not use text analysis, looks at an important intangible, integrity and reputation, by examining whether the SEC can deter financial misconduct.

Chapter 2 of this dissertation examines the impact of a specific aspect of the corporate culture intangible, employee empowerment/flexibility, and its impact on firm value. Corporate executives consider corporate culture to be very important for firms (Graham, Harvey, Popadak, and Rajgopal 2016a) and other academic research has shown that corporate culture has a large impact on firm performance (Guiso and Zingales 2015). This chapter considers the value relevance of psychological empowerment—employee flexibility, defined as employees' ability to accelerate intended changes and to respond to unexpected situations (Bahrami 1992).

According to the theoretical models by Kreps (1990) and Hermalin (2001), employee flexibility acts as an informal contracting mechanism that helps boost firm value, particularly when the firm faces risk or uncertainty. Employee flexibility overcomes incomplete contracting in that flexible employees are able to rapidly react to unforeseen or ex-ante improbable circumstances. Consequently, we expect to see these firms outperform when exogenous risk is higher.

Traditionally, an intangible like employee flexibility is estimated through primary research with firm employees; however, this method is impractical for a large sample of firms over time. To overcome this, I use job reviews published by employees on a career intelligence site as a primary source—I use over 690,000 reviews drawn from 2011-2016 from S&P1500 firms. To analyze this vast quantity of data, I use text analysis to identify words related to empowerment or flexibility in the reviews. I then average the review-level scores by firm and year to obtain a firm-level annual measure of employee flexibility, known as "flex" score.

I find that employee flexibility improves firm value, particularly among firms sensitive to risk or exposed to economic uncertainty. I form a long-short portfolio of high- and low-flex firms and measure hedge profits; high-flex portfolios cumulatively outperform the low-flex portfolios by 25.8% for the value-weighted portfolio. Furthermore, these abnormal returns remain even after controlling for known risk factors: a flexibility-based value-weighted hedge portfolio earns an alpha of 3.9% (annualized) after controlling for the Fama and French (2015) five factors.

Consistent with the theoretical model, employee flexibility matters most to firms with higher exposure to exogenous risk—among firms with high CAPM beta or during periods of economic uncertainty. When I split the flex regressions into firms with above- and below-median beta, we find the high-beta subsample exhibits significant annualized risk-adjusted high-low flex hedge profits while low-beta firms show no alpha. In addition, flexible firms also only demonstrate abnormal returns after an exogenous increase to economic risk—an increase in economic policy uncertainty using the Baker, Bloom, and Davis (2016). Alpha is only apparent following high-uncertainty months.

The results also remain robust after controlling for firm characteristics in a Fama-Macbeth cross-sectional regression. The abnormal returns remain even after examining employee morale, organizational capital (a proxy for management effectiveness and training), and unionization.

The third chapter of the dissertation examines whether the Securities and Exchange Commission (SEC) can deter future financial misconduct through its enforcement actions. Misconduct is a large problem for financial markets as it discourages outsiders from participating, leads to market manipulation, and broker-agency conflicts (Bhattacharya and Daouk 2002; Beny 2005; and Cumming, Johan, Li 2011). Consequently, reducing financial misconduct is critical to ensuring trust in the financial system.

A main part of ensuring this trust in the financial system is the prosecution of financial malfeasance. This prosecution reduces misconduct in two ways: First the guilty individuals are incapacitated (jailed, excluded from industry, etc.) and unable to commit future misconduct.

Second, and more importantly, these prosecutions deter financial misconduct as future criminals fear identification and punishment. In this chapter, I focus on the latter effect as deterrence has been shown to have a much larger effect on reducing other forms of crime (Ehrlich 1996).

In addition, I also examine which target for prosecutions is the best for deterring future financial misconduct. When prosecuting a case, the SEC can target any combination of officers of the company, the company itself, or other groups, such as an auditor or lawyer. By knowing which target of prosecution reduce financial misconduct in the future, the SEC can select cases which will have the maximum deterrence impact.

To test whether enforcement deters future misconduct, I run a logit regression analyzing the probability of misconduct in the years following an enforcement action by the SEC. The results show that an enforcement action in the past two years reduces misconduct in the same industry and MSA. For example, in 2004, the SEC officially sanctioned Worldcom (now known as MCI) for its financial misconduct. In the following year, the regression results predict that the rate of financial misconduct will be 19.2% and 32.4% lower in the industry and MSA, respectively, than if there was no enforcement. The results are robust to the usage of alternative metrics of financial misconduct. The results are similar if self-reported restatements or Fscore, a measure that predicts financial misconduct, are used instead of actual misconduct.

In addition, I examined what target of punishment would be best for reducing future misconduct. I subdivided the enforcement actions into whether they targeted officers of the company, the company itself, other groups, or combinations of the previous three. The results show that enforcements against a company have the largest deterrence on misconduct in the same industry and MSA. On the other hand, targeting the officer and other entities has lower or no statistically measurable effect on financial misconduct rates in the industry or MSA.

These results will be useful in the ongoing debate over how to deter future financial misconduct. The Department of Justice (DOJ) has reached record settlements with banks involved in the financial crisis; however, it has failed to successfully pursue any of the bank CEOs or other officers.

The fourth chapter of this dissertation examines the impact of mandatory corporate disclosure on another intangible--firm innovation. Innovation is important to macroeconomic growth and on a microeconomic level, innovation can help firms withstand competition and improve their firm performance. Corporate disclosure reduces information asymmetry, improves capital market efficiency, and other benefits, and regulatory agencies across the world have steadily increased disclosure requirements. However, increased disclosure may not bring uniform benefits to firms Two theoretical models have hypothesized that improved disclosure does not benefit all firms. The first shows that less disclosure is desirable when the manager cannot easily report the benefits of investments (Kanodia, Singh, and Spero 2013). The second shows that improved disclosure causes a "crowding-out" of investments among firms with riskier investments (Zhang 2013).

To estimate the amount of disclosed risks, I download all the 10-K filings from 1993 to 2013 and use the ratio of risk keywords scaled by the total number of words in the 10-K filing to measure corporate risk disclosure. I then use this data to determine the baseline relationship between disclosed risk and innovation. An increase in disclosed risk in a 10-K is associated with a significant decrease in R&D, number of patents, citation-weighted number of patents.

I then use two exogenous shocks and a regression discontinuity design (RDD) to examine the impact of making the disclosure mandatory on firm innovation. In the 2005 shock, firms were required by the SEC to include a risk disclosure section called the Item 1A. This meant that all firms were required to have a discussion of risks that was easily identifiable and comprehensive. Furthermore, in 2008, the SEC exempted smaller reporting companies from having to include an Item 1A risk disclosure section in their 10-K filings. Thus, these companies' risk disclosure was optional.

By examining the 2005 exogenous shock, I find that the mandatory disclosure of risk in the 10-K filings further reduces the amount of innovation—after the mandatory inclusion of the Item 1A, the negative impact of risk disclosure on innovation almost doubles. Furthermore, the 2008 exemption for smaller reporting companies enabled a difference-in-difference (DiD) and RDD test to examine the impact of removing the mandatory disclosure requirement. After 2008, smaller reporting companies showed an increase in innovation after the risk disclosure requirement was removed for them in 2008. The RDD further identifies the mandatory risk disclosure effect, showing that firms just above the threshold for mandatory Item 1A experience lower levels of innovation than firms just below the threshold.

The channel for this relationship appears to be due to financial constraints. I examined the interaction of external financing constraints on the risk disclosure-innovation relationship and found that the effect of risk disclosure was magnified among firms with financial constraints. Consequently, the mechanism appears to be that the market is unwilling to provide additional funds to these firms for fear of the risks these firms may face, similar to what the model in Zhang 2013 predicted.

I ran a variety of robustness checks to ensure the results were valid. Including testing if the results are related to information asymmetry reduction, traditional risk measures (beta and idiosyncratic volatility), and the textual dictionary used. The results stand in all cases.

The fifth and final chapter includes a summary of the results and implications for future research as well as practitioners.

Chapter 2: Employee Flexibility, Exogenous Risk, and Firm Value

2.1 Introduction

The psychological empowerment of employees is crucial to the well-being of a firm and affects a broad range of employee features such as job satisfaction, organizational commitment, and task performance (Seibert, Wang, and Courtright 2011). One form of worker empowerment, employee satisfaction, is shown to boost firm value in markets with low hiring and firing constraints (Edmans 2011, 2012; Edmans, Li, and Zhang 2017). In this paper, we consider the value relevance of a related but distinct form of psychological empowerment—employee flexibility, defined as employees' ability to accelerate intended changes and to respond to unexpected situations (Bahrami 1992). In line with the theoretical framework of Kreps (1990) and Hermalin (2001), we hypothesize that employee flexibility acts as an informal contracting mechanism that helps the firm react to exogenous shocks, and we examine whether employee flexibility enhances firm value.

We expect employee flexibility to improve firm value by increasing the firm's ability to cope with exogenous shocks. Since employee flexibility can supplement incomplete contracts by enabling coordinated employee actions in response to unforeseen or ex-ante improbable circumstances, the ability of employees to react to novel situations should be positively related to firm value.

However, just as maintaining employee satisfaction entails costs (Edmans 2011; Edmans, Li, and Zhang 2017), firms face a trade-off in developing and maintaining flexibility. First, creating flexibility requires investments such as hiring and training employees with multiple skillsets, reorganizing work, and building an information infrastructure suitable for a flexible working environment. Moreover, firms need to maintain flexibility even during periods of low uncertainty, thereby bearing heavy sunk costs. We therefore expect that the net benefits of employee flexibility will be large enough only when firms have high exposure to exogenous risk, because these are precisely situations where incomplete contracting is more likely and costly. Appendix A.1 presents an airline case study to illustrate how employee flexibility may improve firm value.

We use stock returns as the main metric of firm value creation (following Edmans (2011, 2012) and Edmans, Li, and Zhang (2017)). Endogeneity issues of reverse causality, omitted variable and selection biases, and measurement error are challenges inherent to corporate finance tests when ratio-based metrics such as Tobin's Q and ROA are used to assess firm value or performance. Stock returns, by contrast, are free of these endogeneity concerns because public information, including employee flexibility, is not expected to predict future returns in a sufficiently efficient market. In addition, examining future returns tends to give conservative estimates of the value effect of intangibles because measurement error of employee flexibility will lead to weakened return predictability.[1]

Employee flexibility, or employees' ability to respond to contingencies (Bahrami 1992), is clearly intangible and difficult to quantify. Traditionally, corporate culture constructs are estimated through in-depth interviews with selected firm employees (e.g. Hofstede, 1984). This method is however impractical for our purposes because we aim to measure employee flexibility for a large sample of firms. Instead, we turn to the job reviews published by employees on a career intelligence website as a surrogate for interviews.[2,3] Our goal is to quantify, for each job

---

[1] We provide further identification of causal effects by using an exogenous shock, as measured by levels of economic policy uncertainty, to examine how flexible and non-flexible firms perform in periods of high and low uncertainty.

[2] Executives interviewed by Graham, Harvey, Popadak, and Rajgopal (2016b) recommend employee opinions published on external websites as one of the primary data sources to estimate corporate intangibles such as employee flexibility or corporate culture.

review, the most salient features related to employee flexibility. We use an increasingly popular technique to extract information from text documents—textual analysis, in which we construct a list of key words (lexical field) pertinent to flexibility, and compute the frequency of these key words in each job review.[4]

Specifically, we retrieve job reviews from a career intelligence website that aggregates company reviews from current and former employees of more than 8,000 companies. We collect approximately 690,000 reviews, published between 2011 and 2016, for S&P 1500 firms and their subsidiaries, and we perform textual analysis of the free-form component of the reviews, computing the relative frequency of words associated with flexibility for each review. To minimize concerns of ex post data fitting, we use Fiordelisi and Ricci's (2014) lexical field related to creativity, but to capture employee flexibility, we expand their lexical field using WordNet's thesaurus to incorporate additional words pertaining to flexibility.[5] We average the review-level scores by firm and year to obtain a firm-level annual measure of employee flexibility, which we refer to as the "flex" score.

Of course, any text-based measure of an intangible asset contains noise and may be measured with error. First for external validation, we compare our flex scores with an external list, FlexJob's "Most Flexible Companies" and find that 84% of firms on their list had above-

---

[3] A related aspect of work flexibility is the employer's flexibility to hire and fire employees or change work hours. Both employee flexibility and employer flexibility should enhance the firm's ability to respond to external shocks. Our flex score is based on textual analysis of employee's job reviews and therefore should primarily reflect flexibility from the perspective of employees.

[4] Since the work of Tetlock (2007), textual analysis has been employed to study a range of finance and accounting topics; see the survey of Loughran and McDonald (2016). Dougal, Engelberg, Garcia, and Parsons (2012) find that journalists associated with more pessimistic column tone are linked to negative short-run market returns. Cohen, Malloy, and Nguyen (2016) use textual analysis of 10-K forms to detect changes in reporting practices, which they link to financial performance. Tremblay (2018) uses textual analysis of 10-K forms to construct measures of corporate culture differences between acquirers and targets in mergers. We follow this emerging strand of the textual analysis literature to provide a measure of corporate intangible asset.

[5] In the original Competing Values Framework of Cameron, DeGraff, Quinn, and Thakor (2006) which Fiordelisi and Ricci (2014) use, flexibility is closest to the creativity dimension. Section 3.1 motivates our choice of flexibility words by describing the theoretical relations between creativity and employee flexibility.

median flex scores in 2016.[6] More importantly, we verify the validity of our employee flexibility score by its ability in predicting stock returns in a large cross-section of firms. If market participants fail to fully value intangibles such as employee flexibility, and if our flex score adequately captures what it is designed to measure, the flex score should predict risk-adjusted returns in ways predicted by our hypothesis—a feature extremely difficult to accomplish if the flex score contains mostly noise. Furthermore, if there is an error-in-variables problem and flexibility is measured with error, this would result in an underestimate of the regression coefficients of flexibility (Griliches and Hausman 1986). Consequently the flex coefficients noted in this paper are more likely to be an underestimate of the true effect.

We find that our measure of employee flexibility has a major impact on firm value. Each year, we sort firms into high- and low-flex portfolios at the end of June, using the firm-level flexibility scores for the year immediately preceding the sorting month. We form a long-short portfolio of high- and low-flex firms and measure hedge profits. During our sample period from July 2011 to December 2016, high-flex portfolios cumulatively outperform the low-flex portfolios by 19.2% and 25.8% for equal-weighted and value-weighted portfolios, respectively. Furthermore, these differential returns remain even after controlling for risk: the flexibility-based hedge portfolio earns annualized alphas of 3.2% (t = 3.12) and 3.9% (t = 1.72) for equal-weighted and value-weighted portfolios, respectively, after controlling for the Fama and French (2015) five factors.

Consistent with our hypothesis, the impact of employee flexibility on stock returns concentrates among firms with higher exposure to exogenous risk—among firms with high CAPM beta or during periods of economic uncertainty. When we split the sample into firms with above- and below-median beta, we find the high-beta subsample exhibits annualized risk-

[6] Appendix A.5 has the list of 39 most flexible and popular firms published on the FlexJobs website.

adjusted high-low flex hedge profits of 5.4% (t = 3.34) and 8.2% (t = 2.55), for equal-weighted and value-weighted hedge portfolios, respectively. In contrast, low-beta firms have alphas that are statistically indistinguishable from zero.

To further identify the results, we use an exogenous shock—increases in the Economic Policy Uncertainty (EPU) index from Baker, Bloom, and Davis (2016)—to see if flexible firms perform better during periods of high risk. Accordingly, we find significant high-low flex alphas only in periods immediately following high-uncertainty months. The annualized five-factor alpha during high-uncertainty periods are 5.2% and 9.5% (p = 0.001 for both) for the equal-weighted and value-weighted hedge portfolios, respectively.

We provide further evidence on earnings announcement returns (EARs). A key advantage of EARs is that they are measured over a very short window and are unlikely to be driven by risk and hence will not be subject to any omitted variables that may be driving firm risk. We find that among high-beta firms, high-flex firms experience excess EARs while low-flex firms do not. This result suggests that employee flexibility is valuable to firms sensitive to exogenous risk, but investors do not fully account for the flexibility intangible in their valuation, consistent with Edmans' (2011, 2012) argument that the market is slow in reflecting information in intangibles. However, the positive effects of employee flexibility on EARs exist only when the exogenous risk is high; in fact, among low-beta firms, high-flex firms experience negative EARs—suggesting that maintaining a flexible workforce entails costs.

Our results are confirmed by Fama-MacBeth monthly return regressions. We find that high-flex firms earn higher monthly returns after controlling for firm size, value, momentum, and industry, and this effect concentrates in firms with higher betas. These results are also robust to different specifications. For example, the results remain qualitatively similar if we adjust the cultural scores to account for the negation of flexibility words in the reviews, trim cultural scores, or include only firms with more than five reviews.[7] In addition, the flexibility effect remains if we control for the quality of employee treatment (Bae, Kang, and Wang 2011), organizational capital (Eisfeldt and Papanikolaou 2013), management quality, employee morale (Edmans 2011; Edmans, Li and Zhang 2017), and unionization (Hirsch and Macpherson 2003), highlighting the empirical as well as theoretical differences between our flex score and these measures.

Finally, we estimate panel regressions of gross profitability on the flex score, and find that high-flex firms earn higher gross profits than low-flex firms. In line with Novy-Marx (2013) who finds that firms with higher gross profitability are associated with excess future stock returns, we consider the positive relation between gross profitability and employee flexibility to be further evidence that employee flexibility improves firm value.

Even though data availability restricts our sample to the period 2011-2016, the employee flexibility effect we document is comparable in magnitude to past studies on the value of corporate intangibles.[8] Additionally, our text-based employee flex score is subject to noise, which weakens the power of our flex score to predict returns. Therefore, our estimates likely represent a lower bound on the true wealth effects of employee flexibility in firms sensitive to exogenous risk.[9]

---

[7] Results remain qualitatively similar if we use stricter filters. Section 4.4 discusses the alternative thresholds we use.

[8] For example, Edmans (2011) finds the list of "100 Best Companies to Work for in America" leads to a value-weighted four-factor annual alpha of 3.5%; Eisfeldt and Papanikolaou (2013) documents another form of intangibles, organizational capital, generates an equal-weighted annual abnormal return of 4.6%.

[9] One might conjecture that firms with *financial* flexibility (i.e., with less financial constraints) have a similar advantage to firms with a high flex score in dealing with exogenous uncertainties. In unreported tests, we find that financial constraints are unrelated to stock returns during our sample period (or even during a longer period of 2000-2015); we measure financial constraints using the Kaplan-Zingales (1997) index (the 4-variable definition excluding Tobin's Q as in Baker, Stein, and Wurgler (2003)) or the Whited-Wu (2006) index. In addition, the flex score

Our paper contributes to the literature on the value of human capital and intangible assets. Consistent with other studies that document market underreaction to the value of intangibles (e.g., Edmans 2009; Eisfeldt and Papanikolaou 2013; Li, Qiu, and Shen 2016), we find that market participants do not fully account for the value of employee flexibility. Our paper is closely related to Edmans (2011) and Edmans, Li, and Zhang (2017) who document that firms on the list of "Best Companies to Work For" earn higher abnormal future returns, supporting the notion that investors do not fully value employee satisfaction.

Our paper differs from those two papers in several ways. First, we focus on employee flexibility, which is related to, but different from, employee satisfaction (Denison and Mishra 1995); in fact, the Best Companies list no longer possesses return predictability in the U.S. market during our sample period. Presumably, the market has learned to react to the information in the highly publicized list of Best Companies to Work For, but is still unable to react to the more abstract and hard-to-measure information of workforce flexibility. Second, we examine the interaction of flexibility and exogenous risk and find the benefits of employee flexibility concentrate among firms with high exposure to exogenous risk, which strengthens the economic underpinning of the flexibility effect. Lastly, while the Best Companies list only identifies a relatively small number of top employee satisfaction firms, our measure of employee flexibility sorts a broader sample of firms into high and low-flex portfolios, allowing for better identification of firms with poor employee flexibility.

To the extent that employee flexibility captures a dimension of corporate culture, our paper also contributes to the literature on corporate culture and finance. The survey of executives by Graham, Harvey, Popadak, and Rajgopal (2016a) confirms the pervasiveness of corporate culture

---

remains significant after controlling for financial constraints. This result indicates that the employee flexibility effect on stock performance is different from any effect related to financial constraints.

effects in corporate policies; in particular, adaptability (defined as willingness to experiment, being fast-moving, quick to take advantage of opportunities and taking initiative) is found to be a critical element of firm culture. More specifically, our paper contributes to the literature on the relation between corporate culture and firm performance. For example, Sørensen (2002) uses surveys to examine the influence of managers on operating cash flow and return on investment, and Moniz (2016) uses textual analysis of social media postings to find a link between employee performance-orientation and firms' Tobin's Q and earnings surprises. Several studies find that employee satisfaction is related to firm performance measures such as ROA, ROE and operating margin (e.g., Fauver, McDonald, and Taboada 2015; Huang, Li, Meschke, and Guthrie 2015; Melián-González, Bulchand-Gidumal, and González López-Valcárcel 2015). Our paper differs from the others in that we estimate a measure of employee flexibility that reflects the opinions of employees at different corporate levels among thousands of firms over time, and we measure firm performance with stock returns rather than accounting ratios that are prone to endogeneity concerns.

2.2 Hypothesis Development

Prior literature already documents the impact of financial and operating flexibility on investment policy and firm value. For example, financial flexibility allows firms to invest even during the financial crisis (Campello, Graham, and Harvey 2010; Duchin, Ozbas, and Sensoy 2010). Furthermore, operational flexibility increases firms' ability to adjust to changing circumstances, which in turn relates positively to firm value (Chen, Kacperczyk, and Ortiz-Molina 2011; Donangelo 2014). In this paper, we extend the research on financial and operating flexibility and focus on employee flexibility, because it should be instrumental to firms' operational performance (Denison and Mishra 1995; Bhattacharya, Gibson, and Doty 2005).

Firms that value employee flexibility acknowledge the value of human capital and recognize the importance of employee empowerment for the firm's responsiveness in competitive environments (Spreitzer 1996). Large experimental evidence also confirms the value of empowering employees (e.g., Bloom, Liang, Roberts, and Ying 2015).

We adopt Bahrami's (1992, p. 36) definition of flexibility: "the ability to precipitate intentional changes, to continuously respond to unanticipated changes, and to adjust to the unexpected consequences of predictable changes." This definition is similar to the one offered by Wright and Snell (1998, p.761): "the extent to which the firm's human resources possess skills and behavioral repertoires that can give a firm options for pursuing strategic alternatives in the firm's competitive environment," or VandenBos (2015, p.48): the "capacity to make appropriate responses to changed or changing situations; the ability to modify or adjust ones behavior in meeting different circumstances or different people." Employee flexibility also relates to the psychological empowerment concept of Seibert, Wang, and Courtright (2011), as defined in their integrated framework, where job satisfaction and turnover intentions are associates of employee flexibility. This empowerment can have large impacts on firm productivity—Bloom, Liang, Roberts, and Ying (2015) find that employees in flexible work environments increase productivity by 13%.

Therefore, our concept of employee flexibility captures employees' traits such as adaptability, flexibility, openness, pro-activeness, and resilience, but is different from creativity, job satisfaction, employee turnover, work design characteristics (including part- and full-time employment), or management leadership. It is also different from, for example, Gopalan, Milbourn, and Song's (2010) 'strategic flexibility', which they equate with prospects for firm and industry growth. Employee flexibility is a possible outcome of firms with a culture of adaptability, and can therefore be considered as one aspect of corporate culture.[10]

Theory suggests that corporate culture affects firm value. According to Kreps (1990) and Hermalin (2001), corporate culture acts as an informal contracting mechanism that supplements formal contracts.[11] For example, employees of a strong-culture firm tacitly and rapidly reach an agreement as to which equilibrium to play, either because the strong corporate values supersede personal preferences, or because strong culture makes coordination easier (Hermalin 2001). Similarly, a strong culture can address contingencies by defining ex ante what the employees consider as cooperative behavior, which is necessary given the repeated nature of business interactions. In turn, peer pressure among employees serves as an effective monitoring mechanism to reduce deviations from implicitly agreed-upon norms.[12]

As per the models of Kreps (1990) and Hermalin (2001), if widely agreed upon, even tacitly, these norms within the corporation become especially valuable when the firm faces unforeseen events or when employees must select an equilibrium to play from a set of several equilibria (O'Reilly 1989; Kreps 1990), that is, precisely in instances where incomplete contracting is more likely and costly.

We believe that employee flexibility is especially beneficial in the highly uncertain environments considered by Kreps (1990) and Hermalin (2001). First, profitable opportunities

[10] We use the term "employee flexibility" to refer to the flexibility that employees have in their daily tasks. However, employee flexibility encompasses more than flexible work options, such as an employee developing a product that the company never contracts them to do. For example, the ubiquitous Post-It note was developed accidentally by Spencer Silver and Art Fry at 3M even though the firm had tasked Silver to create a completely different product.
[11] Kreps' (1990) model rests on five elements: formal contracts are costly and ineffective in many situations; firms and their employees are repeat players; it may be easier and cheaper to induce collaboration through repeated play; there may be multiple equilibria and players jointly select which equilibrium they work towards; and there may be unforeseen events. Culture enters the model mainly through the last two elements.
[12] Giannetti and Yu (2017) find that short-horizon investors may impose a similar impact on firm policy and make the firm more readily react to radical changes.

are dynamic and difficult to anticipate; in these environments, flexible workers are better able to identify such opportunities in a timely manner. Second, because of the dynamic nature of the equilibria set, the firm's principals are unlikely to be able to formally design contracts ex ante to ensure all future contingencies are fully anticipated. In fact, inflexible and binding contracts could impede employees' value-creating efforts; the airlines case study of Appendix A.1 illustrates such a case. Alternatively, firms with a flexible workforce could respond to a changing set of equilibria by playing various equilibria simultaneously or in rapid succession, abandoning the unpromising ones. Additionally, employee flexibility supplements formal contracting with social forces, such as peer monitoring (Zammuto, Gifford, and Goodman 2000), that make behavioral cohesion easier to obtain.

Third, in uncertain environments, new ventures' parameters are often estimated with error; a firm that advocates employee flexibility would be more valuable in uncertain environments than a firm that focuses on the efficient use of its scarce resources (Cameron et al. 2006). Examples of such instances where flexibility may be valuable include firms facing periods where rapid product or industry-wide changes are likely, yet unknown (Aghion and Tirole 1994). In addition, periods of economic policy uncertainty impedes information processing, which makes it more difficult for firms' top managers to understand the value of new ventures. This in turn will encourage managers to depend more heavily on a motivated and flexible work force.[13]

For employee flexibility to affect firm value, consistent flexible behavior needs to be widespread within the firm. Unlike the KLD data and similar datasets that record the *existence* of corporate policies but not their intensity, our dataset allows us to measure the degree of

[13] We do not make any claim on what causes employee flexibility; we simply examine whether firms with high employee flexibility outperform those with low flexibility.

employee flexibility in a firm. We can therefore test whether a high degree of firm-level employee flexibility leads to greater value creation.

The literature on intangibles shows that the market tends to underreact to intangibles (e.g. Chan, Lakonishok and Sougiannis, 2001; Edmans, 2001), because market participants with limited attention tend to slowly adjust to the information in intangibles. Therefore, our first hypothesis is:

Hypothesis 1: Firms with a high degree of employee flexibility earn excess returns compared to firms with low employee flexibility.

As noted above, maintaining a flexible workforce is costly for the firm, and the benefits of a flexible workforce should outweigh the costs only when the firm has high exposure to exogenous risk, because these are the firms who have the highest marginal benefit of employee flexibility. A corollary of our first hypothesis is therefore:

Hypothesis 2: The positive effect of employee flexibility on stock returns is stronger for firms with high exposure to exogenous risk.

We measure exogenous risk in two ways. First, we use the CAPM beta to measure firms' sensitivity to systematic risk. We use systematic risk rather than idiosyncratic risk to characterize the type of risk pertinent to employee flexibility because systematic risk is exogenous to firm decision making. Because firms are capable of partially managing their idiosyncratic risk (for example, through hedging, selecting product mix, or pricing strategy), systematic risk is a better measure of unexpected shocks. The exogeneity of systemic risk, relative to idiosyncratic risk, eases the interpretation of results and eliminates a source of endogeneity. Second, we use changes in the EPU index (Baker et al. 2016) to identify exogenous increases to systematic risk—an individual firm has almost no influence on economic policy uncertainty. The EPU index captures uncertainty about currency, fiscal, monetary, regulation, health care, national security, sovereign debt, and trade policies; it is used as a measure of market-wide exogenous shocks in other studies (e.g., Starks and Sun 2016).

Finally, we investigate whether the abnormal returns of the high-flex firms are associated with improved accounting performance. We expect that the shareholder value creation brought about by a flexible workforce should be manifested in accounting profitability, which in turn is shown to lead to abnormal returns (Novy-Marx 2013; Fama and French 2015). Employees in a flexible firm are better able to choose optimal projects; selecting value-maximizing projects should lead to improved profitability. Therefore, we have the following hypothesis:

Hypothesis 3: Firms with high employee flexibility generate superior gross profitability.

We examine gross profitability (*GP*) because workers at all hierarchical levels of the firm are better able to affect gross profitability than items farther down the income statement, such as overhead (*SGA*), depreciation, or other accruals, which partially reflects quasi-static accounting charges. Furthermore, if high-flex firms need higher selling, general and administrative expenses to maintain their employee flexibility, the higher expenses will distort operating profitability, net income, earnings before interest and taxes, or return on assets. Consequently, *GP* is the best metric for measuring the impact of employee flexibility on firm profitability.

2.3 Data

2.3.1 Sample Description

Our measure of employee flexibility comes from the textual analysis of approximately 690,000 unique job reviews of S&P 1500 firms. As mentioned earlier, because conducting in-depth interviews of employees for each S&P 1500 firm for every year is impractical, the online job reviews are used as a substitute for employee interviews. An additional benefit of using publicly available, crowd-sourced job reviews is that firms do not self-select to be evaluated—the anonymous job reviews are posted whether firms give permission or not, but are cross-checked for inconsistencies by the data provider. In line with Popadak (2013), we retrieve reviews from a career intelligence website, where users can review their current or former employment experience. Each review contains the following information: company name, date of publication, reviewer's position (job title), reviewer's status (current or former employee)[14], reviewer's location, and a free-form review. Users optionally can identify the pros and cons of their work experience and rate their employer (on a 1 to 5 scale) on the following categories: job/work life balance, compensation benefits, job satisfaction, management, and job culture.[15] *Star rating* is the mean rating across all five categories. Our sample period is limited by review availability; on our source website, the earliest reviews were published in 2011. Appendix A.3 shows examples of reviews.

While the career website contains reviews for thousands of firms, we limit our sample to publicly traded firms listed on CRSP, and that are included in the S&P 1500 index during at least one year between 2011 and 2016. The stock return data is from CRSP and financial data and index constituents are from Compustat. To be included in the sample, each firm-year needs non-negative total assets (*AT*) and common equity (*CEQ*). Furthermore, firms need to be listed on the NYSE, AMEX, or NASDAQ and have common equity (share code 10 or 11).

We limit the sample to S&P 1500 firms to ensure that on average, there is a sufficient number of employee reviews for the firm and to ensure that the effect is not driven by very small

[14] A large proportion of the reviews are from former employees and removing them will reduce sample size significantly. Therefore we include reviews from both former and current employees.
[15] In robustness tests, we substitute our text-based measure with the firm-level averages of job culture ratings. We find no relation between the rating-based culture measure and stock returns. We attribute this result to noise in the rating-based measure: in fact, as per our theoretical framework, the aspect of corporate culture most related to stock returns should be employee flexibility and not a measure of overall corporate culture.

firms with few published reviews.[16] In addition, we also retrieve reviews for the subsidiaries of these firms and incorporate them under the parent company.[17] Firm subsidiaries were identified through the career intelligence site (which attempts to consolidate reviews), firms' websites, and firms' 10-K documents and annual reports.

We perform textual analysis on the lemmatized and parsed free-form component of the reviews.[18,19] Specifically, we first develop a list of words, or lexical field, that are associated with flexibility/adaptability. In developing the lexical field, we start from Fiordelisi and Ricci´s (2014) list of *Create* words, because it is publicly available and theoretical frameworks maintain that flexibility is an element pertaining to creativity (e.g. Torrance 1965; Kerr and Gagliardi 2003). Out of the four dimensions in Cameron et al.'s (2006) Competing Values Framework, the *Create* dimension is designed to reflect a flexible working environment conducive to creative and innovative activities; this motivates our focus on a modified version of the *Create* dimension as an operationalization of employee flexibility. We extend Fiordelisi and Ricci's (2014) lexical field to flexibility using WordNet's thesaurus.[20] Appendix A.6 presents our complete lexical field.

---

[16] Unlike the restaurant review site Yelp, the job reviews do not appear to have a sampling bias towards very satisfied or dissatisfied reviewers. The distribution of satisfaction among our sample employee reviews is roughly normal, indicating our sample has no bias towards very satisfied or dissatisfied reviewers. Regardless, in the robustness section we trim the top and bottom 5% of reviews based on satisfaction and find the results are largely similar.
[17] When retrieving reviews, we account for spelling mistakes and alternative company names. For example, when retrieving reviews for Consolidated Edison Inc., we search for reviews of "Consolidated Edison" and "Con Edison".
[18] In parsing the reviews, we follow Tetlock (2007) and strip the reviews of the common English stop words and then lemmatize the reviews. We exclude negation words (no, not, neither, none, nobody, nowhere, nor, never) from stop words in order to make the identification of negative loadings on the employee flexibility variable possible. Appendix A.2 gives more details about our parsing procedure.
[19] Using the free-form portion of the review minimizes the possibility of response bias introduced by prompted questions.
[20] To the extent that theoretical frameworks of creative thinking either overlap with flexibility (e.g. Schwartz 1999; Kasof et al. 2007) or require flexibility as a necessary element of creative thinking (e.g. Guilford 1962; Torrance 1965; Kerr and Gagliardi 2003), our measure of flexibility could partially capture corporate creativity. Also, the survey evidence of Graham et al. (2016a) indicates creativity is positively related to the cultural value of adaptability. However, our *flex* lexical field is substantially different from word lists associated with creativity (e.g. Gough, 1960; Fiordelisi and Ricci, 2014).

The firm-level flexibility score, *Flex*, is calculated in two steps. First, for each review, we compute the frequency of each of the words in our lexical field. The review-level flexibility word count is thus calculated by adding +1 each time a word from the review matches a word or expression from the lexical field.[21] We obtain the review-level flex ratio *(Flex_rev)* by scaling the flexibility word count by the number of words in the parsed review to account for variability in the length of the reviews. Second, we compute the yearly firm-level flexibility score, *Flex*, as the average of a firm's review-level flex ratio, for reviews published between July (*t*-1) to June (*t*) for end of June stock portfolio formations,[22] or beginning of financial year to end of financial year for financial ratio regressions. We winsorize *Flex* at the 1%/99% level to reduce the impact of outliers.

We also compute a flexibility score, *Flex_net,* that accounts for negation by computing a "net" review-level flexibility word count that subtracts one from the flexibility word count each time a flexibility word in the review is in the vicinity (three words before or after) of a negation word.[23] The occurrence of negated flexibility words is less than 5% of total flexibility words. This frequency is comparable with the negation frequency in the English language reported by Tottie (1991). There is thus little concern that the flex score is contaminated by undetected negative meanings.

Finally, we also retrieve data on employee treatment and employee morale. The *ETKLD* variable was developed from the MSCI KLD dataset by summing the scores over three categories of employee relations: union relations, cash profit-sharing, and employee involvement

[21] The simple count method has some caveats, among which the possibility that we misinterpret the sense of a sentence. However, more sophisticated methods that attempt to interpret texts are only partially successful, among others because of the prevalence of polysemes in English.
[22] For 2011, the first year of our stock return sample, we use reviews published from January 2011 through June 2011 to calculate *Flex* for the formation of portfolios at the end of June 2011.
[23] Our negation words list includes the following: no, not, neither, none, nobody, nowhere, nor, never.

in stock options plans[24]. The *BC* variable was developed from the "100 Best Companies to Work for" list, which we manually collect from the Forbes website. The earnings announcement data is drawn from I/B/E/S and incorporate all earnings announcements from July 2011 to December 2016. We also use the EPU index from Baker, Bloom, and Davis (2016), which measures policy uncertainty by aggregating three components: The first component uses newspaper coverage of economic uncertainty, the second incorporates federal tax code provisions that will expire in the future, and the final uses disagreement among economic forecasters. Finally, we use Ken French's data for the risk-free rate and pricing factor data.[25]

2.3.2 Summary Statistics

Table 2.1, Panel A, presents review-level descriptive statistics of the sample. In total, the career intelligence website provides nearly 19 million parsed words to identify culture trends both in the cross-section of firms and time-series. There is within-sample heterogeneity in the review-level flex score *(Flex_rev)*: reviews on average have 1.65% flexibility words, but range from a minimum of zero to fifty percent of the words in the review.[26] Examination of the sample also reveals within-industry heterogeneity in *Flex_rev*.

Panel B of Table 2.1 shows the firm-year employee flexibility statistics. The firm-year mean values are similar to the review-level values. Furthermore, the number of reviews for each firm-year is reasonably high given the breadth of the firms—each firm-year has a mean and median of

[24] Two of the indicators in the original ETKLD index, retirement benefits and employee health and safety, were discontinued before the sample period began and thus cannot be included in the ETKLD index.
[25] Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[26] The high maximum flex values arise because we remove stop words, making shorter reviews even shorter. Such high values are also observed in a subsample of outlier reviews; the 99th flex percentile is 14.3%, considerably lower than 50%.

110.3 and 13 reviews, respectively—indicating that the results are not driven by firm-level observations with very few reviews.[27]

Nonetheless, as with any survey or questionnaire data, our dataset could potentially be subject to active response bias which arises when respondents have motivations to skew their answers, either by making them overly optimistic, pessimistic, or uninformative. Our robustness tests find no evidence that the voluntary reviews are biased in a way that would favor our results.[28]

Panels A and B of Table 2.1 also report descriptive statistics for the negation-adjusted flex scores at the review-level (*Flex_net_rev*) and firm-level (*Flex_net*). Unlike *Flex_rev*, *Flex_net_rev* is not bounded at zero; the minimum review-level *Flex_net_rev* score is in fact negative (corresponding to a review where the negated flexibility words outnumber the non-negated ones). Consistent with linguistics studies that document a low frequency of negation in written English, Panel B show that *Flex_net* is very similar to *Flex*.[29] We thus use *Flex* for our tests, but results are robust to using *Flex_net* instead (see Section 4.4).

Consistent with Sørensen (2002) who documents higher behavioral cohesion in strong-culture firms, our main tests contrast the effects of having a high-flex workforce versus having a low-flex one. Each year, we thus split the sample into high- and low-flex subsamples along the yearly *Flex* median. Portfolios are formed at the end of June (or beginning of year for financial ratios) and rebalanced annually. Panel C of Table 2.1 presents statistics of firm characteristics as

[27] To ensure that firms with small number of reviews are not driving the results, we run robustness tests in Section 4.4 which exclude firms with 5 or fewer reviews. Our results remain if we restrict the sample to firms with at least 10, 20 or 30 reviews (results untabulated). In fact, in spite of the much reduced sample size, most of our results remain qualitatively similar when the sample is limited to firms with at least 100 reviews. In addition, our sample includes 1,723 of the 1,932 firms listed in the S&P 1500 over our sample period, for a coverage rate of 89.2%.
[28] Specifically, we find that our results are not driven by overly optimistic or pessimistic reviews, or by firms with less than five published reviews. Tables 10 and 11 provide further details.
[29] Tottie (1991) finds that negation (all types) accounts for 1.28% of words in written English, contrasted with 2.67% in speech. Therefore, even if written negation is affixal (e.g. *un*necessary, *in*adequate, etc.) and thus not detected by our algorithm, the low frequency of negation makes this non-detection nonconsequential.

well as the results of *t*-tests for the differences in means between the subsamples. High-flex firms are significantly larger in terms of both market capitalization ($19.4 billion versus $11.1 billion at portfolio formation) and book assets ($39.4 billion versus $18.9 billion),[30] but are similar to low-flex firms with respect to their B/M ratio and beta. Untabulated tests indicate that the selling, general, and administrative (SG&A) expenses are statistically higher for high-flex firms after controlling for other firm attributes, suggesting that maintaining employee flexibility increases costs.

The literature has established that larger size, lower B/M, and lower beta firms tend to have lower stock returns. However, as Panel D of Table 2.1 reports, high-flex firms earn higher returns than low-flex firms, in spite of their larger market capitalization, lower B/M ratios and lower beta. The high-flex portfolio generates monthly returns approximately 14 basis points more than the low-flex portfolio. While momentum ($Return_{-12,-2}$) is higher for high-flex firms, the positive excess returns of high-flex firms remain after controlling for this and other factors, as shown in Section 2.4.1.

Panels A and B of Figure 2.1 graphically present the stock performance of high- and low-flex firms. It shows the cumulative return of the high-flex and low-flex portfolios that are formed at the end of June 2011, rebalanced at the end of each June, and held to December 2016. Over our sample period, the equal-weighted (value-weighted) high flex portfolio has cumulative returns that are 19.2% (25.8%) higher than the low flex portfolio (untabulated). These univariate results provide preliminary evidence for our first hypothesis: high-flex firms earn higher excess returns.

[30] The mean book assets figure may be high compared to some other corporate finance papers because we include in our sample financial firms which tend to have high asset values compared to market values.

Before considering multivariate tests, we validate our measure of employee flexibility by estimating Pearson correlation coefficients between *Flex* or *HiFlex* (an indicator variable equal to 1 if the firm's flex score is above median) and firm characteristics that might be determinants of a highly flexible corporate environment. The results, reported in Table 2.2, tend to conform to intuition. For instance, *HiFlex* and *Flex* are negatively correlated with rigid and regulated environments, which we proxy by the percentage of unionized employees in the same state as the firm's headquarters (*UnionMemb*, as in Hirsch and Macpherson (2003)).[31] Also, as expected, *HiFlex* is positively correlated with employee satisfaction (measured by an indicator for being on the "Best Companies to Work for" list, *BC*), or an indicator of high KLD score of employee treatment (*HiETKLD*), and intangibles such as R&D (*RDA*) and organizational capital (*OK*). However, the low correlation coefficients highlight fundamental differences between employee flexibility and its related concepts, namely employee satisfaction and intangibles (Denison and Mishra 1995).

To provide further evidence that our flex score captures relevant information about employee flexibility, we compare the flex scores in our sample to a publicly available source—the "Most Flexible and Popular Companies" list compiled by FlexJobs. FlexJobs ranks firms based on job popularity data from LinkedIn and their own company database to determine which companies offer flexible work options. Appendix A.5 shows the list of 39 most flexible and popular firms. Such a list does not span a sufficiently long period for an in-depth analysis on the relation between job flexibility and firm performance. In addition, as discussed in Section 2, our flex score captures more than flexible work options. However, the flex score correlates strongly to FlexJob's "Most Flexible Companies"—over 84% of firms on their list had above-median flex scores in 2016, lending credence to our flex score measurement.

[31] UnionMemb is available from http://www.unionstats.com.

2.4 Results

2.4.1 Employee Flexibility and Excess Returns

To test Hypothesis 1, we estimate regressions of monthly returns for high flex, low flex, and high-low flex portfolios. We use both the Carhart (1997) 4-factor (FF4) and Fama and French (2015) 5-factor (FF5) regressions:

$$R_{it} = \alpha + \beta_{MKT}\,(MKT\text{-}RF_t) + \beta_{SMB}\,SMB_t + \beta_{HML}\,HML_t + \beta_{MOM}\,MOM_t + \varepsilon_{it} \quad (1)$$

$$R_{it} = \alpha + \beta_{MKT}\,(MKT\text{-}RF_t) + \beta_{SMB}\,SMB_t + \beta_{HML}\,HML_t + \beta_{RMW}\,RMW_t + \beta_{CMA}\,CMA_t + \varepsilon_{it}, \quad (2)$$

where R_{it} is the return over the risk-free rate from portfolio i at time t; for the high-low flex hedge portfolio, the risk-free rate is not subtracted from the hedge return. R_{it} is regressed on the market premium ($MKT\text{-}RF_t$), and SMB_t, HML_t, MOM_t, RMW_t, and CMA_t factors. Alpha (α) is the intercept that captures the abnormal monthly returns of the portfolio after controlling for the 4 or 5 risk factors. We also run similar regressions for industry or characteristics-adjusted portfolio returns.

Table 2.3 shows the results from these regressions. Consistent with our hypothesis that high-flex firms earn higher excess returns, the alphas for the high-low flex portfolio is positive and significant for both the Fama-French 5-factor and Carhart 4-factor risk-adjustment and for both equal-weighted and value-weighted portfolios. For equal-weighted excess returns, the high-low flex portfolios earn a five-factor monthly alpha of 0.269% (t = 3.12), or an annualized alpha of 3.2%. We also note that most alphas are greater for value-weighed portfolios than for equal-weighted ones, suggesting that the effect of employee flexibility in forecasting returns is stronger among large firms. For example, for value-weighted portfolios, the five-factor alpha is 0.327% (t = 1.72), or an annual alpha of 3.9%.

In addition, we examine the results by industry to see if the effect is isolated to only a handful of industries. We calculate the high-flex and low-flex portfolio returns (results untabulated) for each FF12 industry and find that in ¾ of the industries the high-flex portfolio outperforms the low-flex portfolio. This is true in industries as diverse as manufacturing, energy, business equipment, and finance, which all benefited from high-flex employees. This result confirms that the flex effect is not driven by a very small number of industries.

2.4.2 Employee Flexibility, Exogenous Risk, and Excess Returns

Employee flexibility should matter most to firms sensitive to exogenous shocks, proxied here by market risk or uncertainty. In these cases, formal contracting is unlikely to be able to cover all the contingencies and firm employees have to rely more on informal mechanisms, such as those offered by employee flexibility, to optimize their decisions. To test Hypothesis 2, we use two proxies: *Beta*, the firm's exposure to systematic risk; and *HiUncert*, which captures market-wide policy uncertainty and derives from the EPU index. Extending Kreps' (1990) and Hermalin's (2001) arguments, the flexibility effects should concentrate in firms with comparatively high sensitivity to risk.

Figure 2.1, Panel C, D, E, and F graphically presents the stock performance of high- and low-flex firms in above-median and below-median beta subsamples. As can be seen in Panels C and D, high-flex firms in the high-beta subsample clearly outperform low-flex firms on both an equal-weighted and value-weighted basis. Furthermore, Panels E and F show that in the low-beta subsample, high-flex and low-flex portfolio returns are very similar, particularly on an equal-weighted basis. We conduct two types of regression tests to show statistical relationships between flex scores and future returns: the time-series regressions of monthly returns on risk factors, and the Fama-MacBeth cross-sectional regressions of monthly returns on firm and risk characteristics.

In the time-series regressions, we split the sample into firms with above- and below-full-sample median *Beta* at portfolio formation each year and run the FF4 and FF5 regressions for the high beta and low beta subsamples. Table 2.3 presents the results. Despite the reduced number of observations and associated reduction in test power, the high-low flex hedge portfolio exhibits substantial profit but only in the high beta subsample. The annualized 5-factor alpha for the equal-weighted and value-weighted flex hedge portfolios are 5.3% (t = 3.34) and 8.2% (t = 2.55), respectively. In untabulated portfolio tests we find that our results are robust to using raw returns instead of alpha to measure firm performance.

In the high-beta subsample, even though the high-low flex hedge portfolio is significant, the hedge profit is driven by the poor performance of the low-flex firms rather than the high abnormal returns of the high-flex firms. This suggests that when systematic risk is high, it is extremely costly if the firm does not have a flexible workforce to respond to the changing environment. Importantly, this finding is consistent with the interpretation that investors underreact to information in the flex score: investors do not fully appreciate the value of employee flexibility and overvalue low-flex and high-beta firms at the portfolio formation time, and the market gradually corrects this misvaluation in subsequent periods, delivering lower returns for those firms. On the other hand, in the low-beta subsample, even the low-flex firms earn positive alphas, possibly because not having to ensure employee flexibility is cost-efficient for firms with little exposure to exogenous risk. The Fama-MacBeth regressions shown in Table 2.5 control for firm characteristics and show that high-flex firms actually underperform unless they have a high beta.

To further identify the results of Hypothesis 2, we test whether high-flex firms outperform low-flex firms during periods of high exogenous uncertainty. We use the EPU index as a measure of systematic risk and we define *HiUncert* as an indicator variable that equals one during high-risk months when EPU values are above the 10-year rolling median uncertainty index value, and zero otherwise—firms will have no control over whether EPU is higher or lower in a period. We include the lagged *HiUncert* indicator variable into the FF4 and FF5 regressions as shown in the regression equations below:

$$R_{it} = \alpha + \alpha_H HiUncert_{t-1} + \beta_{MKT} (MKT\text{-}RF_t) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \varepsilon_{it.} \quad (3)$$

$$R_{it} = \alpha + \alpha_H HiUncert_{t-1} + \beta_{MKT} (MKT\text{-}RF_t) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_{it,} \quad (4)$$

Table 2.4 shows that alpha is insignificant for the high-low flex portfolio in both FF4 and FF5 specifications. However, the coefficient of *HiUncert* (α_H) is statistically significant in all the specifications: 0.298% (t = 1.78) for equal-weighted portfolio and 0.833% (t = 3.66) for value-weighted portfolio based on the FF5 regressions. Therefore, the abnormal returns only occur in high uncertainty months. The annualized 5-factor combined alpha (the sum of $\alpha + \alpha_H$) is 5.2% (p = 0.001) for the equal-weighed portfolio and 9.5% (p = 0.001) for the value-weighted portfolio in high uncertain periods. In short, Table 2.3 and Table 2.4 show that alphas of high-low flex portfolios are only generated in periods of high economic uncertainty or among firms with high systematic risk, consistent with Hypothesis 2.

To further examine the interaction with risk sensitivity and employee flexibility, we run Fama-MacBeth tests, with *Beta* and a *HiFlex*Beta* interaction term included in the regression. As noted earlier, firms with higher sensitivity to risk should receive higher flexibility benefits than other firms. We use *Beta* instead of the uncertainty index because the former provides cross-sectional variation, and we estimate the following equation:

$$R_{it} = a_0 + a_1 HiFlex_{it-1} + a_2 HiFlex_{it} * Beta_{it-1} + a_3 Beta_{it-1} + a_4 X_{it-1} + \varepsilon_{it,} \quad (5)$$

where R_{it} is firm i's monthly return for month t, *HiFlex* is an indicator variable equal to 1 if firm i in month t-1 is above median flex score for that year, $Beta_{it-1}$ is a firm i's *Beta* in month t-1 estimated over the previous 60 months and *HiFLex**Beta* is an interaction variable between the two. X_{it-1} is a vector of control variables for firm i observable in month t-1, including *LogBM*, *LogMEjun*, and various momentum measures such as the cumulative return from the previous month ($Return_{-1,1}$), previous year ($Return_{-12,-2}$), and previous three years ($Return_{-36,-13}$).

Table 2.5 reports the results. Consistent with Table 2.3, high-flex firms are associated with higher returns (Column 1). However, we find that the inclusion of the *HiFlex**Beta* interaction flips the sign on the *HiFlex* indicator variable, while the *HiFlex**Beta* interaction is significantly positive. These two values show that employee flexibility is not valuable in itself, and employee flexibility matters most when a firm is most likely to need it—i.e. when it is sensitive to risk. In fact, among low-beta firms, having a high flexibility workforce is overly costly and hurts firm value. This result is not simply the impact of *Beta* on firm returns. When the Fama-MacBeth regression is run with *Beta* but without *HiFlex* or the *HiFlex**Beta* interaction (untabulated), *Beta* has no statistically positive impact on returns.

4.2.1 Earnings Announcement Returns

In line with Edmans (2011), we also examine earnings announcement returns (EARs) as supplementary evidence on whether market participants value the flexible workforce intangible. Since EARs are measured in a short window, they are much less sensitive to the specific models used to measure abnormal returns and will avoid any problems with omitted risk factors that could cause abnormal returns.

We calculate EAR by subtracting the market return from a firm's stock returns for the three-day window centered on the earnings announcement (-1, +1).[32] We estimate panel regressions of the following form to determine the effect of *HiFlex* on EARs:

$$EAR_{itq} = b_0 + b_1\,HiFlex_{it-1} + b_2\,HiFlex_{it-1}{*}Beta_{it-1} + b_3\,Beta_{it-1} + b_4\,X_{it-1} + \varepsilon_{itq}, \qquad (6)$$

where EAR_{itq} is the EAR for firm $\underline{i}$ in year t for quarterly announcement q. $HiFlex_{t\text{-}1}$ is an indicator variable set to 1 if a firm is above median *Flex* in the previous year and X is a vector of control variables including *LogBM*, *LogMEfyr*, and year and industry fixed effects. Finally, we add our risk sensitivity proxy, *Beta*, to the earnings announcement return regressions to test whether the effect of employee flexibility on stock returns depends on market risk exposure.

Table 2.6 reports the results. Columns 1 and 2 show that high-flex firms earn similar EARs to low-flex firms. As noted in our hypothesis, *HiFlex* matters most when firms are exposed to risk. However, when *Beta* is included in the regression (Column 3), *HiFlex* has a negative effect on EAR (-0.251%; t = -2.76) and the interaction between *HiFlex* and *Beta* is significantly positive (0.219%; t = 2.26), showing that the market is only positively surprised in firms that have both flexible employees and high sensitivity to market risk.

A common theme emerging from the Fama-MacBeth monthly return regressions of Table 2.5 and the earnings announcement return regressions of Table 2.6 is that, when *HiFlex* is interacted with exogenous risk (*Beta)*, *HiFlex* itself has a negative effect on returns. This result again indicates that employee flexibility benefits firms only if the firm has high exposure to external risk. For firms with low risk exposure, maintaining employee flexibility is costly and may even hurt firm performance. This also helps explain why not all firms maintain high levels

[32] In unreported robustness tests, we measure abnormal returns using a market model with beta and the results are qualitatively similar.

of employee flexibility—among firms with low exogenous risk, employee flexibility at best does not enhance performance, and could even be detrimental to firm value.

2.4.3 Employee Flexibility and Profitability

To test the hypothesis that high-flex firms have high gross profitability (Hypothesis 3), we estimate panel regressions of the following form:

$$GP_{it} = b_0 + b_1\, HiFlex_{it-1} + b_2\, X_{it-1} + \varepsilon_{it}, \tag{8}$$

where GP_{it} is the gross profitability for firm i in year t, scaled by year t-1 total assets and multiplied by 100, $HiFlex_{t-1}$ is an indicator variable that equals 1 for firm-years where the flex score is above the full-sample, year t-1 median flex value, and X_{it-1} is a vector of control variables for firm i at time t-1. These controls include log of total assets (*logAT*), book-to-market ratio (*BM*), debt/assets (*DA*), cash scaled by assets (*Cash*), and firm age (*Age*). To deal with potential endogeneity issues, the regression uses $Flex_{it-1}$, the flexibility score in the previous financial year, to forecast financial ratios in year *t*.

For these tests, we adjust the time windows over which we estimate *Flex* to match the firms' fiscal years. The *Flex* metric for financial year *t* is measured over the previous financial year (for example, January to December for a firm with a December financial year end.) This ensures that every firm receives consistent measurement of their flex score regardless of their financial year end.

Columns 1 and 2 of Table 2.7 show that a high-flex workforce in the previous year enhances profitability in the current year, in line with Hypothesis 3. A high-flex firm in year *t*-1 is more likely to have improved gross profitability (*GP*) in year *t* than a low-flex firm. These results hold, even when controlling for size, B/M, leverage, cash levels, firm age, and year and industry fixed effects.

Even though the relationship between employee flexibility and accounting profitability does not clearly indicate causality (we use stock returns as the main measure of firm value to reduce the concern of reverse causality), the finding that high-flex firms have higher gross profitability helps illustrate why the market values high-flex firms more. Employee flexibility leads to more profitable projects that make better usage of assets, which in turn leads to better profitability. When investors do not fully incorporate the employee flexibility intangible into their valuation, the higher profitability of high-flex firms translates into greater future returns.

2.4.4 Robustness

We run a variety of robustness tests to confirm that a high degree of employee flexibility leads to excess stock returns. In Table 2.8, we repeat the tests in Table 2.3 using various robustness subsamples. In columns 1-2 we require firms to have more than 5 total reviews to be included in the sample; the significant abnormal long-short returns show that scarcely reviewed firms are not driving the results. Further tests reveal that our results remain if we impose stricter filters of at least 10, 20, 30 or 50 reviews (results untabulated), and many results remain if we restrict the sample to firms with at least 100 reviews. In columns 3-4, we repeat the tests using the negation-adjusted flexibility score, *Flex_net*, instead of *Flex*. The results remain, highlighting that negated flexibility words in the reviews are a minor concern and are not biasing the results. In columns 5 and 6 we drop subsidiary reviews from the dataset (for example, Old Navy reviews are excluded from Gap Inc.'s flex metric). Considering only the parent company reflects a trade-off: on the one hand, the smaller sample may reduce the power of tests. On the other hand, because subsidiaries and parents may have different levels of employee flexibility, the parent-only flex measure is a purer metric of the listed firm's employee flexibility. We find that our results remain qualitatively similar to those reported in Table 2.3.

In addition, we trim reviewers that are extremely satisfied or dissatisfied with the firm, to control for the possibility that extremely positive or negative reviews are written by employees with distorted incentives. For example, the owner of a small firm may publish fake positive reviews to attract job-seekers. Alternatively, a fired employee may seek revenge by posting extremely negative reviews. We proxy employee satisfaction by using review *star rating* (which is the average of the five numerical ratings on job/life work-balance, compensation benefits, job satisfaction, management, and job culture categories) included with most reviews. Using this satisfaction proxy, we trim reviewers that are above the 1%/99% level (Columns 7 and 8) or the 5%/95% level (Columns 9 and 10). The flexibility effect remains regardless of whether these outlier reviews are included. Finally, as an additional robustness test (untabulated), we remove very short reviews (less than 6 parsed words, or the shortest 1% of the reviews) from the analysis and the main alpha and Fama-MacBeth tests show similar results.

Table 2.9, Panel A, performs Fama-MacBeth monthly return regressions by imposing various restrictions on the sample. We report the results of the tests where firms have more than 5 total reviews (Column 1), the *Flex_Net* score is used (Column 2), no subsidiary reviews are included (Column 3), or extremely low and high *star ratings* are trimmed at the 1%/99% and 5%/95% levels (Columns 4 and 5), respectively. The interaction term *HiFlex*Beta* maintains its positive relationship with returns in all cases, while *HiFlex* generally has a negative effect on returns with marginal statistical significance. These results confirm the robustness of the employee flexibility effect.

To further address the omitted variable bias, we test other firm characteristics that may be correlated with employee flexibility. Table 2.9, Panel B, reports the results of Fama-MacBeth regressions that test the robustness of the *HiFlex*Beta* interaction effect after controlling for related pricing effects such as employee morale, organizational capital, R&D, and unionization. Edmans (2011) shows that employee morale is an intangible corporate resource that enhances future returns. As employee flexibility and employee morale may be intertwined with one another, we test two different aspects of employee morale to determine if the flexibility effect stands on its own. In Column 1 we create an indicator variable for whether the firm is on the "100 Best Companies to Work for" (BC) list for that year. In Column 2, we use the KLD-based employee treatment index developed in Bae, Kang, Wang (2011) to define *HiETKLD*, which is equal to one for firms with above-median employee treatment KLD score (*ETKLD*) in that year, and zero otherwise.[33] Columns 1 and 2 show that the positive *HiFlex*Beta* effect persists even after controlling for these employee morale variables.[34]

Eisfeldt and Papanikolaou (2013) show that organizational capital (*OK*) has a positive effect on returns in the cross-section: firms that invest in marketing and staff reap superior returns over the next year. As employee flexibility may be related to organizational capital, we verify the incremental value of employee flexibility by incorporating *OK* into our Fama-MacBeth tests. Column 3 shows that after including organizational capital (*OK*) as a control, *HiFlex*Beta* continues to positively affect returns. Furthermore, to ensure that the results are not related to management quality, we include *CEOtenure*, the length of tenure of the CEO, as a proxy for management quality. As can be seen in Column 4, after controlling for management quality, the results are qualitatively similar to before.

In column 5, we use R&D expenditures scaled by lagged assets (*RDA*) as a proxy for the innovativeness of the company, and we examine whether flexibility is related to firm innovation.

[33] Specifically, for each firm-year, we compute an employee treatment score by summing the scores over three categories of employee relations: union relations, cash profit-sharing and employee involvement in stock options plans. The total Employee Treatment index ranges between zero and three.
[34] When using *ETKLD*, our sample size decreases significantly, which possibly explains the decrease in statistical significance of the *HiFlex* interaction term.

We find that *HiFlex*Beta* interaction effect continues to be significantly positive, suggesting that results are applicable to more than just innovative firms. In addition, Columns 6 and 7 control for the effect of unionization: Column 6 uses *UnionMemb*, which is the unionization rate in a firm's headquarter state (a proxy for the unionization at the firm), whereas Column 7 uses *Unionreviews*, which counts mentions of union-related words in the employee reviews.[35] In both cases, the result for *HiFlex*Beta* remains similar.

Finally, column 8 shows that the excess returns for high-flex firms remain even after controlling for *BC*, *HiETKLD*, *OK*, *CEOtenure*, *RDA, UnionMemb,* and *Unionreviews* altogether, suggesting that the employee flexibility effect is distinct from the major identified employee morale factors that affect stock returns.

One might also expect that employee flexibility is related to managerial agency issues. On the other hand, these effects may operate separately because employee flexibility primarily influences employee behavior and corporate governance mainly controls executive agency issues. In unreported tests we include proxies for agency related variables in the Fama-MacBeth monthly return regressions. We use two agency-related control variables that are known to be positively related to firm value: the *Democracy* variable of Gompers, Ishii, and Metrick (2003), and the *E_0* variable of Bebchuk, Cohen, and Ferrell (2009). We use the 2006 values for both variables since both measures are only publicly available until that year. We find that *Democracy* is unrelated to returns in our sample, and while *E_0* has a marginal positive effect on returns, *HiFlex*Beta* remains significant after controlling for *E_0*. Consequently, corporate governance does not appear to explain the employee flexibility effect.

[35] Specifically, we compute the frequency of the following expressions (and their declinations): union, unionized, unionization.

Finally, we test in the Fama-Macbeth regressions whether state-level or industry-level measures of the ability to fire employees (labour flexibility) affect the HiFlex returns (results untabulated). As the ability to fire may be related to employee flexibility, we control for state-level factors such as good faith employment laws, wrongful dismissal laws, unemployment benefits, and labour mobility and find the *HiFlex-Beta* effect on stock returns remains. In addition, we control for layoff-separation rates by industry and find that our employee flexibility effect remains. Consequently, the employee flexibility is distinct from the ability to fire employees.

2.5 Conclusion

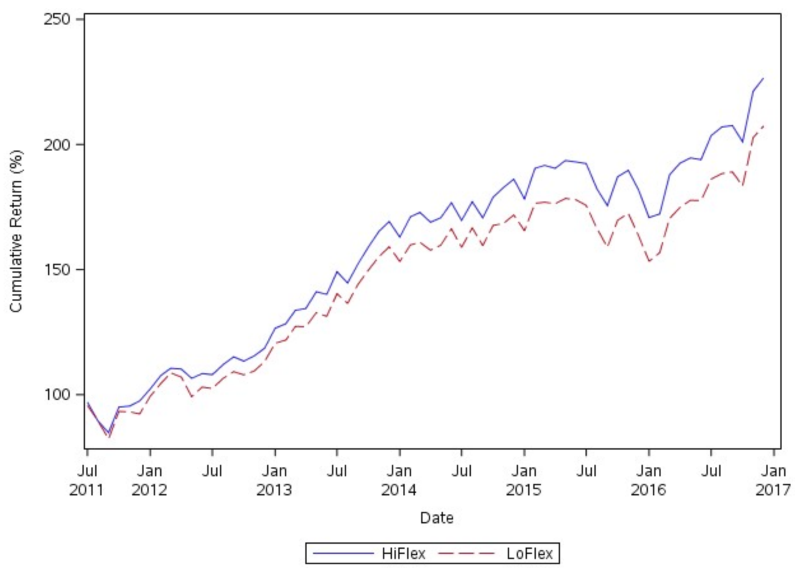
This paper studies the importance of employee flexibility to firm value. Using textual analysis of company reviews, we construct a novel measure of employee flexibility, and relate it to future stock returns. This paper shows that firms with a flexible workforce tend to outperform those that do not—a high degree of employee flexibility results in high risk-adjusted stock returns. Furthermore, the benefits of a flexible workforce concentrate in firms exposed to exogenous risk—the impact of employee flexibility on returns is evident only among firms with high betas or during periods of economic uncertainty. Finally, we find evidence that investors and analysts do not fully incorporate employee flexibility into their valuation.

Our evidence has major implications for corporate executives, investors, and researchers. For corporate executives, it shows the importance of building and maintaining a culture that encourages employee flexibility, as flexibility is positively associated to firm value, profitability, and resilience in the face of uncertainty. Relatedly, investors can design a hedge strategy based on firms' employee flexibility, and such a strategy would be especially profitable among high-beta stocks or during uncertain periods. More generally, our paper provides a methodology to measure employee flexibility over a large sample of firms. This measure is admittedly an imperfect representation of the true workforce flexibility, but even with such a measure, our evidence indicates that employee flexibility matters for firm value in ways predicted by theory. Further research to improve measures of employee flexibility and other corporate intangibles may offer new insights into the impact of workplace environment on firm performance.

Figure 2.1 Cumulative Portfolio Returns

This figure shows the cumulative portfolio returns over the sample period for a high-flexibility (*HiFlex*) and low-flexibility portfolio (*LoFlex*) and for a subsample of firms with above-median beta (high-beta) or below-median beta (low-beta). Portfolios are formed at the end of June 2011, rebalanced in June of each year, and then held to December 2016. The solid (dashed) line plots the long (short). The starting value of each portfolio is normalized to be 100. Panel A shows the equal-weighted results and Panel B the value-weighted results for the full portfolio. Panels C and D shows the equal-weighted and value-weighted results for the high-beta portfolio while Panels E and F show the equal-weighted and value-weighted results for the low-beta portfolio.

Panel A: Equal-Weighted Returns, All Firms



Panel B: Value-Weighted Returns, All Firms

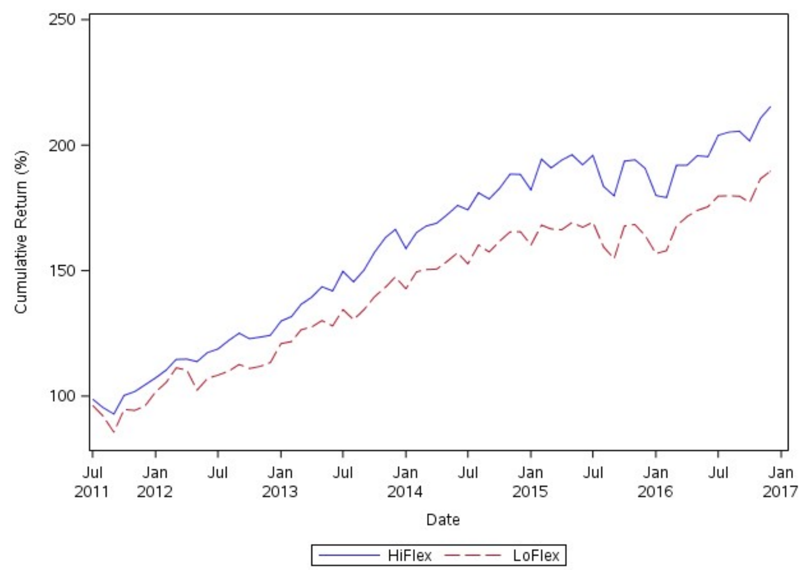
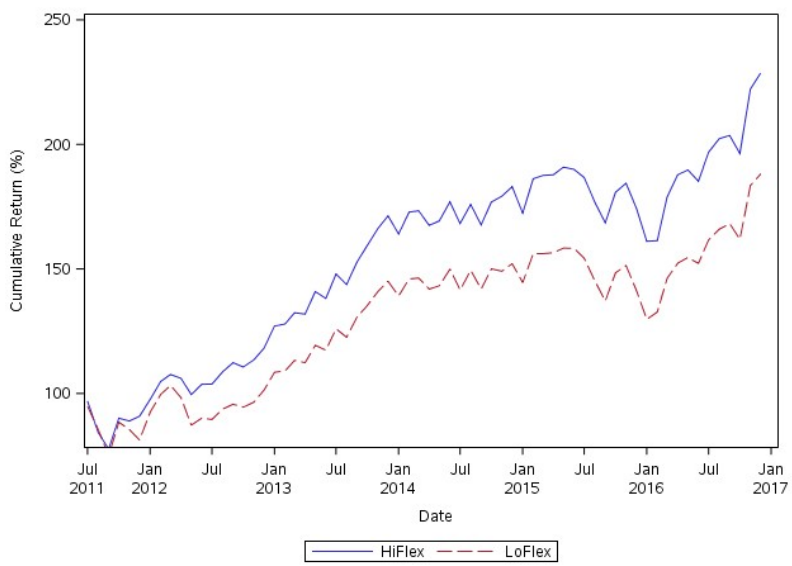


Figure 2.1 (Continued). Cumulative Portfolio Returns

Panel C: Cumulative EW Returns, High-Beta Firms



Panel D: Cumulative VW Returns, High-Beta Firms

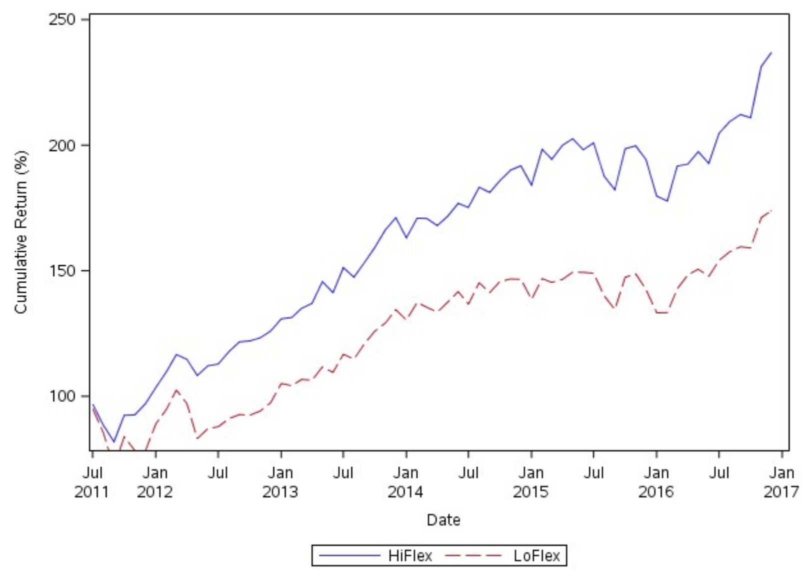
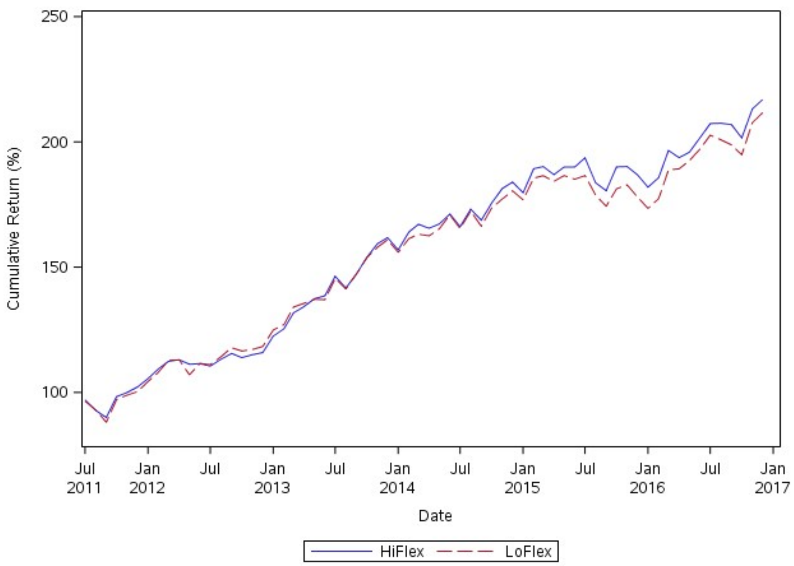


Figure 2.1 (Continued). Cumulative Portfolio Returns

Panel E: Cumulative EW Returns, Low-Beta Firms



Panel F: Cumulative VW Returns, Low- Beta Firms

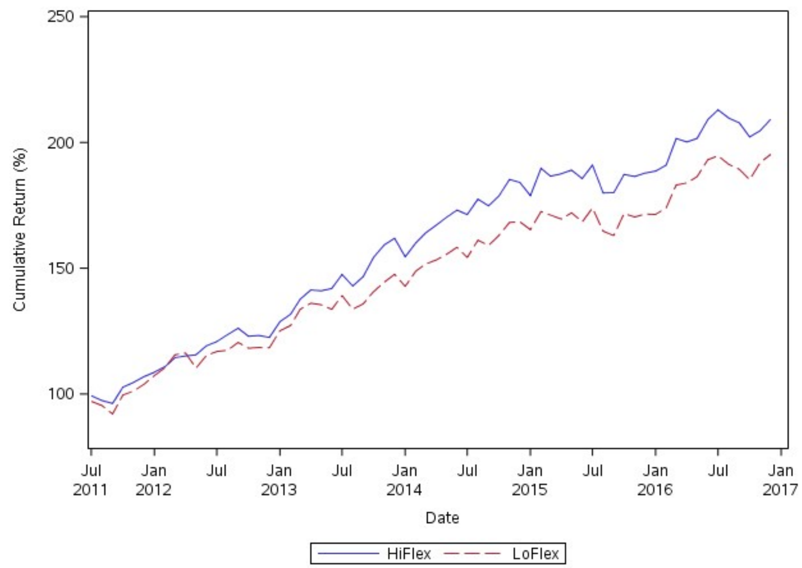


Table 2.1 Descriptive Statistics

Panel A. Review-Level Statistics

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum
Flex_rev (%)	688,647	1.65	0	3.35	0	50
Flex_net_rev (%)	688,647	1.58	0	3.30	-12.5	50
Len_review	688,647	27.34	19	24.71	1	648
Star rating	609,390	3.43	3.6	1.13	1	5
# Unique firms	1,723					

Panel B. Firm-Year Employee Flexibility Statistics

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum
Flex (%)	5,945	1.67	1.50	1.80	0	28.6
Flex_net (%)	5,945	1.60	1.43	1.77	0	15.4
Len_review	5,945	26.76	26.11	11.29	4	146.0
Star rating	5,853	3.43	3.45	0.58	1	5.0
# Reviews in firm-year	5,945	110.30	13.00	431.75	1	10805.0

Panel C. Firm-Year Means

	Full Sample	*HiFlex*	*LoFlex*	*t*-stat (Difference)
Flex (%)	1.67	2.67	0.68	50.28
MEjun (Billions $)	15.20	19.41	11.05	8.20
BM	0.52	0.51	0.53	-1.93
AT (Billions $)	29.07	39.41	18.85	5.35
GP (%)	32.97	34.08	31.87	3.55
Beta (End of June)	1.20	1.20	1.21	-0.06
N	5,925	2,944	2,981	

Table 2.1 (Continued). Descriptive Statistics

Panel D. Firm-Month Mean Returns (%)

	Full Sample	*HiFlex*	*LoFlex*	*t*-stat (Difference)
Ex_ret	1.34	1.41	1.27	1.96
Mkt_rf	1.12	1.13	1.11	0.60
$Return_{-12,-2}$	11.61	11.96	11.29	2.49
N	62,875	30,289	32,586	

This table provides summary statistics for *Flex* and related variables, at the review, firm-year, and firm-month levels. Panel A reports statistics at the review level and Panel B reports statistics for *Flex* at the firm-year level. Panels C and D show, respectively, annual and monthly mean statistics for high and low flexibility firm-years (firm-months). *HiFlex* (*LoFlex*) are the firm-years with *Flex* above (below) the same-year median *Flex* value. The last column reports the results of *t*-tests for the differences in means between the *HiFlex* and *LoFlex* subsamples. Total assets and market value of equity are in 2016 dollars.

Table 2.2 Pearson Correlation Coefficients

Variable	*Flex*	*HiFlex*	*Union Memb*	*Union Reviews*	*BC*	*HiETK LD*	*Star rating*	*OK*	*RDA*	*KZ*	*AT*	*BM*	*INV*	*GP*
Flex	1													
HiFlex	**0.56**	1												
UnionMemb	-0.009	-0.032	1											
UnionReviews	**-0.020**	-0.011	**0.202**	1										
BC	0.009	**0.056**	**-0.072**	-0.016	1									
HiETKLD	0.021	**0.055**	**0.041**	0.007	**0.067**	1								
Star rating	**0.026**	**0.024**	**0.042**	**-0.036**	**0.078**	**0.039**	1							
OK	0.001	**0.045**	**-0.224**	**-0.056**	0.027	**-0.052**	**-0.067**	1						
RDA	**0.057**	0.008	**-0.197**	**-0.041**	**0.076**	**0.049**	**0.058**	**0.227**	1					
KZ	-0.001	-0.021	**0.123**	0.017	**-0.059**	**-0.029**	0.010	**-0.261**	**-0.123**	1				
AT	-0.009	**0.074**	**-0.035**	-0.007	**0.044**	**0.087**	**0.044**	**-0.128**	**-0.066**	**0.042**	1			
BM	-0.007	-0.021	**0.028**	0.004	**-0.065**	**-0.028**	-0.005	**-0.243**	**-0.198**	**0.247**	**0.173**	1		
INV	0.000	**-0.029**	**-0.037**	-0.013	0.010	-0.024	-0.019	0.023	**0.139**	**0.031**	**-0.033**	**-0.121**	1	
GP	0.000	**0.042**	**-0.206**	**-0.059**	**0.062**	**-0.052**	**-0.075**	**0.835**	**0.260**	**-0.368**	**-0.158**	**-0.419**	**0.201**	1

This table reports Pearson correlations of selected variables from 2011 to 2016. *INV* is (AT_{t-1} / AT_{t-2} -1). *UnionMemb* is the percentage of unionized employees in the firm's state. *UnionReviews* is the firm-level average frequency of union-related words ("union", "unionized", "unionization") in the free-form reviews. *RDA* is R&D expenditures scaled by total assets and *KZ* is the Kaplan Zingales index of financial constraints. All other variables are defined in Appendix A.4. Bold values are significant at the 5% level.

Table 2.3 Risk-Adjusted Returns

Panel A: Equal-Weighted

	All		High *Beta* Firms		Low *Beta* Firms	
	FF4	**FF5**	**FF4**	**FF5**	**FF4**	**FF5**
LoFlex Alpha	0.110	0.038	-0.168	-0.322**	0.376**	0.379***
	(1.48)	(0.45)	(-1.59)	(-2.28)	(2.43)	(3.67)
HiFlex Alpha	0.343***	0.307***	0.205	0.124	0.427***	0.436***
	(2.92)	(3.21)	(1.47)	(0.72)	(3.43)	(5.05)
Hi-Lo Flex Alpha	0.234**	0.269***	0.373**	0.446***	0.051	0.057
	(2.48)	(3.12)	(2.24)	(3.34)	(0.69)	(0.65)

Panel B: Value-Weighted

	All		High *Beta* Firms		Low *Beta* Firms	
	FF4	**FF5**	**FF4**	**FF5**	**FF4**	**FF5**
LoFlex Alpha	-0.039	-0.045	-0.537***	-0.586***	0.246	0.251**
	(-0.49)	(-0.58)	(-2.64)	(-4.91)	(1.62)	(2.46)
HiFlex Alpha	0.294*	0.282**	0.133	0.098	0.367**	0.354***
	(1.70)	(2.09)	(0.62)	(0.40)	(2.15)	(3.31)
Hi-Lo Flex Alpha	0.334	0.327*	0.670**	0.684**	0.121	0.103
	(1.51)	(1.72)	(2.01)	(2.55)	(0.66)	(0.65)

This table reports the alphas from regressions of monthly returns of a portfolio of low flex (*LoFlex*) firms, high flex (*HiFlex*) firms, and a long-short portfolio of high and low flex (*Hi-Lo Flex*) firms, respectively. The returns are regressed on the Carhart 4 factors and the Fama-French 5 factors and (*MKT, HML, SMB*, *MOM, INV,* and *OP*). The high and low flex portfolio returns are the excess over the risk-free rate. Low beta (high beta) firms are firms with below (above) median *Beta* for that year. Panel A shows equal-weighted returns and Panel B shows value-weighted returns. *T*-statistics are in parentheses and use Newey-West standard errors. The sample returns are from July 2011 to December 2016.

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.4 Risk-Adjusted Returns and Policy Uncertainty

Panel A: Equal-Weighted

	FF4		**FF5**	
	Alpha	*$HiUncert_{(t-1)}$*	*Alpha*	*$HiUncert_{(t-1)}$*
LoFlex	0.129*	-0.041	0.063	-0.056
	(1.84)	(-0.28)	(0.78)	(-0.29)
HiFlex	0.189**	0.334**	0.199***	0.241
	(2.06)	(2.10)	(2.74)	(1.48)
Hi-Lo Flex	0.060	0.375**	0.136	0.298*
	(0.76)	(2.38)	(1.43)	(1.78)

Panel B: Value-Weighted

	FF4		**FF5**	
	Alpha	*$HiUncert_{(t-1)}$*	*Alpha*	*$HiUncert_{(t-1)}$*
LoFlex	0.073	-0.242**	0.091*	-0.304***
	(1.17)	(-1.97)	(1.81)	(-2.61)
HiFlex	-0.009	0.655***	0.046	0.529***
	(-0.09)	(2.83)	(0.56)	(3.17)
Hi-Lo Flex	-0.082	0.897***	-0.045	0.833***
	(-0.63)	(3.18)	(-0.40)	(3.66)

This table reports the intercept (alpha) and coefficient on an indicator variable for high uncertainty (*$HiUncert_{t-1}$*) of regressions of monthly returns of a portfolio of low flex (*LoFlex*) firms, high flex (*HiFlex*) firms, and a long-short portfolio of high and low flex (*Hi-Lo Flex*) firms, respectively. The returns are regressed on the Carhart 4 factors or the Fama-French 5 factors (*MKT, HML, SMB*, *MOM*, OP, and *INV*) and lagged indicator variable for high economic policy uncertainty (*$HiUncert_{t-1}$*); see equations (3) and (4) in the text. The *HiUncert* dummy is set to 1 if the month *t*-1 Economic Policy Uncertainty Index is above the 10-year rolling median, and zero otherwise. Panel A shows equal-weighted returns and Panel B shows value-weighted returns. *T*-statistics are in parentheses and use Newey-West standard errors. The sample returns are from July 2011 to December 2016.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.5 Fama-MacBeth Cross-Sectional Return Regressions

	(1)	(2)
HiFlex	0.186**	-0.366*
	(2.09)	(-1.88)
*HiFlex*Beta*		0.473**
		(2.65)
Beta		-0.587**
		(-2.25)
LogBM	0.007	0.027
	(0.05)	(0.22)
LogMEjun	0.017	-0.004
	(0.23)	(-0.06)
Return $_{-1,-1}$	-0.023	-0.025*
	(-1.45)	(-1.72)
Return $_{-12,-2}$	0.003	0.002
	(0.47)	(0.29)
Return $_{-36,-13}$	0.000	0.001
	(0.10)	(0.40)
N	56,948	56,827
Months	66	66

This table reports Fama-MacBeth (1973) regressions of monthly stock returns on a high flex score indicator (*HiFlex*) and other control variables. In column 1, *HiFlex* is tested for abnormal returns and Column 2 includes an interaction of *HiFlex* with *Beta*. All variables are defined in Appendix A.4. *T*-statistics are in parentheses and use Newey-West standard errors. The sample period is July 2011 to December 2016.

* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.6 Earnings Announcement Returns

	(1)	(2)	(3)
HiFlex	-0.001	0.003	-0.251***
	(-0.01)	(0.03)	(-2.76)
*HiFlex*Beta*			0.219**
			(2.26)
Beta			0.190**
			(2.53)
LogBM		0.022	-0.009
		(0.24)	(-0.09)
LogMEfyr		-0.032	-0.013
		(-0.92)	(-0.37)
N	19,413	19,413	19,329
R-Squared	0.000	0.001	0.002
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

This table reports results of the panel regressions of abnormal earning announcement returns on an indicator variable *HiFlex*. Abnormal returns are calculated over a three-day window centered on the earnings announcement date (-1, +1) as the daily firm return in excess of the market return. Returns are in percentages. All variables are defined in Appendix A.4. The regressions include year and industry fixed effects and an intercept, which are not reported for brevity. *T*-statistics in parentheses use standard errors clustered by firm and year.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.7 Gross Profitability Regressions

	GP (1)	*GP* (2)
HiFlex	3.417***	2.174***
	(3.77)	(2.71)
LogAT	-4.660***	-2.745***
	(-13.97)	(-8.30)
BM	-26.453***	-19.035***
	(-6.21)	(-5.51)
DA	-0.240***	-0.284***
	(-4.39)	(-7.03)
Cash	0.085**	0.140***
	(2.07)	(3.82)
Age	-0.013	-0.005
	(-0.48)	(-0.17)
N	4,295	4,295
R-Squared	0.396	0.541
Year FE	Yes	Yes
Industry FE	No	Yes

This table reports the results of panel regressions of gross profit (*GP*) on the *HiFlex* indicator variable and controls. *GP* is measured from year *t*. The independent variables are measured using data from financial year *t*-1. All variables are described in Appendix A.4. Columns 1 and 2 show the panel regression results without and with industry fixed effects, respectively. All values are in percentages. The intercept is not shown for brevity. *T*-statistics in parentheses use standard errors clustered by firm and year.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.8 Robustness: Risk-Adjusted Returns

Panel A: Equal-Weighted

	More than 5 Reviews		**Flex_net**		**No subsidiaries**		**Trim 1/99**		**Trim 5/95**	
	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LoFlex Alpha	0.046	-0.300**	0.076	-0.322**	0.050	-0.291*	0.035	-0.322**	0.038	-0.321**
	(0.55)	(-2.25)	(0.88)	(-2.28)	(0.57)	(-1.83)	(0.42)	(-2.28)	(0.46)	(-2.31)
HiFlex Alpha	0.317***	0.141	0.278***	0.124	0.348***	0.177	0.309***	0.123	0.305***	0.121
	(3.39)	(0.84)	(3.31)	(0.72)	(2.77)	(0.79)	(3.18)	(0.71)	(3.13)	(0.69)
Hi-Lo Flex Alpha	0.270***	0.441***	0.202**	0.446***	0.298***	0.468***	0.274***	0.445***	0.267***	0.442***
	(3.01)	(3.21)	(2.43)	(3.34)	(2.71)	(2.72)	(3.17)	(3.31)	(3.13)	(3.38)

Panel B: Value-Weighted

	More than 5 Reviews		**Flex_net**		**No subsidiaries**		**Trim 1/99**		**Trim 5/95**	
	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta	Full	Hi Beta
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LoFlex Alpha	-0.041	-0.573***	-0.010	-0.586***	-0.106	-0.600***	-0.060	-0.597***	-0.048	-0.557***
	(-0.53)	(-5.21)	(-0.12)	(-4.91)	(-1.30)	(-4.94)	(-0.93)	(-5.11)	(-0.75)	(-4.75)
HiFlex Alpha	0.281**	0.101	0.258*	0.098	0.300**	0.109	0.289**	0.103	0.285**	0.079
	(2.10)	(0.40)	(1.86)	(0.40)	(2.31)	(0.44)	(2.33)	(0.42)	(2.33)	(0.32)
Hi-Lo Flex Alpha	0.322*	0.674**	0.269	0.684**	0.406**	0.709***	0.349**	0.700***	0.333**	0.636**
	(1.70)	(2.44)	(1.30)	(2.55)	(2.20)	(2.65)	(2.17)	(2.67)	(2.12)	(2.35)

This table reports the alphas from monthly risk-adjusted regressions of returns on a long-short portfolio of high flex firms and low flex firms for the full sample and the high beta subsample. The returns are regressed on the Fama-French 5 factors (*MKT, HML, SMB*, *RMW*, and *CMA*). The portfolio returns are the excess over the risk-free rate. Panel A presents results for equal-weighted returns and Panel B shows results for value-weighted returns. Columns 1 and 2 include firms that have more than 5 published reviews. In Columns 3 and 4, *HiFlex* is defined using *Flex_net* instead of *Flex* and includes firms that have a total of more than five reviews. Columns 5 and 6 excludes reviews of the firm's subsidiaries. Column 7 and 8 (9 and 10) excludes reviews with *Star ratings* above the 99th (95th) percentile, or below the 1st (5th) percentile of the full-sample distribution of *Star ratings*. *T*-statistics in parentheses use Newey-West standard errors.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 2.9 Robustness: Fama-MacBeth Return Regressions

Panel A: Additional restrictions on sample or alternative flex measure

	(1)	(2)	(3)	(4)	(5)
HiFlex	-0.363*	-0.442*	-0.425*	-0.331	-0.344
	(-1.72)	(-1.86)	(-1.90)	(-1.62)	(-1.66)
*HiFlex * Beta*	0.473**	0.517**	0.550**	0.453**	0.462**
	(2.51)	(2.51)	(2.51)	(2.44)	(2.44)
Beta	-0.590**	-0.616**	-0.580**	-0.573**	-0.578**
	(-2.30)	(-2.33)	(-2.36)	(-2.20)	(-2.22)
N	54,375	54,375	52,954	56,827	56,750
Months	66	66	66	66	66
Controls	Yes	Yes	Yes	Yes	Yes

Panel B: Additional controls that correlate with employee flexibility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HiFlex	-0.256	-0.241	-0.252	-0.273	-0.335	-0.309	-0.298	-0.348
	(-1.29)	(-1.20)	(-1.29)	(-1.31)	(-1.63)	(-1.56)	(-1.47)	(-1.46)
*HiFlex *Beta*	0.308*	0.296	0.298*	0.357*	0.348*	0.308*	0.333*	0.398*
	(1.74)	(1.67)	(1.74)	(1.79)	(1.94)	(1.77)	(1.88)	(1.82)
BC	-0.056							-0.165
	(-0.26)							(-0.74)
HiETKLD		0.066						0.057
		(0.46)						(0.43)
OK			0.049					0.092
			(0.70)					(1.16)
CEOTenure				0.013				0.013
				(1.51)				(1.66)
RDA					0.002			-0.010
					(0.08)			(-0.34)
UnionMemb						0.010		0.010
						(0.59)		(0.60)
UnionReviews							0.101	0.138
							(0.33)	(0.45)
N	53,111	53,111	53,111	51691	53,395	53,138	53,313	51646
Months	66	66	66	66	66	66	66	66
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.9 (Continued). Robustness: Fama-MacBeth Return Regression

This table reports Fama-MacBeth regressions of monthly returns on *HiFlex* and *Hiflex*Beta* interaction, variables that correlate with *Flex*, and control variables comprising *LogBM*, *LogMeJun*, *ret (-1,-1), ret(-12,-2),* and *ret(-36,-13)*. The dependent variable is the firm's monthly stock return. Panel A shows the results after imposing additional restrictions on the dataset. Column 1 limits the sample to firms with more than five published reviews. Column 2 requires more than five reviews per firm and uses *Flex_net* instead of *Flex*. Column 3 excludes reviews of subsidiaries; Columns 4 and 5 exclude reviews with *Star* ratings above the 99th (95th) percentile, or below the 1st (5th) percentile of the full-sample distribution of Star ratings. Panel B shows robustness tests of the *HiFlex * Beta* interaction with various controls related to job satisfaction, managerial talent (*BC*, *HiETKLD*, *CEOtenure*, *OK*, *RDA*), or unionization (*UnionMemb*, *UnionReviews*). Variables are defined in Appendix A.4. *T*-statistics are in parentheses and use Newey-West standard errors.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Chapter 3: The Effectiveness of SEC Enforcement in Deterring Financial Misconduct

We brought important cases against financial institutions, major companies and senior executives for violations relating to financial reporting violations, trading abuses, sales of complex financial instruments and Foreign Corrupt Practices Act violations, among others— Mary Jo White, former SEC chair, on her time at the SEC (Feb 15, 2017)

We need to undo many regulations which have stifled investment in American businesses, and restore oversight of the financial industry in a way that does not harm American workers— Donald Trump, President of the US, on his new SEC nominee, Walter "Jay" Clayton (Jan 4, 2017)

3.1 Introduction

Following the financial crisis, the Securities and Exchange Commission (SEC) took a position on pursuing and prosecuting financial misconduct in order to deter future wrongdoing. However, the media has speculated that the change in SEC chairs in 2017 is moving the agency away from enforcement to a more regulatory approach (Lynch 2017; Picker 2017). This paper seeks to understand whether the SEC's prosecutions of financial misconduct reduces the likelihood of other companies from committing fraud in the future—i.e. what is the prosecution's impact on deterring future fraud. Furthermore, this paper also investigates what target for prosecution is best for deterring future misconduct in other companies. The SEC can choose to prosecute officers, companies, or other entities (such as auditors or attorneys) and determining who to prosecute will help the SEC allocate resources and best determine how to deter future misconduct.

Reducing financial misconduct is critical for ensuring a well-functioning financial system. Capital markets allow the flow of funds between savers and borrowers and trust smooths these flows. For example, insider trading tilts the market in favor of insiders and consequently discourages outsiders from participating--Bhattacharya and Daouk (2002) find that the cost of equity is lower in countries that have prosecuted at least one insider trading case. In addition, Beny (2005) and Cumming, Johan, and Li (2011) note that rules restricting market manipulation, such as "pump and dump" scams, and broker-agency conflicts, such as front running (where the broker trades before the client), lead to better liquidity. Finally, after a financial institution has been sanctioned for misconduct, it improves credit conditions to attract new borrowers (Roman 2017).

Part of ensuring trust in the financial system is by reducing the frequency of financial misconduct. Deterrence is more important than incapacitation (jailing guilty individuals or barring them from the financial industry) for reducing misconduct. Detecting, trying, and jailing a criminal is very expensive, but it can have a large multiplier effect by deterring future criminals from committing crime (Ehrlich 1996). For example, in a study of violent felonies, deterrence had a greater impact on reducing property crime than incapacitation (Levitt 1998). By determining what forms of punishment work best, legislators can create laws with effective deterrents, and regulators/prosecutors can apply these laws to maximum effect.

Following the financial crisis, Dodd-Frank gave enhanced powers to many of the US agencies to improve the detection and punishment of financial misconduct. One agency that received a large expansion was the SEC. The SEC received enhanced powers, such as enhanced powers over investment advisors, an improved whistle-blower bounty program, oversight of executive compensation, and greater exemptions from the US Freedom of Information Act. These expanded powers make the SEC one of the most important agencies for ensuring the proper functioning of financial markets. However, the recent nomination of Walter "Jay" Clayton may indicate a shift away from enforcement. Consequently, understanding the impact of the SEC's enforcement actions on deterring misconduct will help inform whether the SEC should move away from enforcement or focus more heavily on enforcement.

The results show that the SEC enforcement causes a significant decline in the probability of financial fraud in future years in the same industry and Metropolitan Statistical Area (MSA). To determine what impact enforcement has on future misconduct, I run a logit regression predicting financial misconduct and include an enforcement indicator variable set to 1 if there was an enforcement in the industry or MSA over the past 2 years. The results show that enforcement reduces misconduct in the future—the coefficient is -0.268 (t = -3.57) and -0.208 (t = -2.73) for an enforcement in the industry and MSA, respectively. For example, in 2004, the SEC officially sanctioned Worldcom (now known as MCI) for its financial misconduct. In the following year, the regression results predict that the rate of financial misconduct will be 19.2% and 32.4% lower in the industry and MSA, respectively, than if there was no enforcement.[36]

Another contribution of this paper is examining whether the target of enforcement affects the deterrence rate of financial misconduct. An enforcement action typically targets an officer of the company, the company itself, other entity (such as an attorney or auditor) or some combination of the three. As the SEC's resources are limited, focusing investigative and prosecution resources on a small group can help extend its reach.

The results show that enforcement actions targeting a company has the largest deterrence on misconduct in the same industry and MSA. Targeting a company reduces financial misconduct in the same industry (-0.125; t = -2.14), while targeting the company significantly reduces financial misconduct in the same MSA (-0.292; t= -4.38). On the other hand, targeting

[36] Probability = e(predicted value) / (1+e(predicted value). I use average firm values to calculate probabilities and then either set the enforcement indicator to 0 for no enforcement or 1 for enforcement.

the officer and other entities has lower or no statistically measurable effect on financial misconduct rates in the industry or MSA.

The differences between targeting an officer and other groups may be the result of a few factors. Officers and other groups are typically no longer associated with the firm by the time the SEC prosecutes the case. As a result these, "bad apples" may no longer be viewed to be part of the same industry or MSA. In addition, companies are invariably better known than their officers or support staff, consequently, competitors in the industry and MSA are more likely to be aware of SEC actions focused on a company than on an officer or support staff.

The results are robust to the usage of alternative metrics of financial misconduct. When company restatements are used in lieu of actual misconduct in the logit regressions, firms evidenced a reduced incidence of restatements following an enforcement action in the same industry. In addition, when Fscore, a measure predicting financial misconduct (Dechow, Ge, Larson, & Sloan 2011), is used the panel regressions show that an enforcement in the same industry reduces the Fscore for firms. This provides further evidence that firms are responding to regulatory actions and curtailing their misconduct rates.

These results will be useful in the ongoing debate over how to deter future financial misconduct. The Department of Justice (DOJ) has reached record settlements with banks involved in the financial crisis; however, it has failed to successfully pursue any of the bank CEOs or other officers. There has been a large amount of media criticism (Irwin 2013; Nocera 2011; Weidner 2011) about how few bank executives that have been prosecuted for the financial crisis; however, my analysis gives credence to both sides of the argument: misconduct is reduced more in companies in the same industry when an officer is targeted, but more in the same metropolitan statistical area (MSA) when a company is targeted. Regardless, targeting other entities, such as auditors, attorneys, or other firms/individuals, has no measurable effect on deterring future misconduct.

3.2 Related Research and Hypothesis

There is a large amount of research on financial misconduct; however, there has been scant analysis on what can deter future misconduct. For example, previous research shows that the market and regulators exact a large penalty on firms and managers that commit misconduct. On average, firms that are caught committing financial misconduct lose any gains from the misconduct plus more in fines and decreased market capitalization (Karpoff, Lee, & Martin 2008a). Furthermore, managers that are caught face large chances of being fired, financial penalties, and even jail time (Karpoff, Lee, & Martin 2008b). The issuance of an AAER has a large immediate effect on the market capitalization of a firm when an SEC investigation is announced (Feroz, Park, & Pastena 1991) and the SEC eventually levies fines or other punishments (Dechow, Sloan, & Sweeney 1996). However, this research has not looked at how these market and regulator imposed punishments have affected the rates of future financial misconduct.

In addition, while there has been a large amount of research in the area of financial misconduct, it primarily has focused on macro regulatory changes that affect the entire market. For example, several papers find that passage of insider trading laws reduces the incidence of insider trading (Bris 2005, and Bhattacharya and Daouk 2002). In addition, Cumming, Johan, & Li (2011) document that stricter stock exchange rules on insider trading and manipulation improves exchange liquidity, and greater enforcement power and resources leads to more misconduct detection. Given these paper focus on large regulatory events, they primarily focus on a handful of changes in the time-series or a cross-section of different markets across countries.

This paper provides a view into the micro effect of regulatory enforcement on different segments of the market. By examining an array of SEC enforcements, the paper is able to analyze the effect of regulatory intervention in both the cross-section and time-series. Moreover, as the SEC focuses on the US market, the paper allows an analysis within the same market, which removes much of the noise from analyzing across different countries. Finally, the paper is able to look at specifics of who is punished in order to tease out the impact of enforcement on different groups.

3.3 Hypothesis Development

Firms in the same industry should be discouraged from misconduct if they see one of their peers punished for misconduct. Industry competitors pay close attention to one another's activities and the revelation of fraud is no different. Goldman, Peyer, & Stefanescu (2012) find that in competitive industries, the revelation of fraud impacts the other firms in the industry. In addition, earnings management and the lack of enforcement can lead to contagion as other firms copy the fraudulent firm (Kedia, Koh, & Rajgopal 2015). Logically, the results should also flow in reverse so that enforcement on misconduct deters fraudulent behaviors of peer firms.

Deterrence may also occur if firms see a geographically close firm punished. Kedia et al. (2015) find that earnings management can spread through firms both industry and geographic proximity. Furthermore, other studies have found that geographic proximity to other firms affects analyst accuracy and compensation (Malloy 2005; Kedia and Rajgopal 2009). Finally, Kedia and Rajgopal (2011) find that SEC enforcement is highly dependent on proximity to the SEC offices. Consequently, firms that are geographically close to one another, such as in the same metropolitan statistical area (MSA), are likely to be aware of enforcement against its peers and thus perceive that enforcement is higher in their area.

Furthermore, the deterrence effect should be more noticeable as misconduct typically clusters together over time—misconduct is not a rare event that happens sporadically. Previous research has shown that misconduct in an industry or MSA leads to greater misconduct as firms see rival firms' improved results and then employ their own misconduct (Kedia, Koh, Rajgopal 2015). Consequently, if there was no enforcement effect, the number of misconducts should rise over time rather than decline.

My first hypothesis is therefore:

Hypothesis 1: An enforcement will reduce the probability of fraud in other firms in the same industry and MSA.

The exact entity who is punished in the enforcement will also affect the amount of future fraud in the industry. I test whether individual vs. corporate punishments work better at deterring misconduct. These results are germane to regulatory bodies across the world as they are taking different approaches to prosecuting cases. For example, prosecutors in Iceland jailed bank CEOs for their role in the crisis, while the US Department of Justice (DOJ) won large settlements from investment banks for their misconduct during the financial crisis. Finally, this is particularly relevant following the financial crisis as more than half of the charges laid by the SEC have been against officers[37]. Consequently, this analysis will be able to analyze whether the SEC's effort is well targeted.

While individual punishments would increase the magnitude of the punishment, company punishments increase the probability a guilty party is punished at the cost of punishing innocent

[37] http://www.sec.gov/spotlight/enf-actions-fc.shtml

shareholders, officer, or employees of the firm. On the other hand, severe regulatory actions can have powerful real effects on customers; consequently, the regulatory actions may need to be targeted to avoid "collateral" damage (Danisewicz, McGowan, Onali, & Schaek 2017). Furthermore, regulatory actions against financial institutions do not change the corporate culture in a firm (Fiordelsi, Raponi, & Rau 2015), leaving the possibility that future misconduct may occur. With officer punishments, the value of the potential punishment is very high on the individual officer and should have a negative impact on others' likelihood to pursue crime.

This argument may be tipped by several distinct reasons. First, given the difficulty regulatory authorities have in detecting financial misconduct (Dyck, Morse, & Zingales 2010), group punishment by targeting the firm will be more effective than individual punishment (Miceli & Segerson 2007). Second, individual punishments may be the equivalent of "closing the barn door after the horse has bolted." Over 60% of individuals that are identified as having committed financial misconduct leave their firms on or before the initial investigation (Karpoff, Lee, & Martin 2008b). Consequently, these individuals have likely already left the industry and MSA and punishing them will not be as noticeable than if they were still within those networks.

Furthermore, targeting a company will increase the awareness of the event. The awareness of companies is typically much greater than the awareness of the officers at those companies. Consequently, targeting companies will have a greater awareness than targeting an individual at those companies. Finally, a guilty officer or other entity may be simply viewed as a "bad apple" and that the punishment is due to that particular individual's misconduct—individuals are less likely to cheat when they see a member of an outsider group cheat (Gino, Ayal, & Ariely 2009). Regardless, by targeting a company, other companies will take notice to ensure that they do not suffer the same fate.

Hypothesis 2: Enforcement actions targeting a company will reduce misconduct in an industry and MSA.

Finally, there is little reason to expect that prosecuting an auditor, attorney, or other entity will reduce future misconduct. These individuals are typically not part of the firm, can easily be replaced by the firm, and are not core to firm operations. Consequently, prosecuting these groups will have little to no effect on deterring future misconduct. This discussion motivates the third hypothesis:

Hypothesis 3: Enforcement actions punishing officer and other entities will have no measurable impact on deterring misconduct.

By identifying whether assigning individual responsibility or corporate responsibility deters more misconduct will help regulators to magnify the power of their prosecutions. This is particularly important as the DOJ has won large sanctions against financial institutions arising from misconduct during the financial crisis, but has not won any cases against the top officers of those financial institutions.

3.4 Data

The Center for Financial Reporting and Management (CFRM) Accounting and Auditing Enforcement Releases (AAER) dataset is the main source of misconduct and enforcement actions. The CFRM AAER data was collected from the SEC website and with information supplemented from Lexis-Nexis searches and covers over 1,300 separate incidents (Dechow, Ge, Larson, & Sloan (2011)). This data includes the company targeted and whether an officer, firm, other entity, or some combination of the 3 was convicted.

The CFRM AAER data are merged with financial data drawn from Compustat and stock return data are from CRSP. Financial and stock data are included for all firms from 1967 to

2016. The first financial year identified as misconduct is 1971; however, data 4 years before are required to develop some of the lagged variables and graphs. Any firms without assets or negative equity are removed from the analysis.

All firms are categorized into 2-digit SIC industries based on Compustat SIC code. In addition, all firm headquarter locations are identified from Compustat and used to identify the MSA of the firm headquarters. The final sample includes 225,319 firm-year observations.

In addition to the CFRM AAER database financial misconduct data was also incorporated from the Securities Class Action Clearinghouse (SCAC) and Audit Analytics (AA) restatements. The former database captures securities class action lawsuits against firms and the latter captures restatements of financial statements by firms. These two databases will serve as controls for other identified sources of financial misconduct to ensure that the results are simply not an after effect of another form of misconduct.

One concern with using SEC enforcement actions is that the SEC is often slow. I examined all the cases where AA restatements identified the same faulty financial statements as AAERs. In 95% of these cases, the announcement date of the restatement was before the AAER. Consequently, the misconduct has typically been identified before the actual enforcement action. Thus, to control for this early announcement, we need to use variables *Restatement* and *SCA*, which are indicator variables set to 1 if a restatement (according to Audit Analytics) or securities class action, respectively, has occurred in the same industry/MSA, as controls.

Panel A of Table 3.1 shows the firm-year summary statistics of the total sample. The results show that firm-years with misconduct or restatements are uncommon. Panel B of Table 3.1 shows the mean values for firm-years that have at least 1 enforcement action in the past 2 years in the same industry/MSA versus those where no enforcement action has been taken in the past 2 years. Columns 1 and show that firm-years in the same 2-digit SIC industry are different than other firm-years. Enforcement firm-years, regardless if the enforcement is in the same 2-digit SIC industry or MSA, have lower BM (more growth firms), leverage, and ROA. Interestingly, these firms are also larger, have greater analyst coverage, and institutional ownership. These univariate results show that size and value and market awareness are related to enforcement action in the same industry and MSA. Consequently, the regressions will have to control for these variables to isolate the effect of the enforcement.

Interestingly, enforcement firm-years are slightly more likely to have misconduct than non-enforcement firm-years. However, the difference is very small between the two groups and these univariate results do not control for other factors that may be associated with misconduct such as ROA.

To provide a more intuitive view of misconduct before and after an enforcement action, Figure 3.1 shows the number of misconduct firm-years in an industry/MSA up to 4 years before and after an enforcement is announced. Panels A and B look at the number of misconduct firm-years following an enforcement in the 2-digit SIC industry and MSA, respectively. As can be seen, the total number of misconducts begins to decline 4 years before the enforcement, but experiences a sharper dip after the enforcement action in year 0. In contrast, industries and MSA that do not experience an enforcement see rising misconduct rates over the same period. Consequently, it appears that the discovery and enforcement by the SEC has a strong deterrence effect on future misconduct.

Table 3.2 shows the correlations of the main dependent and independent variables. Interestingly, misconduct is positively correlated with enforcement in both the industry and the MSA. This is unsurprising given that earnings management is found to lead to “contagion” in other firms in the same industry (Kedia, Koh, & Rajgopal 2015) and misconduct may also lead to a similar contagion if it goes undetected and unpunished. Also, similar to what was found in the summary statistics, misconduct is also correlated to many key firm characteristics, such as size, value, leverage, analyst coverage, institutional ownership, return on assets, and industry concentration. Hence, these variables will be invaluable as control variables.

3.5 Results

To test the first hypothesis, I run the following panel logit regression to identify if enforcement in the industry in the past leads to a reduction in the probability of financial misconduct:

$$Misconduct_{jt} = b_0 + b_1\, Enforce\_IND_{jt} + b_2\, SCA_{jt} + b_3\, Restatement_{jt} + b_4\, X_{jt} + \gamma_t + \delta_j + \varepsilon_{jt} \quad (1)$$

$$Misconduct_{jt} = b_0 + b_1\, Enforce\_MSA_{jt} + b_2\, SCA_{jt} + b_3\, Restatement_{jt} + b_4\, X_{jt} + \gamma_t + \delta_j + \rho_j + \varepsilon_{jt} \quad (2)$$

The dependent, Misconduct, is whether company j's financial statement in financial year t has been identified as problematic by an SEC AAER[38]. $Enforce\_IND_{jt}$ ($Enforce\_MSA_{jt}$) is an indicator variable that equals 1 if there is at least 1 AAER released in the past 2 years (t-1 to t) in company j's industry (MSA)[39]. *SCA* and *Restatement* is an indicator variable set to 1 if there is at least 1 securities class action or restatement in the industry/MSA, respectively, in the past 2 years, and set to 0 otherwise. X_{jt} is a vector of control variables including size (*LogAT*), book-to-market (*BM*), leverage (*DA*), firm age (*Firmage*), analyst coverage (*LogAnalyst*), institutional ownership (*IO*), return on assets (*ROA*), and Herfindahl-Hirschman Index (*HHI*), for company j at time t. In addition, γ_t, δ_j and ρ_j control for the year, industry, and MSA fixed effects, respectively. Errors are clustered by firm and year as per Peterson (2009).

[38] The misconduct is typically identified after it occurs.
[39] When KKLM 2016 data is available, this data will expand the list of enforcement actions by the SEC.

As shown in columns 1 and 2 of Table 3.3, the presence of an enforcement action in the 2-digit SIC industry (-0.268; t = -3.57) or MSA (-0.208; t = -2.73) in the past 2 years (t-1 to t) reduces the likelihood of misconduct from occurring at time t. Interestingly, the *SCA* and *Restatement* variable show no statistical significance—class actions and restatements do not seem to deter misconduct in the way that an SEC enforcement does.

To test Hypothesis 2, enforcement targeted at a company is better at reducing future misconduct, and Hypothesis 3, that enforcement targeted at other entities will have no effect on future misconduct, I run the following two regressions:

$$\begin{aligned} \mathit{Misconduct}_{jt} = {} & b_0 + b_1\, \mathit{Enforce\_IND\_OFF}_{jt} + b_2\, \mathit{Enforce\_IND\_COM}_{jt} + b_3\, \mathit{Enforce\_IND\_OTH}_{jt} \\ & + b_4\, \mathit{SCA}_{jt} + b_5\, \mathit{Restatement}_{jt} + b_6\, X_{jt} + \gamma_t + \delta_j + \varepsilon_{jt} \end{aligned} \qquad (3)$$

$$\begin{aligned} \mathit{Misconduct}_{jt} = {} & b_0 + b_1\, \mathit{Enforce\_MSA\_OFF}_{jt} + b_2\, \mathit{Enforce\_MSA\_COM}_{jt} + b_3 \\ & \mathit{Enforce\_MSA\_OTH}_{jt} + b_4\, \mathit{SCA}_{jt} + b_5\, \mathit{Restatement}_{jt} + b_6\, X_{jt} + \gamma_t + \delta_j + \varepsilon_{jt} \end{aligned} \qquad (4)$$

where the _OFF, _COM, _OTH interactions indicate whether an officer, company, or other entity (such as auditor or lawyer) were charged during the enforcement in the past 2 years. All other variables are similar to equations (1) and (2) above.

As shown in Table 3.4, the type of enforcement matters greatly in reducing misconduct in other firms in the same industry and MSA. Within two years of an AAER targeting a company, the incidence of misconduct falls in the same 2-digit SIC industry (-0.125; t = -2.14) and MSA (-0.292; t=-4.38). Furthermore, targeting an officer in the same industry has no statistically measurable effect in the same MSA (-0.071; t=-0.79) and a small reduction in the same industry (-0.151; t=-1.92). Thus, this evidence supports hypotheses 2 that targeting a company causes a larger reduction in misconduct than targeting an officer.

These results may be due to the following 3 factors. First, guilty officers and other entities have often severed their relationships with the firm before the actual SEC enforcement is finalized—consequently, the guilty officer does not work in the same industry or MSA anymore and punishing them does not appear to have the same impact. Second, most officers and other entities are less well known than the company that they work for. Consequently, news of punishment targeting a company is more likely to spread than punishment targeting an officer. Third, a guilty officer or other entity may be simply viewed as a “bad apple” and that the punishment is due to that particular individual’s misconduct; however, by targeting a company, other companies will take notice to ensure that they do not suffer the same fate.

Finally, the results support hypothesis 3 that targeting another entity has no effect on reducing misconduct. As can be seen in Table 3.4, targeting other entities has no statistically measureable effect in reducing misconduct in the industry or MSA.

3.5.1 Robustness

To ensure that the results are robust to alternative measures of misconduct, I use two additional proxies for misconduct. First, I use financial restatements from the Audit Analytics database. Though many of the restatements are errors rather than fraudulent behavior, by using this broad definition, I can test Hypothesis 1 in the most difficult of settings. *Restatement* is set to 1 if a firm issues a restatement for that financial year (typically in the future), and 0 otherwise. In addition, I use the Dechow et al. (2011) *Fscore* as an another potential metric for misconduct. *Fscore* was developed to predict whether a firm’s statements are fraudulent and is thus a good alternative to estimating using actual misconduct. Note as *Fscore* is a continuous variable, the *Fscore* regressions were run as a standard pooled regression and not as a logit.

As can be seen in Table 3.5, the results are similar for firms in the same industry using both the *restatement* and *Fscore* metrics. In column 1, an enforcement in the same industry leads to reduced incidence of *restatements* (-0.074; t=-2.20) and a lower *Fscore* (-0.002; t = -1.81). Oddly, the results do not hold in the same MSA. *Restatements* show movement in the opposite direction and *Fscore* has no statistical significance. Regardless, these MSA results may be simply be the result of the added noise from using these alternative proxies of actual misconduct.

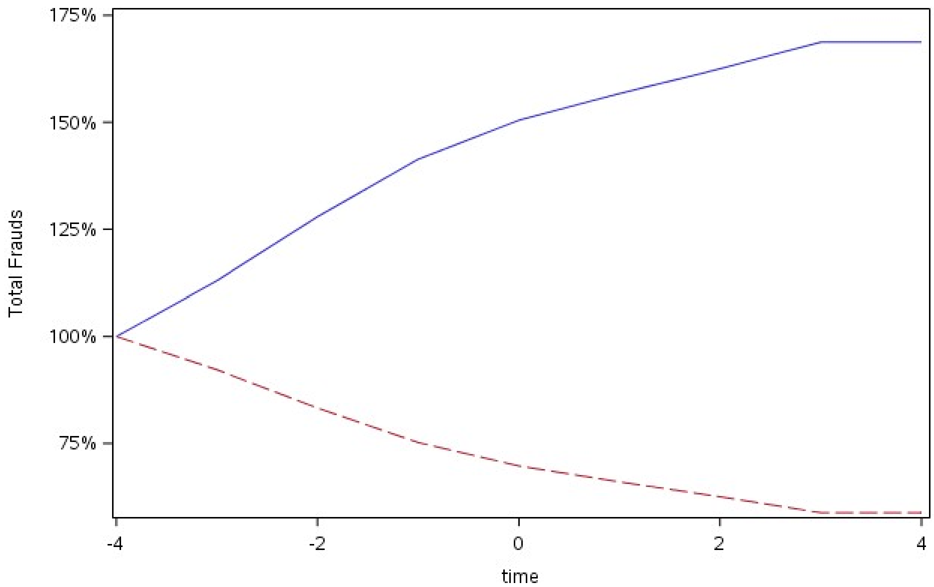
3.6 Conclusion

Financial misconduct creates large losses to investors and erodes public trust in the financial system. Consequently, it is very important to regulatory agencies to ensure as little financial misconduct as possible. However, with a new SEC chair and looming budgetary constraints (Robinson and Bain 2017), the SEC may not have the same ability to conduct enforcement actions.

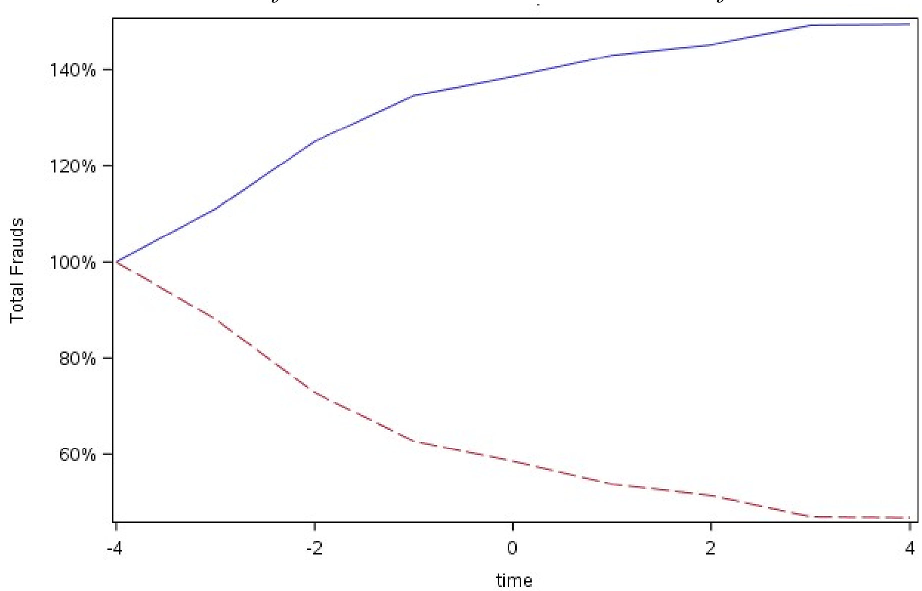
This gives arise to three main policy prescriptions. First, enforcement should remain a priority as deterrence is very important to the reduction of future misconduct. As this research shows, enforcement actions deter future misconduct in the same industry and MSA, extending the SEC's enforcement resources. Second, regulatory agencies should be judicious in their target of prosecution; this is particularly important given the potential reductions in SEC budgets. Targeting a company will be more effective at deterring future misconduct in both the company's industry and MSA. Targeting officers and other entities, on the other hand, has much less impact on future misconduct in the industry or MSA. Therefore, regulatory agencies should focus their limited prosecution efforts to targeting companies and avoid targeting officers, attorneys, auditors, and non-officer individuals.

Figure 3.1 Total Misconducts with and without enforcement

Panel A: Total Misconducts in Industry with and without enforcement



Panel B: Total frauds in MSA with and without enforcement



No Enforcement in industry/MSA
Enforcement in industry/MSA

Panel A shows the total misconduct firm-years in SIC 2-digit industries 4 years before and 4 years after an enforcement action (red dotted line) at t = 0 or if there is no enforcement in the industry (blue line) at t = 0. Panel B is similar to Panel A except that the graph shows the total misconduct firm-years in an MSA. The total misconduct firm-years are scaled by the number of total misconduct firm-years at t = -4. MSA refers to Metropolitan Statistical Area.

Table 3.1 Firm-Year Summary Statistics

Panel A: Summary Statistics for Total Sample

Variable	n (1)	MEAN (2)	STD (3)	MIN (4)	MAX (5)
Misconduct	245,176	0.00	0.07	0.00	1.00
Restatement	245,176	0.06	0.23	0.00	1.00
FScore	107,409	0.11	0.09	0.00	12.81
AT	245,176	5686.2	60046.8	0.0	3771199.9
BM	231,286	0.83	0.81	0.01	11.96
DA	243,433	22.85	19.77	0.00	84.29
Firmage	245,176	14.37	12.15	1.00	66.00
Loganalyst	245,176	0.72	0.99	0.00	3.50
IO	243,730	20.70	28.69	0.00	100.00
ROA	244,787	0.24	23.21	-355.37	82.55
HHI	245,174	0.09	0.09	0.01	0.59

Panel B: Variable means for firms with and without enforcements in the same industry/MSA in the past 2 years

Variable	No Enforce in Ind (1)	Enforce in Ind (2)	No Enforce in MSA (3)	Enforce in MSA (4)
Misconduct	0.00	0.01	0.00	0.01
Restatement	0.04	0.09	0.04	0.10
FScore	0.10	0.11	0.11	0.11
AT	4568.3	7506.7	5549.4	6112.9
BM	0.91	0.70	0.87	0.73
DA	25.37	18.74	23.49	20.85
Firmage	14.21	14.63	14.15	15.07
Loganalyst	0.62	0.87	0.66	0.91
IO	16.50	27.56	17.79	29.82
ROA	2.21	-2.97	0.90	-1.82
HHI	0.10	0.06	0.09	0.08
n	151,897	93,279	185,624	59,552

Panel A shows the total sample statistics. Panel B shows the summary statistics for firm-years where there was no enforcement in the past 2 years in the industry/MSA. Panel B Column (1) 2 shows the summary statistics for firm-years where there was (no) enforcement in the 2-digit SIC industry in the past 2 years (t-1 to t). Column (3) 4 shows when there was (no) enforcement in the MSA in the past 2 years. *Misconduct* = 1 if a firm-year has financial misconduct. *Restatement* = 1 if a firm-year has a restatement according to Audit Analytics. *AT* is total assets, *BM* is the company's total book value of equity/ market capitalization at the end of the financial year. *DA* is the company's debt-to-asset ratio and *Firmage* is the number of years the firm has been in Compustat. *Loganalyst* is the log of the number of analysts covering the firm, *IO* is the institutional ownership of the firm as a %, *ROA* is the return on assets, and *HHI* is the Herfindahl-Hirschman Index. All variables are measured in year t and continuous variables are winsorized at the 1%/99% level (except for *Firmage*). Firms in MSA 0 (not in a MSA) or missing MSA are excluded from the sample.

Table 3.2 Correlation Matrix

Variable	*Enforce _IND* (1)	*Enforce _MSA* (2)	*Misconduct* (3)	*Restatement* (4)	*Fscore* (5)	*AT* (6)	*BM* (7)	*DA* (8)	*Firmage* (9)	*Loganalyst* (10)	*IO* (11)	*ROA* (12)	*HHI* (13)
Enforce_IND	1												
Enforce_MSA	**0.239**	1											
Misconduct	**0.028**	**0.028**	1										
Restatement	**0.109**	**0.107**	**0.133**	1									
FScore	**0.042**	0.004	**0.032**	**0.010**	1								
AT	**0.024**	**0.004**	**0.013**	**0.013**	**-0.035**	1							
BM	**-0.126**	**-0.071**	**-0.021**	**-0.028**	**-0.010**	0.004	1						
DA	**-0.163**	**-0.057**	**0.005**	**-0.005**	**-0.087**	**0.008**	**0.083**	1					
Firmage	**0.017**	**0.033**	0.001	**0.065**	**-0.077**	**0.083**	**-0.014**	**0.028**	1				
Loganalyst	**0.123**	**0.107**	**0.028**	**0.090**	**-0.050**	**0.077**	**-0.201**	**-0.061**	**0.307**	1			
IO	**0.187**	**0.180**	**0.030**	**0.157**	**-0.028**	**0.029**	**-0.179**	**-0.059**	**0.330**	**0.744**	1		
ROA	**-0.108**	**-0.050**	-0.004	**-0.032**	**0.021**	**0.008**	0.002	-0.001	**0.111**	**0.093**	**0.082**	1	
HHI	**-0.223**	**-0.043**	**-0.005**	**-0.022**	**0.043**	**-0.020**	**0.055**	**0.088**	**-0.052**	**-0.078**	**-0.069**	**0.053**	1

This table reports the Pearson correlations of the main variables in the sample. *ENFORCE_IND* (*Enforce_MSA*) is an indicator variable that = 1 if at least 1 AAER was issued in the firm's 2-digit SIC industry (MSA) over the past 2 years (t-1 to t). All continuous variables are winsorized at the 1%/99% level each year except *Firmage*. Variables are defined in Table 3.1. Bold indicates significant at 5% level

Table 3.3 Financial Misconduct Deterrence

Dependent	*Misconduct*	*Misconduct*
Variable	(1)	(2)
Enforce_IND	-0.268***	
	(-3.57)	
Enforce_MSA		-0.208***
		(-2.73)
SCA	0.057	0.123
	(0.36)	(1.14)
AA	0.183	-0.144
	(0.94)	(-1.11)
LogAT	0.262***	0.332***
	(5.45)	(6.78)
BM	-0.407***	-0.447***
	(-3.56)	(-3.29)
DA	0.009***	0.008***
	(2.99)	(2.61)
Firmage	-0.018***	-0.027***
	(-3.33)	(-4.77)
Loganalyst	-0.126*	-0.098
	(-1.87)	(-1.35)
IO	0.008***	0.004
	(2.79)	(1.38)
ROA	0.000	-0.001
	(-0.23)	(-0.61)
HHI	0.294	0.719
	(0.30)	(0.69)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
MSA Fixed Effects	No	Yes
N	229,504	192,149

This table reports the results of logit regressions of the dependent on *Enforce_Ind* (*Enforce_MSA*). The dependent is an indicator variable, *Misconduct*, which measures whether that firm-year has financial misconduct. *ENFORCE_IND* (*Enforce_MSA*) is an indicator variable that = 1 if at least 1 AAER was issued in the firm's 2-digit SIC industry (MSA) over the past 2 years (t-1 to t). *SCA* and *Restate* are indicator variables that are set to 1 if at least 1 securities class action or restatement occurred in the past 2 years. *LogAT* is the log of the company's total assets. All other variables are defined in Table 3.1. Standard errors are clustered by firm and year. Intercept excluded for brevity. Indicates * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.4 Financial Misconduct Deterrence, by Type of Punishment

Dependent	*Misconduct*	*Misconduct*
Variable	(1)	(2)
Enforce_IND_Off	-0.151*	
	(-1.92)	
Enforce_IND_Com	-0.125**	
	(-2.14)	
Enforce_IND_Oth	-0.037	
	(-0.37)	
Enforce_MSA_Off		-0.071
		(-0.79)
Enforce_MSA_Com		-0.292***
		(-4.38)
Enforce_MSA_Oth		0.084
Controls	Yes	Yes
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
MSA Fixed Effects	No	Yes
N	229,376	192,149

This table reports the results of logit regressions of the dependent on enforcement variables, depending on who was punished. *Enforce_Off*, *Enforce _Com*, and *Enforce_Oth*, is set to 1 if the enforcement in the 2-digit SIC industry/MSA over the past 2 years (t-1 to t) targeted the officer, company, or other entity, respectively. The dependents and controls are defined the same as in Table 3.3 above. Standard errors are clustered by firm and year. Intercept excluded for brevity. Indicates * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.5 Robustness Tests

Dependent	*Restatement*	*Restatement*	*Fscore*	*Fscore*
Variable	(1)	(2)	(3)	(4)
Enforce_IND	-0.074**		-0.002*	
	(-2.20)		(-1.81)	
Enforce_MSA		0.045*		0.000
		(1.92)		(-0.35)
SCA	0.022	0.068*	-0.004***	-0.005***
	(0.40)	(1.79)	(-3.17)	(-3.21)
Restate	0.444***	0.404***	0.003	0.000
	(3.42)	(5.14)	(1.36)	(0.07)
LogAT	0.036**	0.089***	0.001	0.001
	(2.36)	(6.87)	(0.87)	(1.31)
BM	0.021	0.020	-0.004***	-0.005***
	(0.93)	(1.05)	(-3.94)	(-3.96)
DA	0.007***	0.005***	0.000	0.000
	(7.35)	(7.24)	(0.00)	(0.00)
Firmage	-0.003	-0.006***	0.000	0.000
	(-1.64)	(-4.29)	(0.00)	(0.00)
Loganalyst	-0.109***	-0.148***	-0.004***	-0.003***
	(-4.58)	(-6.56)	(-5.68)	(-4.61)
IO	0.006***	0.006***	0.000	0.000
	(7.86)	(7.43)	(0.00)	(0.00)
ROA	-0.002***	-0.002***	0.000	0.000
	(-3.21)	(-3.50)	(0.57)	(0.24)
HHI	0.077	0.206	0.001	0.003
	(0.19)	(0.81)	(0.06)	(0.21)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
MSA Fixed Effects	No	Yes	No	Yes
N	229504	192220	106900	98234

This table reports the results of logit and standard pooled regressions using alternative dependents, *Restatement* and *Fscore*, respectively. *Restatement* is an indicator variable set to 1 if a firm has to restate the results for that financial year and 0 otherwise. *Fscore* is a probability score developed by Dechow et al. (2011) to predict financial misconduct. The other variables are defined the same as in Table 3.3 above. Standard errors are clustered by firm and year. Intercept excluded for brevity. Indicates * significant at 10%; ** significant at 5%; *** significant at 1%.

Chapter 4: Too Much of a Good Thing? Mandatory Risk Disclosure and its Impact on Corporate Innovation

4.1 Introduction

Corporate disclosure affects the functioning of capital markets, affects firm performance, and reduces information asymmetry. Enhancing corporate disclosure has been a driving force for regulators since SOX and IFRS adoption and has been credited with reducing information asymmetry between firm managers and investors, and consequently, the cost of capital[40].

However, can there be too much of a good thing? That is, can regulators mandate so much disclosure that it negatively impacts firm performance? Two theoretical models have hypothesized that improved disclosure does not benefit all firms. For example, one model shows that less disclosure is desirable when the manager cannot easily report the benefits of investments. Another model shows that improved disclosure causes a "crowding-out" of investments among firms with riskier investments.[41]

To test whether there can be too much disclosure, we examine whether mandatory disclosure of firm risk negatively impacted firm innovation. Mandatory risk disclosure has been shown to have real impacts on metrics of firm risk and firm value[42]. We focus our tests on a particular form of investment—innovation. Innovation fits the criteria for the theoretical models above quite well: First, the risks of innovation are easily identified, but the benefits of innovation are not easily reported as they are either uncertain or would reveal competitive secrets (Kanodia et al. 2005). Second, innovation is generally riskier, the exact types of projects that will be crowded out by increased disclosure (Zhang 2013). Consequently, the usage of innovation

[40] See Benston 1973; Healy and Palepu 2001; Verrecchia 2001; Porta, Lopez-de-Silanes, and Shleifer 2006; and Lambert, Leuz, and Verrecchia 2007

[41] Kanodia, Singh, and Spero (2005) and Zhang (2013), respectively.

[42] See Kravet and Mulsu 2013; Campbell, Chen, Dhaliwal, Lu, and Steele 2014

enables the examination of these theories amongst firms most sensitive to increased mandatory disclosure.

To answer whether mandatory risk disclosure impacted firm innovation, we ask two main questions: First, what is the relationship between risk disclosure and corporate innovation in general? Second, do the enhanced mandatory risk disclosure rules hamper innovation? Finally, we examine potential channels for this risk disclosure and innovation relationship.

To identify the amount of disclosed risks, we use the ratio of risk keywords scaled by the total number of words in the10-K filing to measure corporate risk disclosure. First, we download all the 10-K filings from Securities and Exchange Commission (SEC) EDGAR database and then, based on the lexical fields from Campbell, Chen, Dhaliwal, Lu, and Steele (2014), use text analysis to classify risk disclosure in 10-K filings into four main categories: aggregate risk (*Avgrisk*), systematic (*Syst*), idiosyncratic (*Idio*), and other (*Othrisk*), which is the average of all non-systematic and non-idiosyncratic risks. The *Idio* lexical field includes many innovation related words and is more likely to reflect the status quo of a firm's innovation activities.[43] We thus use it as a control variable to capture the firm's propensity to report risk, while the other risk scores are used to identify the amount of total, systematic and other risk a firm is disclosing in its 10-K filing.

To answer the first question, we regress risk disclosure on future innovation and show that an increase in the aggregate, systematic, or other risk disclosure is negatively related with future research and development (R&D), number of patents filed, and the number of patent citations. A 1% increase in aggregate risk (*Avgrisk*) in a 10-K is associated with a 23.822% (t = -3.43) decrease in R&D scaled by assets (*RD*) and a decline in the log number of patents (*Fnpats*)

[43] Campbell et al (2014)'s dictionary for idiosyncratic risk includes words like "innovation," "intangible," and "intellectual." Consequently, idiosyncratic risk is highly related to firm innovation by construction.

and truncation-adjusted citation-weighted number of patents (*TCW*) by 3.236% (t = -2.74) and -4.218% (t = -3.00), respectively. The direction and magnitude are similar when looking at systematic or other disclosed risk as well.

To answer the second question on the impact of mandatory risk disclosure on innovation, we exploit two exogenous regulatory changes that the SEC imposed in 2005 and 2008. Prior to 2005, firms were not required to have a risk disclosure section; hence, firms disclosed their risks in an inconsistent way, with some firms having a separate section while other included them in other areas such as in the management discussion and analysis or notes. Starting in 2005, however, the SEC mandated that firms to include a risk disclosure section called the Item 1A. This meant that all firms were required to have a discussion of risks that was easily identifiable and comprehensive. Furthermore, a second exogenous regulatory change occurred in 2008, when the SEC exempted smaller reporting companies[44] from having to include an Item 1A risk disclosure section in their 10-K filings. Thus, smaller reporting companies were no longer required to include an Item 1A section and thus their risks are less identifiable.

On one hand, the inclusion of a comprehensive risk disclosure section should lead to a better information environment and reduce information asymmetry between managers and shareholders—allowing firms to more readily access the financial market for additional capital and boost investment in innovation (Li, Moshirian, Tian, and Zhang 2017). On the other hand, while risks are easy to disclose, the benefits of innovation are not easily disclosed as they are uncertain and may be competitively sensitive information (Kanodia et al. 2005). Moreover, the model presented in Zhang (2013) shows that though improved disclosure lowers cost of capital

[44] A firm with a public float of $75 million or revenues less than $50 million. See the following SEC link for the formal definition https://www.sec.gov/info/smallbus/src-cdinterps.htm.

on average, firms with riskier projects are "crowded out" as investment capital is redirected to less risky firms.

Our results support the latter models. By examining the 2005 exogenous shock, we find that the mandatory disclosure of risk in the 10-K filings is negatively associated with innovation. After 2005, the negative impact of risk disclosure on the R&D, filed patents, and patent citations almost doubles. Furthermore, we used the 2008 exogenous shock to set up a difference-in-difference (DiD) test to examine the impact of removing the mandatory disclosure requirement. Treated firms, smaller reporting companies, defined as firms with <$50 million in sales[45], showed an increase in innovation output after the risk disclosure requirement was removed for them in 2008. In contrast, untreated firms (non-smaller reporting companies) did not experience a rebound in innovation after 2008, and in fact experienced a further decline. Consequently, this negative relationship with risk disclosure and innovation is unlikely to be the result of an unobservable variable.

Finally, we use a regression discontinuity design (RDD) to further identify the mandatory risk disclosure effect. In this test, we exploit the discontinuity for the risk disclosure exemption after 2008—firms with >=$50 million in revenues have to incorporate an Item 1A risk section while smaller firms do not. Thus, firms with slightly less than $50 million in revenues and those with slightly more than $50 million in revenues should be similar to one another. However, the discontinuity analysis shows that firms just above $50 million in revenue (where they had to include a risk disclosure section) experienced statistically lower levels of filed patents and citation-weighted value of patents than firms with just below $50 million in revenue (which were

[45] Firms with less than $75 million public float are also defined as smaller reporting companies; however, public float data is not available for the sample. The results are similar if firms with market capitalization less than $75 million are included as smaller reporting companies as well—public float is always less than market capitalization.

exempt from the risk disclosure section requirement). This further supports that mandatory risk disclosure is negatively associated with innovation.

Given the tension that improved disclosure may both improve and reduce innovation, we examine the two channels related to this potential improvement and reduction—information asymmetry and external financing constraints. Several papers show that the adoption of consistent accounting standards reduces information asymmetry as measured by analyst forecasts and investment.[46] Nevertheless, our tests showed that information asymmetry was unrelated to the risk disclosure-innovation relationship. In addition, we examined the effect of external financing constraints[47] on the risk disclosure-innovation relationship and found that the effect of risk disclosure was magnified among firms with financial constraints. Consequently, the mechanism appears to be that the market is unwilling to provide additional funds to these firms for fear of the risks these firms may face, similar to what the model in Zhang 2013 predicted.

Two alternate hypotheses are that managerial investment sensitivity or managerial learning are the channel for the risk disclosure-innovation relationship—that is after disclosing risks, managers see that investors are depressing the firm's stock price and then reduce innovation or learn from the market about what shareholders want[48]. In both cases there is no measurable relationship between investment sensitivity and managerial learning with risk disclosure-innovation.

We ran a variety of robustness checks to ensure the results were valid. First, we include traditional firm risk metrics, like *Beta* and idiosyncratic volatility (*IVOL*), as controls. If it is a firm's risk environment that is causing the negative relationship between risk disclosure and

[46] See Byard, Li, Yu 2011; Defond, Hu, Hung, Li 2011; and Horton, Serafeim and Serafeim (2013)

[47] Both Brown, Fazzari, and Peterson 2009 and Brown, Martinsson, and Peterson 2012 show that external financing constraints can impact firms' R&D expenditures.

[48] See Loureiro and Taboada (2015)

innovation, then traditional metrics, such as *Beta* and idiosyncratic volatility should absorb the effect. The results are robust to the inclusion of the traditional risk measures of Beta and idiosyncratic volatility (*IVOL*).

Furthermore, our results are robust to the usage of a more strict textual analysis that only counts risk words if it fell under two different risk dictionaries (Kravet and Muslu 2013 and Campbell et al. 2014). Consequently, these results are not due to text analysis misidentifying risk words in the 10-K filings. Finally, the results were robust to many other tests as well including, alternative methods of dealing with missing R&D values, orthogonalizing the risk to variables known to be associated with risk disclosure in 10-K filings, capitalizing R&D, and using future innovation output.

The rest of the paper is organized as follows. In the next section, we discuss prior research and develop our main hypotheses. Section 3 describes sample and research design. Section 4 reports empirical analyses on the effect of mandatory risk disclosure on firm innovation, with robustness tests in section 4.4. Finally, we conclude in section 5 with a brief summary of the results and implications for practitioners, regulators, and future researchers.

4.2 Literature and Hypothesis Development

Our study contributes to the ongoing debate on whether firms should disclose more information about themselves. A number of studies (Benston 1973; Healy and Palepu 2001; Verrecchia 2001; Porta, Lopez-de-Silanes, and Shleifer 2006; and Lambert, Leuz, and Verrecchia 2007) suggest that there is an improvement to firms and capital markets from increased disclosure. However, a variety of newer models all points to the effects of enhanced mandatory disclosure to have uneven effects depending on the firm's situation [Kanodia et al. (2005); Gao (2010); Zhang (2013); and Dutta and Nezlobin (2017)]. This study adds to the literature by helping show that the latter argument has credence—more mandatory disclosure can hurt firm outcomes.

Interestingly, the evidence from Li et al. (2017) supports the former theoretical models on information disclosure—the paper finds that a shift to IFRS allows firms to overcome external-financing constraints and improve managerial learning. However, our paper differs in it only focuses on mandatory risk disclosure rather than enhanced comparability from the switch to IFRS. Mandatory risk disclosure allows us to explore the specific aspects of the theoretical models noted above. In Kanodia et al. (2005), the model shows that imprecision in accounting is superior when the drawbacks are clearly seen, but the benefits difficult to explain—mandatory risk disclosure definitely means that drawbacks are included with no corresponding increase in benefit discussions. Gao (2010) and Dutta and Nezlobin (2017) show that enhanced disclosure increases the volatility of the firm, which benefits future investors; however, current investors suffer as the value of their investment declines with the increase in volatility—mandatory risk disclosure is definitely linked to increased firm volatility (Kravet and Muslu 2013; Campbell et al. 2014). Finally, Zhang (2013) notes that enhanced disclosure may crowd out more risky projects, such as innovation, as better information leads investors to less risky projects.

This paper also extends the examination of real effects of risk disclosure on firms. For example, Kravet and Muslu (2013) find that risk disclosures are informative as market volatility and analyst activity increases when the disclosures are individualized to the firm (i.e. not boilerplate). Campbell et al. (2014) find that how risk disclosures affect firm risk and value. Emerging research examines risk disclosures over time and how these vary appropriately with firms' new and old risks (Gaulin 2017), examines the specificity of risks in the risk disclosure and market reaction with more specificity (Hope, Hu, and Lu 2016), and looks at risk and important corporate policies, such as leverage, investment and R&D (Avramov, Li, and Wang 2017). Finally, Gu and Li (2003) examine under what circumstances innovation is voluntarily disclosed. Overall, our paper extends the research noted by Kanodia and Sapra (2016) on how disclosure can have real effects on firms.

Our paper extends the previous studies by examining the impact of risk disclosure on one of the most important real corporate activities, innovation. Innovation is important to economic growth—helping society become wealthier as a whole—and innovation can help firms withstand competition and improve their firm performance.[49] In particular, we are able to measure risk disclosure's impact on corporate innovations from both the input (R&D expenditure levels) and output (how many patents are produced) perspectives. We further use regulatory changes in risk reporting requirements as exogenous shocks to identify the relationship between the two.

This research also extends the research into innovation and market scrutiny. For example, He and Tian (2013) find that increased analyst coverage leads to reduced innovation and Bernstein (2015) showed that after going public, which exposes a formerly private firm to market scrutiny, innovation output drops. On the other side, reduced market attention can improve innovation output. For example, higher antitakeover provisions results in both more patents and more cited patents (Chemmanur and Tian 2016) and declassifying boards (removing staggered boards) resulted in declines in firm value, particularly among firms focused on research and innovation (Cremers and Sepe 2017). Our research complements this by examining the effect of increased scrutiny—in this case risk disclosure—on innovation.

[49] See, for example, Solow (1957); Porter (1991); Grossman and Helpman (1993); Eberhart, Maxwell, Siddique (2004); Hirshleifer, Hsu, and Li (2013); and Hombert and Matray (2015).

4.3 Hypotheses

To set a baseline for our regression tests, we must first establish the relationship between risk disclosure and innovation. Innovation is an irreversible investment that has very uncertain outcomes and the effects are typically only seen in the long-term (Holmstrom 1989). Consequently, there will be a large real option value to delaying innovation, particularly when faced with increased short-term risk—if a firm is faced with greater risk, it becomes more valuable to delay or cancel investment in innovation until the risk has lessened (Bernanke 1983; Pindyck 1990). Hence, if a manager perceives increase in risks in the future and truthfully disclose them, innovation will likely be one of the first items that a risk-averse manager will cut back. This leads to the first hypothesis.

Hypothesis 1: Risk disclosure in 10-K filings is negatively associated with corporate innovation.

On one hand, mandatory risk disclosure should lead to a better information environment and reduce information asymmetry between managers and shareholders—allowing firms to more readily access the financial market for additional capital and boost investment in innovation (Li et al. 2017). On the other hand, while risks are easy to disclose, the benefits of innovation are not easily disclosed as they are uncertain and may be competitively sensitive information (Kanodia et al. 2005; Kanodia and Sapra 2016). In addition, the model presented in Zhang (2013) shows that though improved disclosure lowers cost of capital on average, firms with riskier projects are "crowded out" as investment capital is redirected to less risky firms. Consequently, this leads to the following hypothesis.

Hypothesis 2: Mandating enhanced risk disclosure 10-K filings will further reduce innovation

The mechanism for reducing innovation will be through reduced opportunities for financing. Financial constraints have been shown to cause a reduction in investment (Holmstrom and Tirole 1997; Fazzari, Petersen, Blinder, and Poterba 1988; Duchin, Ozbas, and Sensoy 2010). Furthermore, access to external equity and financing constraints have been shown to affect younger firms' R&D levels (Brown, Fazzari, and Peterson 2009; Brown, Martinsson, and Peterson 2012). Consequently, risk disclosure will have the greatest effect on firms that are financially constrained and unable to continue to invest in R&D without outside resources.

4.4 Data

4.4.1 Risk Disclosure Scores

We use a text-based analysis of firm 10-K documents to measure the risk contained in the filings. The risk disclosure score was calculated and collected in several stages. First, all 10-Ks filed from January 1995 through March 2013 were downloaded from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. The risk disclosure sample includes data from financial years 1994 through to 2013; however, we only use the data from 1994 through to 2010 to match the patent data period (see next section).

The paper then follows Campbell et. al. (2014) to construct the sample:

1) Exclude 10-Ks with less than 1,000 words, and late fillings such as NT 10-K, NT 10-KA, and NTN 10-K under Rule 12b25 of inability or timely file all or part of the 10-Ks.
2) EDGAR identifies firms that file 10-Ks using Central Index Key (CIK). the Wharton Research Data Services (WRDS) CIK-PERMNO file was used to match CIK and filing dates from 10-Ks with PERMNO and filing dates from the CRSP-COMPUSTAT merged data. All firms for which there was no match for CIK to GVKEYs and the filing dates were excluded.
3) Firms which had no data in COMPUSTAT were excluded.

Textual analysis was then performed on the 10-K documents. Specifically, the analysis uses the lexical field from the Campbell et al. (2014), which lists the words for different kinds of risk: idiosyncratic (*Idio*), systematic (*Syst*) and several other types of risk. Other risks identified in Campbell et al. (2014), such as financial, legal and regulatory, and tax, are also categorized and then averaged into a variable *Othrisk*. To summarize the risk disclosure scores, we calculate an aggregate risk score, *Avgrisk*, which is the mean of all risk disclosure scores[50]. The development of these different scores allows me to identify if the results are driven by only one type of risk.

To ensure that the textual analysis results are valid, a manual check was done on the top 10 most commonly found risk words listed in the major risk categories. In the manual check 10 sentences that contained each top word were randomly drawn from the text and then checked manually (approximately 500 checks in total) to see if the software identified risk properly. In the manual sample, 84.4% of the manually checked instances correctly identified risk. In addition, a robustness test in section 4.4.4 uses an even stricter word dictionary wherein a sentence must contain words from both the Campbell et al. 2014 and the Kravet & Muslu 2013 dictionaries to be included.

While a comprehensive risk disclosure section was not required by the SEC until 2005, the text analysis software combed through the entire 10-K document to identify risk. This means the risk score is independent of how risk is packaged in the 10-K. Thus, the risk score will be similar regardless of whether the risks are spread out or concentrated in an easy to find risk disclosure section, which will prove useful in testing Hypothesis 2.

The yearly risk disclosure score for each category of risk is calculated in three steps. First, for each 10-K, we compute the frequency of each of the risk words in the entire 10-K

[50] The results are similar if idiosyncratic risk is excluded from aggregate risk.

document in the Campbell et al. lexical field for the relevant risk. The raw risk score is then calculated by summing the total of times a word/expression from the 10-K matches a word/expression from the lexical field. Next, we scale the raw risk scores by the number of words in the 10-K to account for variability in the length of 10-Ks and multiply by 100 to turn the values into percentages. If there are multiple 10-K documents for the same financial year (for example there is an addendum), we average the risk scores and weight them based on document length.

While there is some concern that risks in the 10-Ks may be "boilerplate" and not representative of the firm's actual risk, other research has found that risks in the 10-K filings have real effects on firms. Research has found that that risk content in the 10-Ks affects information asymmetry, abnormal returns, trading volume, and firm volatility (Campbell et al. 2014; Kravet and Muslu 2013; Hope, Hu, & Lu 2016). Consequently, we can be confident that the risk in the filings has an effect on firms.

4.5 Innovation Inputs and Outputs

Innovation is measured by three distinct measures, including *RD*, *Fnpats*, and *TCW*. To measure the inputs firms put into innovation, we use R&D expenditures scaled by lagged total assets (*RD*) from Compustat. If R&D expenditures are missing, often because many firms have no R&D or do not report it, we set the value to 0. To measure the innovation output of firms, we use the patent database provided by Kogan, Papanikolaou, Seru and Stoffman (2017). This database covers patents per year from 1990 to 2010, inclusive, includes *Fnpats*, the log of the number of patents filed +1, and *TCW*, the log of the truncated-adjusted and citation-weighted number of patents filed + 1, for each year and firm (identified by permno). This data is then integrated with the risk disclosure scores above as well as data from Compustat to create the panel data file. Finally, firms that do not file any patents or do not report R&D expense over the entire sample period are excluded from the analysis. This ensures the sample is limited to only firms that can reasonably be expected to innovate.

Fnpats is useful for measuring the total innovation output of a firm; however, it does not measure the importance of the innovation—the innovations could be ground-breaking or simply iterative. To incorporate the importance of the patents, we use *TCW* which weights the patents based on the number of citations it receives in the future—more citations indicating that a patent is more influential. In addition, the *TCW* value adjusts for the fact that patents published later in the sample period have fewer years to accumulate citations.

4.6 Other data

The majority of the remaining data was drawn from Compustat or CRSP. To be included in the sample, each firm-year needs non-negative total assets (*AT*) and common equity (*CEQ*). All risk disclosure, innovation, and Compustat variables, except indicator variables and Firmage, are winsorized at the 1%/99% level each year to reduce the impact of outliers. Furthermore, only data from financial year 1994 to 2010 is included as 1994 is the lower limit of the risk data and 2010 is the upper limit of the patent data.

In addition, CRSP was used to calculate Beta and idiosyncratic volatility (*IVOL*). These values are only calculated for firms that have > 0 shares, are traded on the NASDAQ, AMEX, or NYSE, and that have common shares. *Beta* and *IVOL* are both calculated using daily data over each financial year of the firm. *Beta* is calculated by regressing excess company returns (return – risk free rate) against excess market returns. *IVOL* is the residual after regressing the excess company returns against the Fama-French 3 factors, Rm-Rf, SMB, and HML. We annualize *IVOL* by multiplying by the square root of the number of trading days. Finally, to ensure firms have an adequate trading history in the financial year, we set *Beta* and *IVOL* to missing if there are fewer than 125 trading days over the firm's financial year.

Finally, institutional ownership (*IO*) was calculated using Thomson 13F Institutional Holdings database and *LogAnalyst*, the log of the number of analysts covering each firm, was calculated using Thomson's IBES database.

4.7 Summary Statistics

Table 4.1 shows the summary statistics for approximately 7,100 unique firms over more than 44,000 firm-years. Risk scores are small at less than 1% of the words in the 10-K for Avgrisk and less than 2% for *Idio* and *Syst*. As can be seen, *Syst* and *Idio* are more than 4 times higher than *Othrisk*, showing that these two risk scores are higher than any of the other risk disclosure categories.

Fnpats0 and *TCW0*, the two measures of patents prior to the log transformation, are highly skewed with 50% of the firm-years in the sample having 0 patents—this is even after limiting the sample to only firms that have at least 1 patent or 1 reported R&D expense over the sample period. Consequently, to address this right-skew, we use *Fnpats*, which is the natural log of (*Fnpats0* + 1), and *TCW*, which is the natural log of (*TCW0* + 1).

Table 4.2 shows the correlation of the various risk and patent variables. As can be seen in columns 1 and 2, both *Fnpats0* and *TCW0* are negatively correlated with the *Avgrisk* and *Othrisk* risk measures at the 1% level. *Syst* is negatively related with *RD* at the 1% level and is also negatively related to patent measures on a directional basis. This gives some preliminary evidence that innovation output is affected by risk disclosure in firms.

To test the hypotheses, we will use the aggregate of all risks disclosed (*Avgrisk*), systematic risk disclosed (*Syst*), and an average of all other non-idiosyncratic, non-systemic risk disclosure scores (*Othrisk*). We use idiosyncratic risk disclosure (*Idio*) as a control in the regressions because idiosyncratic risk is highly correlated with innovation as the word dictionary for *Idio* contains many innovation related words This is evidenced in Table 4.2 where the correlation between *RD* and *Idio* is positive—higher R&D expenditures (as a percentage of assets) is related to higher idiosyncratic risk. Firms may choose to increase their idiosyncratic risk by engaging in a high-risk innovation strategy—for example, Target, which pursues a relatively low-risk retail strategy with little innovation, had an average idiosyncratic risk disclosure score of 0.01 and RD of 0.00 from 2002–2010 while, Amazon, which pursues an online retail strategy with much innovation, had an *Idio* score of 0.10 and *RD* of 0.12, over the same period (results untabulated). Given this endogenous relationship, we will use *Idio* as a control rather than as one of the independent variables of interest.

A second reason to use *Idio* as a control is to account for varying propensities of managers to disclose risk. Some managers may be overly cautious and disclose a great deal of risk in their firms' 10-Ks while others may be overly optimistic and disclose little risk in their firms' 10-Ks. By including *Idio* as a control variable, we also introduce a way of controlling for this propensity to disclose or not disclose risk.

Other controls include *LogAT*, *BM*, *DA*, *Firmage*, *HHI*, HHI^2, *LogAnalyst*, *IO*, *CAPXA*, *Tang*, *ROA*, and Length which are all related to *RD*, *Fnpats*, or *TCW* or are key firm characteristics.

4.8 Research Design and Results

In the baseline analysis, we ran the following panel regressions to examine the impact of risk on future innovation output. The first regression above will show the impact of risk on R&D scaled by assets, the major input into firm innovation. The second regression will show how risk affects the number of patents filed in the following year after controlling for most of the major inputs into innovation. Finally, the third regression will examine how risk affects the quality of patents:

$$RD_{it} = \alpha + \beta \{\text{Risk}\}_{\text{it-1}} + \gamma\, RD_{it\text{-}1} + \delta\, X_{\text{it}} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \tag{1}$$

$$Fnpats_{it} = \alpha + \beta \{\text{Risk}\}_{\text{it-1}} + \gamma\, RD_{it} + \delta\, X_{\text{it}} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \tag{2}$$

$$TCW_{it} = \alpha + \beta \{\text{Risk}\}_{\text{it-1}} + \gamma\, RD_{it} + \delta\, X_{\text{it}} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \tag{3}$$

RD is R&D expenditures scaled by lagged total assets, *Fnpats* is the log of the number of patents filed and *TCW* is the log of the truncation-adjusted and citation-weighted number of patents for firm i at time t. $\{\text{Risk}\}_{\text{it-1}}$ is a text based metric of risk, either *Avgrisk*, *Syst*, or *Othrisk* for firm i at time t-1. $RD_{t\text{-}1}$ is used as a control in regression 1 and RD_t is used as a control in regressions 2 and 3. X_{it} is a vector of control variables including $Idio_{it\text{-}1}$, $BM_{t\text{-}1}$, $LogAT_{t\text{-}1}$, $DA_{t\text{-}1}$, *Firmage*, Herfindahl-Hirschman index (HHI_t), $HHI^2{}_t$, $logAnalyst_t$, IO_t, $CAPXA_t$, $TANG_t$, ROA_t, and $LogLength_t$. The lagged value of {Risk} and some control variables is used to reduce endogeneity by examining the relationship of future innovation against the previous year's independent and control variables. ϕ and ϖ control for year and FF49 industry fixed effects, respectively.

Idio is used as a control as it is endogenous with innovation and also controls for the firm's amount of risk disclosure. *BM*, *LogAT*, *DA*, *Firmage*, *TANG*, and *ROA* control for major firm characteristics while *HHI* and HHI^2 control for the effects of industry concentration. As firm innovation is known to be related to market scrutiny, *LogAnalyst* and *IO* are used as controls for this effect. Finally, firms that create difficult to read 10-K filings may have different methods of disclosing risk. Consequently, we include *LogLength* to control for the readability of the document as longer documents are more difficult for investors to understand (Li 2008)—the results are similar if an alternative measure of readability, log of the 10-K file size (Loughran and McDonald 2014), is used instead.

4.8.1 Hypothesis 1 Results

Table 4.3 shows the baseline results for the relationship between risk disclosed in 10-K filings and innovation inputs and outputs. For innovation inputs, *RD* declines when the firm is exposed to higher aggregate total risk, systematic risk, or other risk; an increase in *Avgrisk* (col 1), *Syst* (col 4) and *Othrisk* (col 7) are all associated with lower *RD*. This table also shows that aggregate, systematic, and other risk all affect innovation and not just 1 specific type of risk. The results are similar for innovation output, the number of patents filed, *Fnpats*, and truncated adjusted citation-weighted patent counts, *TCW*, even after controlling for the lower level of research and development that year. As shown in Table 4.3, the results show that innovation output falls if *Avgrisk*, *Syst* and *Othrisk* increase (col 2-3, 5-6, 8-9) even after controlling for the decline in R&D spending. These results illustrate that when faced with increased risk, firms have reduced innovation inputs and outputs.

4.8.2 Hypothesis 2 Results

Though Li et al (2017) and Kanodia et al. (2005) provide opposing views of what will happen after mandatory risk disclosure is imposed. The former shows that innovation improves after there is a mandatory shift to consistent IFRS standards, while the latter notes that mandating disclosure may actually decrease investment in difficult to explain projects, like innovation. To resolve this tension, we will exploit two natural experiments on how risk is included in 10-K filings. The first experiment involves the 2005 SEC requirement for a comprehensive Item 1A risk disclosure section and the second involves the 2008 SEC elimination of this requirement for smaller reporting companies.[51]

In the first exogenous shock, the SEC required firms to include a comprehensive Item 1A risk disclosure section in their 10-K filings starting in 2005—consequently, firm risk disclosure became mandatory in 2005 and afterwards.[52] Thus, by examining the impact of risk disclosure before 2005 and after 2005, we will be able to see if mandatory risk disclosure benefits or hurts firm innovation. The regressions are run as in equations (1) to (3) except an interaction term of $\{\text{Risk}\}_{it-1}$*$\mathit{Post2005}$ is included in each regression. This variable is an interaction of the risk disclosure variable and *Post2005*, an indicator variable set to 1 if the financial year is greater than 2005 and 0 otherwise[53]. The risk scores are measured in year t-1 so it will take 1 year after the implementation of the new rule change before the risk scores measure the new format. Note that the year fixed effects, ϕ, automatically obviate the need for a standalone *Post2005* variable, as ϕ is a linear combination of *Post2005*.[54]

As can be seen in Table 4.4, the results for the coefficient, β, for the risk without interaction are very similar to Table 4.3. For all the columns, the size, direction, and significance for β are nearly identical to one another—they are all significantly negative at the 1% level.

On the other hand, the coefficient for the interaction of the {Risk}* *Post2005* variable illustrates the effect of mandatory risk disclosure reporting has on innovation. Li et al. (2017) point to improved innovation after 2005 while Kanodia et al. (2005), Gao (2010), Zhang (2013) and Dutta and Nezlobin (2017) all point to a reduction in innovation after 2005. Furthermore, a

---

[51] https://www.federalregister.gov/documents/2008/01/04/E7-24965/smaller-reporting-company-regulatory-relief-and-simplification
[52] In a hand check of 30 firms, none of the firms had an Item 1A before 2005. Some pre-2005 filings had a section on future risk but these were not as comprehensive as the Item 1A sections.
[53] The results are similar if post2005 is defined as >=2005 rather than >2005.
[54] The results are similar if a post2005 indicator variable is used instead of year fixed effects.

variety of research has shown that innovation is negatively impacted by increased exposure to market scrutiny (He and Tian 2013; Bernstein 2015; Chemmanur and Tian 2016). Given this, a comprehensive risk disclosure section would have a negative impact on innovation.

This negative association between risk salience and innovation is borne out in the results. After 2005, increased *Avgrisk*, *Syst*, and *Othrisk* lead to even larger declines in *Fnpats* and *TCW* (Col 2-3, 5-6, 8-9) than prior to 2005. The coefficient for *Avgrisk* and *Avgrisk* **Post2005* is -2.527 (t = -2.15) and -2.679 (t = -3.68), respectively, for *Fnpats* and -3.458 (t = -2.43) and -2.879 (t = -3.29) for TCW. This shows that not only is aggregate risk negatively associated with filed patents and patent-citations, but that the implementation of the new risk disclosure section after 2005 makes the negative relationship between risk and patents even larger. This effect is also similarly found when using Syst and Othrisk.

Research development seems to be curtailed as well. The coefficients for *Avgrisk***Post2005*, *Syst** *Post2005*, and *Othrisk** *Post2005* were both negative and significant at -17.041 (t = -1.97), -4.141 (t = -1.85) and -40.024 (t = -2.12), respectively, showing that, post-risk disclosure requirement, firms reduce R&D even further when risk rises.

Finally, it is unlikely that these results were driven by an increase in risk in 2005 or afterwards. The summary statistics in Table 4.1 panel B shows that the mean aggregate, systematic, and other risk scores actually decline in 2005 and remain below 2004 levels until the end of the sample period.

These results support the theoretical models for Kanodia (2005) and Zhang (2013) that enhanced disclosure can negatively impact some forms of firm investment, such as innovation.

Differences-in-Differences

While Table 4.4 helped identify that mandatory risk disclosure is associated with a drop in innovation output, there could be unobservable variables driving the results in 2005. Luckily, another exogenous regulatory shock occurred in 2008 that enables a further identification of this effect. In 2008, the SEC exempted smaller reporting companies from having to include an Item 1A risk disclosure section in their 10-K filings. This second exogenous shock shows the impact of a removal of the disclosure in 2008 for smaller reporting companies, but no change in the requirements for all other firms. This shock provides a natural experiment where one class of firms (smaller reporting companies) does not have to report a risk disclosure section while other firms are unchanged. This provides a nice opportunity to analyze the results as a DiD regression--SM is equivalent to a "Treatment" indicator variable and Post2008 is equivalent to an "After" indicator variable.

The variables in the regressions are similar to equations (1) to (3); however, four new interaction variables, $\{\text{Risk}\}_{it-1}$**Post2008*, $\{\text{Risk}\}_{it-1}$**SM*, $\{\text{Risk}\}_{it-1}$* *Post2008*SM*, and *Post2008*SM* are included. The first variable is an interaction of the risk disclosure variable and *Post2008*, an indicator variable set to 1 if the year is greater than 2008 and 0 otherwise[55]. $\{\text{Risk}\}_{it-1}$**SM* and $\{\text{Risk}\}_{it-1}$* *Post2008*SM* are interactions of *SM* and the other variables. *SM* is an indicator variable set to 1 if a firm is a smaller reporting company and 0 otherwise. *Post2008*SM* is an interaction between *Post2008*and *SM*. As before, the year fixed effects, ϕ, automatically obviate the need for a standalone *Post2008* variable as ϕ is a linear combination of *Post2008*.

Table 4.5 shows that for all the risks, mandatory risk disclosure results in less innovation as evidenced by the coefficient of $\{\text{Risk}\}_{it-1}$, with similar directions for systematic and other risk;

[55] The results are similar if Post2008 is >=2008 rather than >2008.

however, this is the baseline effect of risk on innovation and each additional interaction builds upon or reduces this effect.

To understand the effect of treatment, we examine the interaction coefficient for $\{\text{Risk}\}_{it-1}$* *Post2008*SM* (equivalent to treatment*after). This interaction coefficient is significantly positive for *Fnpats* and *TCW* for nearly all types of risk—smaller reporting companies produce more and better patents after the requirement for a distinct risk disclosure section is lifted. This provides further evidence the risk disclosure is affecting innovation—these smaller reporting companies are not making forced to disclose risks in their 10-Ks after 2008 and, hence there is less pressure to reduce innovation. Interestingly, there is no significant effect on the amount of R&D in this case, so mandatory disclosure doesn't seem to reduce the investment in R&D, but simply the amount of innovation outputted by the firm.

The increase in innovation output is simply not the result of an unobservable effect. Untreated firms (regular companies) after 2008 ($\{\text{Risk}\}_{it-1}$* *Post2008*) experienced a decline in innovation output, which is the opposite effect of what smaller reporting companies experienced. Furthermore, it is not due to a different impact of risk on smaller firms. The interaction of $\{\text{Risk}\}_{it-1}$**SM* shows a negative effect for *Fnpats* and *TCW* before 2008. That is smaller firms exposed to risk should experience lower innovation than regular firms—the exact opposite effect of the $\{\text{Risk}\}_{it-1}$* *Post2008*SM* variable. When combined with the results from Tables 4, the results support that it is the mandatory disclosure of risk that contributes to the decline in innovation output.

Regression Discontinuity Design (RDD)

The SEC's removal of the risk disclosure requirement for smaller reporting companies provides an opportunity for a regression discontinuity design (RDD) similar to Chava & Roberts

2008 and Iliev 2010 to test Hypothesis 2. Smaller reporting companies, proxied by firms with <$50 million in revenue, are exempt from including a risk disclosure section. Firms just above and below $50 million in revenues will be remarkably similar to one another; however, once the $50 million revenue threshold is exceeded, the firm must include a risk-disclosure section. Consequently, the only major difference between these firms will be whether a risk disclosure section was mandated by the SEC.

The regressions set up for this RDD are noted below.

$$RD_{it} = \alpha + \beta_1 \{\text{Risk}\}_{it-1} + \beta_2 \{\text{Risk}\}_{it-1} * SM_{it} + \rho\, SM_{it} + \gamma\, RD_{it-1} + \delta\, X_{it-1} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \quad (4)$$

$$Fnpats_{it} = \alpha + \beta_1 \{\text{Risk}\}_{it-1} + \beta_2 \{\text{Risk}\}_{it-1} * SM_{it} + \rho\, SM_{it} + \gamma\, \text{RD}_{it} + \delta\, X_{it-1} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \quad (5)$$

$$TCW_{it} = \alpha + \beta_1 \{\text{Risk}\}_{it-1} + \beta_2 \{\text{Risk}\}_{it-1} * SM_{it} + \rho\, SM_{it} + \gamma\, RD_{it} + \delta\, X_{it-1} + \phi \text{ Year FE} + \varpi \text{ Ind FE} + \varepsilon \quad (6)$$

As noted in the regression equations 4-6 above, the regressions are similar to Table 4.5 except that the sample is limited to only firms that are near the discontinuity ($15.0 – $85.0 million in sales[56]) to ensure that the results are focused on the discontinuity and not other trends in the whole sample. Furthermore, as this smaller reporting company exemption is only available after 2008 and patent data is only available until 2010, the sample is limited to only firm-years in 2008, 2009, or 2010. Consequently, no interaction with *Post2008* is needed in the regression.

Table 4.6 shows further evidence that how risk is disclosed affects firm innovation. First, firms that are exempted from including a risk disclosure section in their 10-K filings ({Risk}**SM* interaction) experience greater innovation in terms of both number of patents filed and citation-weighted value of those patents regardless if they are facing higher aggregate, systematic, and

[56] The results are robust to firms with sales between $17.5 – $82.5 million and $12.5 – $87.5 million.

other risk (columns 2-3, 5-6, and 8-9)—this is particularly impressive as the RDD sample size is less than 4.5% of the full sample. Second, it is not a simple size effect as *SM* is statistically indistinguishable from 0 in all the regressions. Thus, it is not that small firms are inherently more or less productive in research. Interestingly, the interaction between risk and *SM* shows that R&D scaled by assets is lower among exempt firms in columns 1 and 7. However, this makes the results from columns 2-3 and 8-9 even more impressive as lower R&D should result in fewer filed patents and citation-weighted value of patents, showing that the effect of disclosure can even overcome the effect of lower R&D.

The RDD provides further evidence that inclusion of mandatory risk disclosure has a negative impact on firm innovation.

4.8.3 Channel

To identify the channel that is causing this decline in innovation, we run the baseline regressions (2) to (3) with one modification. In addition to the standard variables, we include an interaction of risk disclosure and various proxies for financial constraint, {Risk}*{Financial Constraint}. These financial constraints include *ATLo*, an indicator variable set to 1 if a firm is in the bottom tercile of total assets—size has been shown to be related to external financing constraints (Hadlock and Pierce 2010) —and *WWHi*, an indicator variable set to 1 if a firm is in the top tercile of Whited-Wu scores (Whited and Wu 2006). Furthermore, *Recession*, an indicator variable set to 1 if the US economy is in recession as defined by the National Bureau of Economic Research (NBER), is also included as firms are less likely to tap equity and debt markets during recessions, placing an external financial constraint on firms (Covas and Haan 2012; Aghion et al. 2012; Dawling & Haan 2011) and consequently reducing innovation. Finally, as total assets are used to calculate the WW index and *ATLo*, the variables, by construction, will be related to *RD*, which is R&D scaled by assets. Consequently, we do not run the regressions with *RD*.

Table 4.7 shows the results of the financial constraint interactions. Panel A shows that the interaction of *WWHi* with aggregate and systematic risk is negative. For all three types of risk, aggregate, systemic, and other risk, the coefficient on the interaction term between *WWHi* and our proxy for risk disclosure is negative and typically significant. That is financially constrained firms are associated with even less innovation when reporting higher risk.

Panels B and C also support the Whited-Wu index results. Panel B shows the interaction of firm size and risk. Smaller firms (*ATLo*) exposed to levels of aggregate risk experience even greater declines in innovation than other firms. Panel C shows that during recessions, the negative impact of all forms of reported risks on innovation are even more pronounced than in normal economic periods. Table 4.7 thus suggests that financial constraint is a possible channel for risk disclosure to negatively affect future innovation activities.

The results are not due to risk disclosure reducing information asymmetry. We use the average bid-ask spread over the firm's past year as a proxy for information asymmetry and then interact the results with an indicator variable, *SpreadHi*, that equals 1 if the firm is above median bid-ask spread. Panel A of Table 4.8 shows firms with high information asymmetry seem to experience a decline in R&D—a reduction in information asymmetry should help firms to raise capital and fund innovative projects, not reduce innovation. Furthermore, these high asymmetry firms do not seem to suffer a significantly different decline in *Fnpats* or *TCW* than low asymmetry firms. Consequently, information asymmetry does not seem to be the channel for the relationship between innovation and risk disclosure.

To show that the results are not due to price-investment sensitivity, we ran a two stage analysis. First we regressed capital expenditures scaled by assets (*CAPXA*)[57] against *Q*, inverse total assets, and cash flow. We then used the coefficient for *Q* as a proxy for the firm's investment sensitivity and divided firms into above median and below median sensitivity (Q_*CAPXAHi*). This variable was then interacted with risk to identify if firms with higher investment sensitivity reacted differently to risk disclosure. As shown in Panel B of Table 4.8, the results show that investment sensitivity has no statistically measurable effect on the relationship between risk and innovation and increased risk continues to be associated with decreased innovation. Consequently, we can rule out investment sensitive firms being the cause of this change in innovation.

Furthermore, a similar test was run to test the effect of managerial learning. In untabulated results, we estimated managerial learning and then interacted it with the risk disclosure scores and found no effect. It does not appear that the results are driven by information asymmetry, investment sensitivity, or managerial learning.

4.8.4 Robustness

Beta and Idiosyncratic Volatility

One counterargument to the hypotheses is that firm managers or investors are reacting to traditional risk metrics rather than the risk in the filings. Thus, it is a possibility that firm managers are actually adjusting their innovation output due to increased exposure to systemic risk (as proxied by Beta) and idiosyncratic risk (as proxied by idiosyncratic volatility {*IVOL*}) as opposed to the text-based risk measures.

[57] R&D expenditures were excluded as including them would create a mechanical relationship between investment sensitivity and *RD*.

There are two main reasons *Beta* and *IVOL* differ slightly from the text-based risk measures. First, both *Beta* and *IVOL* are backward looking measures of risk, while the text-based risks captures managers forward looking views of risks. Thus, the risk in 10-Ks captures risks that the insiders may be aware of, but the market does not (Myers and Majluf 1984). Second, both *Beta* and *IVOL* are clearly apparent to the market as any investor can calculate them. In contrast, the risk in the 10-Ks is not always apparent to the market. Prior to 2005, there was no mandatory risk disclosure section requirement so the risks were not included or were hidden within the 10-K. On the other hand, *Beta* and *IVOL* are easily visible to the firm's managers and investors so any effect of risk will remain constant over the sample period.

Regardless of these differences, we test whether traditional risk measures actually influence innovation in several regressions. In addition to the variables in the baseline regression, *Beta* and *IVOL*, are used as additional controls to allow for a "horse-race" between the text-based risk measures and the traditional risk measures.

We first look at the control variables, *IVOL* and *Beta*. Similar to past research on volatility (Mazzucato and Tancioni 2012), *IVOL* shows a negative relationship with RD and a positive relationship with patent output in Table 4.9. Furthermore, though Beta has a positive relationship with RD, it has no statistical relationship with patent output. These results are in contrast to the results in Tables 4.3 to 4.5 wherein higher risk disclosure is associated with decreased patent output. Consequently, it is unlikely that the text based risk measures are picking up the same effects as *IVOL* or *Beta*.

Furthermore, even after including *Beta* and *IVOL*, the coefficients and significance for *Avgrisk*, *Syst*, and *Othrisk* are similar to what was seen in Table 4.4. For example, the disclosed risks and post2005 interaction are negatively associated with *Fnpats*, *TCW*, and *RD*, which is similar to Table 4.4. Thus, these risk disclosure variables continue to be negatively associated with innovation inputs and outputs. We can conclude that the text-based risk measures provide additional information that is not contained within *Beta* and *IVOL*.

Text Analysis Robustness

To ensure that the software is correctly identifying risk in the text, we performed two robustness checks on the data. First, we did a manual check of 10 sentences each for the 50 top risk words identified in the sample and found that 84.4% of the time the software correctly identified risk. In addition to this manual check, we ran a more strict textual analysis that only counted a risk word if it was in the Campbell et al. 2014 dictionary and the sentence contained an uncertainty related word from Kravet and Muslu 2013, such as "can/cannot," "could," "may," "might," "risk," "uncertain," etc. Consequently, this more strict definition decreases Type II error of the textual analysis (fewer non-risk words categorized as risk) while increasing Type I error (failing to categorize words that are truly risk related).

Table 4.10 replicates the results from Table 4.4 except it uses the more strict definition of risk words noted above. As can be seen, the results for aggregate risk disclosure (*Avgrisk*), systematic risk (*Syst*) and other risk (*Othrisk*) remain somewhat similar to Table 4.4 showing that even with more strict textual analysis the results remain similar to before. While some of the results have lost significance, this is almost certainly due to the increased Type I error wherein true risk words are not categorized as risk.

Orthogonalized Risk Disclosure

Campbell et al. (2014) note a variety of factors that are associated with increased risk disclosure in 10-K filings. To ensure that the results are not driven by one of these variables, we run a 2-stage regression analysis where we first regress the risk factors (*Avgrisk*, *Syst*, and

Othrisk) against these factors and then use the residuals from the 1st regression to predict innovation rates in the 2nd regression. This will orthogonalize the risk results to the risk factors described in Campbell et al. and ensure only the unexplained portion of the risk disclosure is used to explain innovation inputs and outputs.

As can be seen in Table 4.11 panel A, most of the variables noted in Campbell et al. (2014) are significantly associated with the aggregate, systematic, or other risk scores. Nevertheless, even after the residuals are used in Panel B, the negative association between risk and innovation largely remains—*Fnpats* and *TCW* are negatively associated with risk in nearly all the specifications. This shows that it is not the determinants of risk noted by Campbell et al. (2014) and that the results are not driven by one of those unobserved variables.

Capitalized R&D and Future Patents

One concern is that innovation is a multi-period projects and that one year of disclosure of risk will not greatly impact a firm's innovation strategy. Consequently, this paper examines two alternative specifications to address these concerns.

In the first test, R&D is capitalized (*RDC*) according to Eberhart, Maxwell, and Siddique (2004) where the R&D from the past 5 years (t-4 to t) is totaled with a constant depreciation rate. The RDC variable is then used in lieu of the standard control of *RD* in the main regressions.[58] As can be seen in Table 4.12 panel A, even with the inclusion of the *RDC* variable the results are similar to Table 4.4, though with less significance due to a smaller sample size. Furthermore, in untabulated tests, the results with *RDC* are qualitatively similar for Tables 4.3 and 4.5 even with a slightly smaller sample size.

In the second test, the total number of patents from period t to t+2 are summed together to detect the effect of risk disclosure on innovation in the next few years. *Fnpats_3* and *TCW_3*

[58] Note that RD_t was excluded as a dependent as *RDC* incorporates *RD* from year t.

sum together the number of patents filed and citation-weighted value of those patents from years t to t+2[59]. Table 4.12 panel B shows that the results for these longer term dependents is similar to what was seen in Table 4.4—the increase in risk disclosure is associated with a corresponding decrease in future innovation over a longer term period. In untabulated results, the usage of *Fnpats_3* and *TCW_3* are similar to those in Tables 3 and 5, showing that the main results are robust to the usage of longer time periods for both patents and R&D capitalization.

Missing R&D

Another potential concern is that firms missing R&D values are not similar to firms with 0 R&D as firms may make a conscious choice not to report R&D in their 10-K filings (Koh & Reeb 2015). To control for this possibility, we included two modifications to the regressions run in Table 4.3. First, an indicator variable *RDMiss* is included as a control—*RDMiss* is set to 1 if a firm is missing R&D data and 0 otherwise. Secondly, if research and development is missing, rather than being set to 0, *RD* is set to the industry average *RD* (using 2-digit SIC codes).

In untabulated tests, the effect of aggregate, systematic, and other risk were all similar to the results in Table 4.3. Consequently, the results are not being driven by a difference between missing R&D and 0 R&D reporting firms.

4.9 Conclusion

In conclusion, these results show that mandating disclosure of risk in regulatory filings is associated with lower innovation. Furthermore, by using the natural experiment from SEC regulatory changes in 2005 and 2008, we are able to identify the effect of this mandate on innovation. In addition, these results seem to be exacerbated in firms facing financial constraints

---

[59] This time period was chosen so that there would be at least 1 year of data following the 2008 exemption of smaller reporting companies from the item 1a requirement.

as these firms are associated with even larger reductions in innovation than firms without those constraints.

These findings extend the research on information disclosure. First, mandating increased disclosure may not have uniformly positive effects for firms and investors. Increased risk disclosure reduces firm innovation as managers may not be able to disclose benefits of innovation adequately and may result in riskier projects, such as innovation, getting “crowded out” as investment is redirected to less risky projects.

This research also provides further evidence that firms with less market scrutiny are better able to innovate. Being public, increased analyst coverage, and more democratic corporate governance are all associated with less innovation and our paper adds to this literature by showing that mandatory risk disclosures are associated with lower innovation rates. Thus, enhanced disclosure rules may not be uniformly good for all classes of firms.

This research will be also useful for regulators, such as the SEC. In the past, regulators have focused on reducing information asymmetry as much as possible by increasing disclosure. However, this new research shows that increased disclosure may affect firm performance of some firms. Consequently, regulators may want to weigh future disclosure changes against possible negative side-effects.

Table 4.1 Descriptive Statistics

Panel A: Total Sample Statistics

Variable	n	MEAN	STD	MIN	p25	median	p75	MAX
RD	44,048	11.5	22.0	0.0	0.0	3.9	13.5	286.4
Fnpats0	44,182	11.0	90.7	0.0	0.0	0.0	2.0	5052.0
TCW0	44,182	26.2	218.6	0.0	0.0	0.0	4.8	10161.7
Avgrisk	44,182	0.027	0.030	0.000	0.007	0.018	0.035	0.304
Syst	44,182	0.050	0.071	-0.004	0.004	0.026	0.068	1.144
Othrisk	44,182	0.012	0.013	0.000	0.002	0.008	0.017	0.133
Idio	44,182	0.078	0.109	0.000	0.013	0.044	0.092	1.358
AT	44,136	3371.6	14170.5	0.3	47.8	190.0	1022.4	203318.2
LogAT	44,136	5.5	2.2	-0.6	3.9	5.2	6.9	12.2
BM	44,035	0.5	1.0	-34.9	0.2	0.4	0.7	7.1
DA	43,964	18.7	22.7	0.0	0.4	12.6	29.4	318.4
Firmage	44,182	18.2	14.9	0.0	7.0	13.0	25.0	63.0
HHI	44,182	0.1	0.1	0.0	0.0	0.1	0.1	0.7
HHI^2	44,182	0.0	0.0	0.0	0.0	0.0	0.0	0.5
LogAnalyst	44,182	1.1	1.1	0.0	0.0	1.1	1.9	3.5
IO	44,095	38.9	33.5	0.0	2.5	35.2	69.5	100.0
CAPXA	43,505	6.1	9.3	0.0	1.7	3.6	7.0	178.3
Tang	43,965	23.3	22.8	0.0	7.4	16.5	31.8	247.4
ROA	44,019	-11.1	58.2	-1290.0	-11.3	2.7	8.5	72.7
Beta	42,602	0.9	0.6	-1.3	0.4	0.9	1.3	3.5
IVOL	42,602	60.3	37.6	10.1	32.9	51.1	77.5	257.8
LogLength	44,182	9.7	0.8	6.9	9.2	9.8	10.2	13.0
Unique Firms	7,166							

Panel B: Mean Sample Statistics by Year

Fyear	n	*RD*	*Fnpats0*	*Tcw0*	*Avgrisk*	*Syst*	*Othrisk*	*Idio*
1994	533	5.717	17.989	40.861	0.008	0.017	0.004	0.018
1995	1818	7.870	9.985	23.829	0.009	0.017	0.005	0.026
1996	3118	15.591	7.055	17.290	0.017	0.026	0.008	0.054
1997	3157	12.630	7.126	17.453	0.022	0.034	0.009	0.071
1998	3066	11.555	9.090	22.217	0.031	0.052	0.011	0.107
1999	3028	15.998	9.773	23.917	0.031	0.060	0.011	0.103
2000	3016	16.800	10.219	25.030	0.034	0.072	0.012	0.104
2001	2848	9.424	11.752	28.967	0.035	0.068	0.013	0.111
2002	2614	9.203	12.967	31.651	0.035	0.064	0.014	0.111
2003	2412	9.757	14.427	35.022	0.038	0.072	0.015	0.116
2004	2373	10.616	13.521	32.342	0.038	0.066	0.017	0.117
2005	2369	9.951	14.191	32.821	0.024	0.044	0.011	0.068
2006	2323	11.271	17.143	39.185	0.020	0.037	0.011	0.052
2007	2291	11.723	14.326	33.231	0.021	0.038	0.012	0.051
2008	2089	9.807	16.380	37.053	0.024	0.056	0.012	0.054
2009	2031	9.139	17.721	39.413	0.024	0.054	0.013	0.054
2010	1997	10.037	18.731	41.620	0.024	0.048	0.013	0.055

This table reports the summary statistics of the sample. The variables are defined in Appendix C.1 All variables are winsorized at the 1%/99% level each financial year except for *Firmage*. The sample period is from 1994 to 2010 and only includes firms that have both patent and risk data.

Table 4.2 **Risk Disclosure and Innovation Correlations**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	*Fnpats0*	*TCW0*	*RD*	*Avgrisk*	*Syst*	*Othrisk*	*Idio*
Fnpats0	1						
TCW0	**0.983**	1					
RD	**-0.015**	**-0.012**	1				
Avgrisk	**-0.017**	**-0.013**	**0.028**	1			
Syst	-0.008	-0.008	**-0.080**	**0.792**	1		
Othrisk	**-0.016**	**-0.015**	0.002	**0.867**	**0.584**	1	
Idio	**-0.017**	**-0.012**	**0.106**	**0.911**	**0.543**	**0.703**	1

This table reports the correlations of the main variables in the sample. All variables are winsorized at the 1%/99% level each year except *Firmage*. Variables are defined in Appendix C.1 *Avgrisk*, *Idio*, *Syst*, and *Othrisk* are from year t-1. Bold indicates significant at 5% level.

Table 4.3 Risk Disclosure and Innovation Multivariate Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-23.822***	-3.236***	-4.218***						
	(-3.43)	(-2.74)	(-3.00)						
Syst				-5.060***	-0.527*	-0.652**			
				(-3.62)	(-1.95)	(-2.03)			
Othrisk							-16.758*	-3.423***	-4.723***
							(-1.75)	(-3.03)	(-3.35)
Idio	12.479***	1.012***	1.467***	8.133***	0.362**	0.607***	7.774***	0.476***	0.792***
	(5.46)	(2.93)	(3.43)	(6.11)	(2.24)	(2.91)	(5.82)	(2.82)	(3.55)
RD_t/RD_{t-1}	0.001	0.010***	0.014***	0.001	0.010***	0.014***	0.001	0.010***	0.014***
	(1.10)	(8.75)	(8.99)	(1.10)	(8.77)	(9.01)	(1.10)	(8.77)	(9.01)
BM	-0.355	-0.057***	-0.076***	-0.354	-0.057***	-0.076***	-0.360	-0.058***	-0.077***
	(-1.47)	(-2.65)	(-2.65)	(-1.47)	(-2.66)	(-2.66)	(-1.49)	(-2.68)	(-2.68)
LogAT	-1.205***	0.283***	0.339***	-1.207***	0.282***	0.338***	-1.213***	0.282***	0.338***
	(-7.79)	(11.95)	(12.02)	(-7.79)	(11.87)	(11.92)	(-7.82)	(11.98)	(12.04)
Firmage	-0.008	0.008***	0.007***	-0.008	0.008***	0.007***	-0.008	0.008***	0.007***
	(-0.83)	(4.18)	(3.20)	(-0.83)	(4.16)	(3.18)	(-0.87)	(4.15)	(3.17)
DA	-0.030***	-0.002***	-0.003***	-0.030***	-0.002***	-0.003***	-0.030***	-0.002***	-0.003***
	(-2.92)	(-3.25)	(-3.61)	(-2.93)	(-3.31)	(-3.68)	(-2.95)	(-3.28)	(-3.64)
HHI	7.406	-0.297	-0.309	7.498	-0.301	-0.317	7.146	-0.333	-0.355
	(1.44)	(-0.45)	(-0.37)	(1.46)	(-0.46)	(-0.38)	(1.39)	(-0.50)	(-0.43)
HHI^2	-15.456**	0.637	0.678	-15.589**	0.642	0.689	-15.097*	0.688	0.743
	(-1.99)	(0.62)	(0.53)	(-2.00)	(0.63)	(0.54)	(-1.95)	(0.67)	(0.58)
LogAnalyst	1.866***	0.155***	0.205***	1.877***	0.156***	0.207***	1.871***	0.154***	0.204***
	(8.81)	(4.91)	(5.30)	(8.85)	(4.97)	(5.37)	(8.84)	(4.88)	(5.26)
IO	-0.006	-0.004***	-0.004***	-0.006	-0.004***	-0.004***	-0.006	-0.004***	-0.004***
	(-1.03)	(-4.38)	(-4.20)	(-1.07)	(-4.43)	(-4.27)	(-1.04)	(-4.34)	(-4.16)
CAPXA	0.257***	0.003*	0.007***	0.258***	0.004*	0.007***	0.258***	0.003*	0.007***
	(8.48)	(1.76)	(2.81)	(8.49)	(1.81)	(2.87)	(8.48)	(1.77)	(2.83)
TANG	-0.066***	-0.003***	-0.005***	-0.066***	-0.003***	-0.005***	-0.067***	-0.003***	-0.005***
	(-7.65)	(-2.73)	(-3.43)	(-7.63)	(-2.77)	(-3.49)	(-7.70)	(-2.81)	(-3.52)
ROA	-0.186***	0.000	0.001	-0.186***	0.000	0.001	-0.186***	0.000	0.001
	(-12.95)	(1.05)	(1.24)	(-12.93)	(1.00)	(1.19)	(-12.97)	(1.04)	(1.23)
LogLength	0.958***	0.015	0.043	0.946***	0.012	0.039	0.938***	0.013	0.041
	(4.50)	(0.57)	(1.35)	(4.46)	(0.45)	(1.21)	(4.44)	(0.51)	(1.30)

Table 4.3 Risk Disclosure and Innovation Multivariate Regressions (continued)

Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	43127	39004	39004	43127	39004	39004	43127	39004	39004
R^2	0.5050	0.3535	0.3339	0.5050	0.3532	0.3334	0.5049	0.3533	0.3336

This table reports multivariate regressions of innovation and risk. The dependents are *RD, Fnpats*, or *TCW*. When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. *HHI*, HHI^2, *logAnalyst*, *IO*, *CAPXA*, *TANG*, *ROA*, *logLength* are all at time t, all other independent variables are set at time t-1 unless otherwise specified. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.4 Risk Disclosure and Innovation Multivariate Regressions, Interaction with 2005 Risk Disclosure Requirement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-18.352**	-2.527**	-3.458**						
	(-2.56)	(-2.15)	(-2.43)						
Avgrisk Post2005*	-17.041**	-2.679***	-2.879***						
	(-1.97)	(-3.68)	(-3.29)						
Syst				-3.903**	-0.291	-0.425			
				(-2.30)	(-1.02)	(-1.24)			
Syst Post2005*				-4.141*	-0.879***	-0.855***			
				(-1.85)	(-3.48)	(-2.82)			
Othrisk							-4.891	-2.077*	-3.188**
							(-0.49)	(-1.85)	(-2.20)
Othrisk Post2005*							-40.024**	-5.359***	-6.062***
							(-2.12)	(-4.07)	(-3.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	43127	39004	39004	43127	39004	39004	43127	39004	39004
R^2	0.5049	0.3541	0.3335	0.5049	0.3538	0.3331	0.5048	0.3539	0.3334

This table reports multivariate regressions of innovation and risk. The dependents are *RD* or *Fnpats*, or *TCW*. When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. {Risk}*Post2005 is an interaction between the risk and an indicator variable set to 1 if the financial year is >2005 and 0 otherwise. Controls are the same as Table 4.3. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.5 **Risk Disclosure and Innovation Multivariate Regressions, Interaction with 2008 Risk Disclosure Removal for Smaller Reporting Companies**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-23.850***	-2.634**	-3.496**						
	(-3.35)	(-2.04)	(-2.28)						
*Avgrisk**									
Post2008	-4.807	-2.467***	-2.627**						
	(-0.79)	(-2.72)	(-2.49)						
*Avgrisk*SM*	10.745	-1.946***	-2.792***						
	(1.18)	(-3.37)	(-3.71)						
*Avgrisk**	25.440	3.722**	4.034**						
*Post2008*SM*	(0.35)	(2.25)	(2.02)						
Syst				-4.363***	-0.432	-0.574			
				(-2.83)	(-1.33)	(-1.50)			
*Syst*Post2008*				0.915	-0.541	-0.423			
				(0.55)	(-1.31)	(-0.86)			
*Syst*SM*				-6.621	-0.498	-0.683			
				(-1.42)	(-1.49)	(-1.61)			
*Syst**				-23.976	1.386*	1.602			
*Post2008*SM*				(-1.48)	(1.72)	(1.45)			
Othrisk							-27.048***	-1.493	-2.169
							(-3.05)	(-1.10)	(-1.32)
*Othrisk**							-3.016	-6.018***	-7.039***
Post2008							(-0.25)	(-5.64)	(-5.60)
*Othrisk*SM*							50.871**	-3.043**	-4.405***
							(2.48)	(-2.34)	(-2.59)
*Othrisk**							-5.378	10.924***	12.148***
*Post2008*SM*							(-0.05)	(3.38)	(3.06)
SM	0.117	0.271***	0.306***	0.721	0.234***	0.251***	-0.174	0.249***	0.275***
	(0.17)	(3.45)	(3.23)	(1.05)	(3.07)	(2.70)	(-0.25)	(3.26)	(3.00)
*Post2008*SM*	2.560*	0.158	0.227	3.672***	0.206	0.287	3.070**	0.133	0.197
	(1.66)	(1.07)	(1.33)	(3.18)	(1.33)	(1.61)	(2.26)	(0.94)	(1.22)

Table 4.5 Risk and Innovation Multivariate Regressions, Interaction with 2008 Risk Disclosure Removal for Smaller Reporting Companies (continued)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	43390	39196	39196	43390	39196	39196	43390	39196	39196
R^2	0.5025	0.3614	0.3409	0.5027	0.3607	0.3400	0.5025	0.3609	0.3404

This table reports multivariate regressions of innovation and risk with an interaction after the elimination of the risk disclosures for smaller reporting companies in 2008. The dependents are *RD, Fnpats*, or *TCW*. *Avgrisk*2008*SM*, *Syst*2008*SM*, *OthRisk*2008*SM* are interactions with an indicator variable *post2008* that is equal to 1 if the year is > 2008 and 0 otherwise and an indicator variable *SM* that is equal to 1 if the firm meets the smaller company reporting requirements (Revenues less than $50 million). When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. Intercept removed for brevity. Variables are defined in Appendix C.1. Controls are the same as Table 4.3. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.6 Risk Disclosure and Innovation Multivariate Regression Discontinuity Design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	0.778	-6.661***	-10.358***						
	(0.01)	(-4.35)	(-4.76)						
*Avgrisk*SM*	-48.116*	2.054***	3.862***						
	(-1.89)	(5.22)	(6.33)						
Syst				-3.875	-1.841***	-2.437***			
				(-0.35)	(-4.18)	(-4.21)			
*Syst*SM*				-6.917	0.843**	1.296*			
				(-1.09)	(2.02)	(1.93)			
Othrisk							51.387	-5.979***	-11.743***
							(0.84)	(-4.41)	(-5.36)
*Othrisk*SM*							-90.648**	3.704***	7.684***
							(-2.28)	(5.22)	(6.47)
SM	0.342	0.024	0.045	0.080	0.034	0.064	0.355	0.019	0.034
	(0.22)	(0.56)	(0.69)	(0.05)	(0.71)	(0.89)	(0.23)	(0.48)	(0.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	1875	1737	1737	1875	1737	1737	1875	1737	1737
R^2	0.4491	0.1919	0.1892	0.4488	0.1923	0.1881	0.4491	0.1896	0.1877

This table examine the effect of the discontinuity of $50 million in revenues (below this threshold, firms are exempt from having to include a risk disclosure section in their 10-K filings) on risk and innovation. The discontinuity sample only includes firms with revenues between $15 and $85 million and only for years 2008 and after (when the exemption is allowed). The dependents are *Fnpats*, *TCW*, or *RD*. *SM* is an indicator variable that is equal to 1 if the firm meets the smaller company reporting requirements (revenues less than $50 million). When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. Intercept removed for brevity. Variables are defined in Appendix C.1. Controls are the same as Table 4.3. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.7 Risk Disclosure and Innovation Multivariate Regressions, Interaction with Financial Constraints

Panel A: Financial Constraint Proxied by WWHi

	(1)	(2)	(3)	(4)	(5)	(6)
	Fnpats	*TCW*	*Fnpats*	*TCW*	*Fnpats*	*TCW*
Avgrisk	-3.041***	-3.962***				
	(-2.59)	(-2.84)				
*Avgrisk*WWHi*	-1.502***	-1.989***				
	(-3.27)	(-3.37)				
Syst			-0.445	-0.558*		
			(-1.63)	(-1.73)		
*Syst*WWHi*			-0.660***	-0.762***		
			(-2.95)	(-2.60)		
Othrisk					-2.992**	-4.051***
					(-2.49)	(-2.72)
*Othrisk*WWHi*					-1.592	-2.533*
					(-1.47)	(-1.89)
WWHi	0.171***	0.208***	0.160***	0.188***	0.149***	0.183***
	(7.44)	(7.30)	(7.12)	(6.58)	(6.20)	(6.13)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
n	39004	39004	39004	39004	39004	39004
R^2	0.3553	0.3355	0.3549	0.3349	0.3549	0.3351

Panel B: Financial Constraint Proxied by ATLo

	(1)	(2)	(3)	(4)	(5)	(6)
	Fnpats	*TCW*	*Fnpats*	*TCW*	*Fnpats*	*TCW*
Avgrisk	-3.353***	-4.234***				
	(-2.80)	(-2.98)				
Avgrisk ATLo*	-1.520***	-2.321***				
	(-2.85)	(-3.25)				
Syst			-0.567*	-0.675**		
			(-1.95)	(-1.97)		
Syst ATLo*			-0.160	-0.311		
			(-0.48)	(-0.73)		
Othrisk					-3.309***	-4.390***
					(-2.73)	(-2.97)
Othrisk ATLo*					-1.613	-2.566
					(-1.24)	(-1.49)
ATLo	0.302***	0.311***	0.266***	0.258***	0.276***	0.274***
	(6.53)	(5.69)	(5.77)	(4.72)	(5.62)	(4.72)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
n	39004	39004	39004	39004	39004	39004
R^2	0.3576	0.3364	0.3570	0.3356	0.3571	0.3359

Table 4.7 Risk Disclosure and Innovation Multivariate Regressions, Interaction with Financial Constraints (continued)

Panel C: Financial Constraint Proxied by Recession

	(1)	(2)	(3)	(4)	(5)	(6)
	Fnpats	*TCW*	*Fnpats*	*TCW*	*Fnpats*	*TCW*
Avgrisk	-3.097***	-4.041***				
	(-2.71)	(-2.94)				
*Avgrisk*Recession*	-1.395***	-1.775***				
	(-2.61)	(-3.78)				
Syst			-0.460*	-0.576*		
			(-1.78)	(-1.87)		
*Syst*Recession*			-0.634***	-0.707***		
			(-3.24)	(-4.31)		
Othrisk					-3.220***	-4.480***
					(-2.88)	(-3.17)
*Othrisk*Recession*					-2.026**	-2.423***
					(-2.31)	(-2.95)
Recession	-0.001	-0.001	-0.003	-0.009	-0.017	-0.023**
	(-0.04)	(-0.19)	(-0.40)	(-0.44)	(-1.46)	(-2.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
n	39004	39004	39004	39004	39004	39004
R^2	0.3537	0.3340	0.3534	0.3336	0.3533	0.3337

This table reports multivariate regressions of innovation and risk with interactions with financial constraint metrics. The dependents are *Fnpats* or *TCW*. *WWHi/ATLo* is an indicator variable set to 1 if the firm is in the top/bottom tercile of Whited-Wu score/total assets and 0 otherwise. *Recession* is set to 1 if the time period falls during an NBER recognized recession and 0 otherwise. Controls are the same as Table 4.3. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.8 **Risk Disclosure and Innovation Multivariate Regressions with Interaction with Information Asymmetry and Investment Sensitivity**

Panel A: Investment Sensitivity									
	$Avgrisk_{t-1}$			$Syst_{t-1}$			$Othrisk_{t-1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-8.720	-3.407***	-4.650***						
	(-1.15)	(-2.63)	(-2.91)						
Avgrisk SpreadHi*	-9.267*	0.447	0.967						
	(-1.74)	(0.64)	(1.08)						
Syst				-3.742*	-0.427	-0.544*			
				(-1.75)	(-1.64)	(-1.65)			
Syst SpreadHi*				0.865	-0.123	-0.109			
				(0.37)	(-0.42)	(-0.30)			
Othrisk							7.228	-3.308***	-4.889***
							(0.61)	(-2.61)	(-2.95)
Othrisk SpreadHi*							-32.916***	-0.001	0.624
							(-2.71)	(0.00)	(0.33)
SpreadHi	2.318***	-0.025	1.447***	2.018***	-0.005	0.589***	2.467***	-0.011	0.776***
	(5.21)	(-0.85)	(3.24)	(4.60)	(-0.20)	(2.75)	(5.46)	(-0.38)	(3.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	37161	37225	37225	37161	37225	37225	37161	37225	37225
R^2	0.5419	0.3558	0.3357	0.5418	0.3555	0.3352	0.5419	0.3556	0.3354

Table 4.8 Risk Disclosure and Innovation Multivariate Regressions with Interaction with Information Asymmetry and Investment Sensitivity (continued)

Panel B: Investment Sensitivity									
		$Avgrisk_{t-1}$			$Syst_{t-1}$			$Othrisk_{t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-14.975*	-3.544***	-4.584***						
	(-1.68)	(-2.90)	(-3.12)						
Avgrisk Q_CAPXHi*	-15.267	0.481	0.579						
	(-1.53)	(0.71)	(0.69)						
Syst				-4.773**	-0.550	-0.674			
				(-2.44)	(-1.48)	(-1.51)			
Syst Q_CAPXHi*				-0.674	0.034	0.034			
				(-0.26)	(0.10)	(0.08)			
Othrisk							0.966	-3.400**	-4.623***
							(0.06)	(-2.56)	(-2.68)
Othrisk Q_CAPXHi*							-30.287	-0.067	-0.199
							(-1.51)	(-0.04)	(-0.10)
Q_CAPXHi	-0.258	-0.042	-0.044	-0.628*	-0.030	-0.030	-0.306	-0.028	-0.026
	(-0.59)	(-1.13)	(-0.99)	(-1.71)	(-0.88)	(-0.71)	(-0.75)	(-0.74)	(-0.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	43118	38998	38998	43118	38998	38998	43118	38998	38998
R^2	0.5052	0.3537	0.3340	0.5050	0.3534	0.3336	0.5050	0.3534	0.3338

This table reports multivariate regressions of innovation and risk with interactions with spread and investment sensitivity. The dependents are *RD*, *Fnpats* or *TCW*. Panel A reports regressions with interactions with *SpreadHi*, an indicator variable set to 1 if a firm's average bid-ask spread over the past year is above median and 0 otherwise. Panel B reports regressions with interactions with *Q_CAPXHi; Q_CAPXHi* is an indicator variable set to 1 if a firm has historically displayed above median investment sensitivity and 0 otherwise. *Q_CAPX* is the coefficient from a regression of Tobin's Q on capital expenditures. Controls are the same as Table 4.3. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.9 Risk Disclosure and Innovation Multivariate Regressions, with Beta and Idiosyncratic Volatility as Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-7.879	-2.446**	-3.250**						
	(-1.11)	(-2.04)	(-2.25)						
Avgrisk Post2005*	-18.295***	-2.796***	-3.057***						
	(-2.63)	(-3.66)	(-3.29)						
Syst				-2.126	-0.270	-0.372			
				(-1.25)	(-0.93)	(-1.06)			
Syst Post2005*				-3.978**	-0.946***	-0.975***			
				(-2.00)	(-3.62)	(-3.05)			
Othrisk							4.288	-1.939*	-2.898**
							(0.44)	(-1.74)	(-2.02)
Othrisk Post2005*							-38.069**	-5.496***	-6.307***
							(-2.57)	(-4.09)	(-3.69)
Beta	1.697***	0.000	0.054	1.703***	0.003	0.058	1.706***	0.001	0.056
	(4.60)	(0.00)	(1.28)	(4.63)	(0.09)	(1.36)	(4.62)	(0.03)	(1.31)
IVOL	-0.039***	0.001**	0.001**	-0.039***	0.001**	0.001**	-0.039***	0.001**	0.001**
	(-6.73)	(2.38)	(2.07)	(-6.69)	(2.46)	(2.14)	(-6.75)	(2.35)	(2.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	37514	37601	37601	37514	37601	37601	37514	37601	37601
R^2	0.5491	0.3564	0.3357	0.5491	0.3561	0.3353	0.5491	0.3561	0.3355

This table reports multivariate regressions of innovation with traditional measures of risk as controls. The dependents are *RD*, *Fnpats*, or *TCW*. When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. *Beta* is calculated by using daily firm return data over the past financial year regressed against the market return in excess of the risk-free rate. *IVOL* is the residual from the regression of the firm's daily returns over the past financial year against the Fama-French 3 factors. Controls are the same as Table 4.4. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.10 Risk Disclosure and Innovation Multivariate Regressions, Using Stricter Risk Textual Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	2.549	-2.289*	-3.310**						
	(0.30)	(-1.89)	(-2.30)						
*Avgrisk * Post2005*	-40.216***	-0.566	-0.536						
	(-5.47)	(-0.67)	(-0.48)						
Syst				3.028	0.039	-0.080			
				(1.27)	(0.12)	(-0.20)			
*Syst * Post2005*				-10.831***	-1.059***	-1.048***			
				(-3.96)	(-3.36)	(-2.69)			
Othrisk							5.097	-2.496**	-3.973***
							(0.47)	(-2.15)	(-2.81)
*Othrisk * Post2005*							-60.450***	-1.987*	-1.647
							(-4.31)	(-1.67)	(-1.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	43034	38915	38915	43034	38915	38915	43034	38915	38915
R^2	0.5042	0.3534	0.3339	0.5037	0.3535	0.3337	0.5040	0.3537	0.3342

This table reports multivariate regressions of innovation and risk disclosure using the more strict textual risk analysis described in the text. The dependents are *RD*, *Fnpats*, or *TCW*. When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. Controls are the same as Table 4.4. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.11 Orthogonalized Risk Disclosure and Innovation Multivariate Regressions

Panel A: 1st Stage Regressions

	(1)	(2)	(3)
	AvgRisk	*Syst*	*OthRisk*
BM	0.001***	0.002***	0.000***
	(4.34)	(5.19)	(3.43)
LogAT	0.000	0.003***	0.000***
	(0.73)	(11.21)	(4.81)
Ret0_12	0.000	0.000	0.000
	(-0.99)	(-1.14)	(-0.79)
DA	0.000***	0.000	0.000
	(-6.50)	(0.13)	(-1.62)
Ivol	0.000***	0.000***	0.000***
	(7.87)	(6.54)	(6.61)
Beta	0.004***	0.005***	0.001***
	(16.30)	(7.51)	(10.75)
Skew_Ret	0.000**	0.000	0.000
	(-2.46)	(-0.66)	(-1.62)
Turn	0.001***	0.001	0.000***
	(4.42)	(1.46)	(2.74)
BigN	0.004***	0.004***	0.002***
	(9.21)	(4.62)	(9.85)
DNI	0.000	0.000	0.000
	(-0.33)	(1.16)	(-0.38)
LogAnalyst	0.001**	0.000	0.000***
	(2.53)	(0.63)	(-3.43)
IO	0.000	0.000	0.000***
	(-0.65)	(0.07)	(4.38)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
n	40507	40507	40507
R^2	0.1234	0.1555	0.0823

Table 4.11 Orthogonalized Risk Disclosure and Innovation Multivariate Regressions (continued)

Panel B: Residual Risk Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RD	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*	*RD*	*Fnpats*	*TCW*
Avgrisk	-9.167	-3.360***	-5.158***						
	(-1.08)	(-2.95)	(-3.86)						
*Avgrisk * Post2005*	-9.020	-2.732**	-2.772**						
	(-1.29)	(-2.37)	(-2.01)						
Syst				-2.400	-0.376	-0.604*			
				(-1.33)	(-1.24)	(-1.68)			
*Syst * Post2005*				-2.314	-1.262***	-1.321***			
				(-1.14)	(-3.14)	(-2.73)			
Othrisk							-2.986	-2.935**	-4.799***
							(-0.28)	(-2.28)	(-2.96)
*Othrisk * Post2005*							-15.531	-3.524**	-3.416
							(-1.19)	(-2.06)	(-1.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	34839	34839	34839	34839	34839	34839	34839	34839	34839
R^2	0.3639	0.3639	0.3639	0.3639	0.3639	0.3639	0.3639	0.3639	0.3639

This table reports regressions of innovation and risk orthogonalized to known predictors of risk disclosure. Panel A shows the 1st stage regression results of predictors of risk against the risk scores. Panel B shows the results of the regressions using the residuals from the 1st stage regression in Panel A. The dependents are *fnpats*, *TCW*, or *RD*. When *RD* is the dependent, RD_{t-1} is used as an independent in the regression instead of RD_t. Controls are the same as Table 4.3. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors in Panel B are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 4.12 Capitalized R&D (t-4 to t) and Sum of Future Patents (t to t+2)

Panel A: Capitalized R&D (RDC) (t-4 to t) as Control

	(1)	(2)	(3)	(4)	(5)	(6)
	Fnpats	*TCW*	*Fnpats*	*TCW*	*Fnpats*	*TCW*
Avgrisk	-2.796**	-3.771**				
	(-2.25)	(-2.57)				
*Avgrisk * Post2005*	-1.704	-1.711				
	(-1.50)	(-1.28)				
Syst			-0.294	-0.446		
			(-1.00)	(-1.28)		
*Syst * Post2005*			-0.779***	-0.709**		
			(-2.78)	(-2.10)		
Othrisk					-2.131*	-3.302**
					(-1.74)	(-2.17)
*Othrisk * Post2005*					-3.824**	-4.102*
					(-2.09)	(-1.85)
RDC	0.004***	0.006***	0.004***	0.006***	0.004***	0.006***
	(10.09)	(10.22)	(10.24)	(10.37)	(10.06)	(10.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
n	33789	33789	33789	33789	33789	33789
R^2	0.3690	0.3542	0.3689	0.3539	0.3687	0.3539

Panel B: Sum of Future Fnpats & TCW (t to t+2) as Dependent

	(1)	(2)	(3)	(4)	(5)	(6)
	Fnpats	*TCW*	*Fnpats*	*TCW*	*Fnpats*	*TCW*
Avgrisk	-9.784**	-13.228***				
	(-2.57)	(-2.94)				
*Avgrisk * Post2005*	-5.623	-6.177				
	(-1.55)	(-1.48)				
Syst			-1.021	-1.524		
			(-1.11)	(-1.40)		
*Syst * Post2005*			-2.258**	-2.126**		
			(-2.50)	(-2.01)		
Othrisk					-9.775**	-14.368***
					(-2.53)	(-2.97)
*Othrisk * Post2005*					-11.157*	-12.148*
					(-1.88)	(-1.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
n	32770	32770	32770	32770	32770	32770
R^2	0.4092	0.4026	0.4086	0.4018	0.4089	0.4024

This table reports regressions of innovation and risk disclosure with capitalized R&D (*RDC*) or cumulative patents. Panel A shows the regressions using t-4 to t capitalized R&D (Eberhart, Maxwell, and Siddique 2004) as a control. Panel B shows the results of the regressions cumulative future patents (*Fnpats_3* or *TCW_3*) from years t to t+2. Other controls are the same as Table 4.3. Variables are defined in Appendix C.1 Intercept removed for brevity. Standard errors are clustered by firm and year. * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Chapter 5: Conclusion

In conclusion, this dissertation examines several intangibles and identifies their effects on firms. Chapter 2 examines the effect of employee flexibility on future firm performance. I create a novel measure of employee flexibility using text analysis of online job reviews. The results show that firms with more flexible employees earn higher returns than other firms, particularly when the firm is exposed to systematic risk. Chapter 3 shows that the SEC's enforcement deters future financial misconduct and that punishment of the company has a larger deterrence effect than punishment of an officer or other entity. Finally, Chapter 4 shows risk disclosed in firm filings is associated with lower innovation and that mandating additional disclosure of risk results in even lower innovation.

These results bring up a variety of implications for researchers. Chapter 2 shows that how firm employees are organized has an impact on firm performance—future research can examine other ways that firms are organized and their impact on firm outcomes. Chapter 3 is important as it lays the ground work for investigating other methods to reduce future financial misconduct. Chapter 4 is valuable as it gives fuel to the debate about increasing mandatory disclosure—more disclosure is not always best for the firms and investors.

These results are also critical for practitioners. The second chapter is important for firm executives as it shows to them that how they structure their employees can have a large impact on firm value—more flexible employees can aid their firm during times of risk or uncertainty. The third chapter is important for regulators as it shows that their efforts are valuable at reducing future financial misconduct. Furthermore, given tight budgets for regulatory agencies, the research shows that targeting a company will be more effective at deterring future misconduct in both the company's industry and MSA. Finally, regulators have focused on increasing disclosure as the best way to improve market outcomes. With the results from the fourth chapter, regulators may want to rethink this orthodoxy and examine the trade-off between increased disclosure against possible negative side-effects.

Altogether, this dissertation adds to the mounting evidence of the importance of intangibles and looks at 3 specific ways that intangibles such as employee flexibility, integrity, disclosure and innovation, can have on firms. Furthermore, it shows how text analysis can be used to provide a measure of intangibles that can be used in academic research. Finally, it provides future paths for research to examine other intangibles that may affect firms.

Bibliography

Chapter 2 References

Aghion, P., Tirole, J. (1994). The Management of Innovation. *Quarterly Journal of Economics*, 109, 1185–1209.

Bae, K.-H., Kang, J.-K., Wang, J. (2011). Employee treatment and firm leverage: A test of the stakeholder theory of capital structure. *Journal of Financial Economics*, 100, 130–153.

Bahrami, H. (1992). The emerging flexible organization: Perspectives from Silicon Valley. *California Management Review*, 34, 33-52.

Baker, M. P., Stein J.C., Wurgler, J. (2003). When does the market matter? Stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics*, 118, 969–1005.

Baker, S. R., Bloom, N., Davis, S. J. (2016). Measuring economic policy uncertainty. Working Paper, National Bureau of Economic Research (No. w21633).

Bhattacharya, M., Gibson, D. E., Doty, D. H. (2005). The effects of flexibility in employee skills, employee behaviors, and human resource practices on firm performance. *Journal of Management*, 31, 622-640.

Bebchuk, L., Cohen, A., Ferrell, A. (2009). What matters in corporate governance? *Review of Financial studies*, 22, 783-827.

Bloom, N., Liang, J., Roberts, J., Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. *Quarterly Journal of Economics*, 130, 165-218.

Bowen, B.D., Headley, D.E. (2017). Airline Quality Rating 2017, Retrieved from http://commons.erau.edu/aqrr/27.

Carhart, M., (1997). On persistence in mutual fund performance. *Journal of Finance*, 52, 57–82.

Cameron, K. S., DeGraff, J., Quinn, R. E., Thakor, A. V. (2006). Competing values leadership: Creating value in organizations. Cheltenham, U.K.: Edward Elgar Publishing.

Campello, Murillo, John R. Graham, and Campbell R. Harvey. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of financial Economics,* 97, 470-487.

Chan, L. K., Lakonishok, J., and Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, 56, 2431-2456.

Chen, H. J., Kacperczyk, M., and Ortiz-Molina, H. (2011). Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis*, 46, 25-58.

Cohen, L., Malloy, C., Nguyen Q. H. (2016). Lazy prices. Working Paper, Harvard University.

Denison, D. R., Mishra, A. K. (1995). Toward a theory of organizational culture and effectiveness. *Organization Science*, 6, 204-223.

Donangelo, A. (2014). Labor mobility: Implications for asset pricing. *Journal of Finance*, 69, 1321-1346.

Dougal, C., Engelberg, J., Garcia D., Parsons, C. A. (2012). Journalists and the Stock Market. *Review of Financial Studies,* 25, 639–79.

Duchin, Ran, Oguzhan Ozbas, and Berk A. Sensoy. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97, 418-435.

Edmans, A. (2009). Blockholder trading, market efficiency, and managerial myopia. *Journal of Finance*, 64, 2481–2513.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, 101, 621–640.

Edmans, A. (2012). The link between job satisfaction and firm value, with implications for corporate social responsibility. *Academy of Management Perspectives*, 26, 1–19.

Edmans, A., Li, L., Zhang, C. (2017). Employee satisfaction, labor market flexibility, and stock returns around the world. Working Paper, London Business School.

Eisfeldt, A. L., Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *Journal of Finance*, 68, 1365–1406.

Fama, E. F., French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116, 1–22.

Fama, E. F., MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81, 607-636.

Fauver, L., McDonald, M. B., Taboada, A. (2015). Does it pay to treat employees well? International evidence on the value of an employee-friendly culture. Working Paper.

Fiordelisi, F., Ricci, O. (2014). Corporate culture and CEO turnover. *Journal of Corporate Finance*, 28, 66–82.

Giannetti, M., Yu, X. (2017). Adapting to radical change: The benefits of short-horizon investors. European Corporate Governance Institute (ECGI) - Finance Working Paper No. 467/2016.

Gompers, P., Ishii, J., Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, 118, 107-155.

Gopalan, R., Milbourn, T., Song, F. (2010). Strategic flexibility and the optimality of pay for sector performance. *Review of Financial Studies*, 23, 2060-2098.

Gough, H. G. (1960). The adjective check list as a personality assessment research technique. *Psychological Reports*, 6, 107-122.

Graham, J. R., Harvey, C. R., Popadak, J., Rajgopal, S. (2016a). Corporate culture: Evidence from the field. Working Paper, Duke University.

Graham, J. R., Harvey, C. R., Popadak, J., Rajgopal, S. (2016b). Corporate culture: The interview evidence. Working Paper, Duke University.

Griliches, Z., Hausman, J. A. (1986). Errors in variables in panel data. *Journal of econometrics*, 31, 93-118.

Guilford, J. P. (1962). Creativity: Its Measurement and Development, in S. J. Parnes and H. F. Harding (Eds.): A Source Book for Creative Thinking, New York: Charles Scribner's Sons.

Guiso, L., Sapienza, P., Zingales, L. (2014). The value of corporate culture. *Journal of Financial Economics*, 117, 60–76.

Hermalin, B. (2001). Economics and Corporate Culture. The Handbook of Organizational Culture and Climate. John Wiley and Sons.

Hirsch, B. and Macpherson, D., (2003) Union membership and coverage database from the current population survey: Note. *Industrial and Labor Relations Review*, 56, 349-54.

Hofstede, G. (1984) *Culture's consequences: International differences in work-related values*. Beverly Hills: Sage Publications.

Huang, M., Li, P., Meschke, F., Guthrie, J. P. (2015). Family firms, employee satisfaction, and corporate performance. *Journal of Corporate Finance*, 34, 108–127.

Kaplan, S. N., Zingales L. (1997). Do financial constraints explain why investment is correlated with cash flow? *Quarterly Journal of Economics*, 112, 169–216.

Kasof, J., Chen, C., Himsel, A., Greenberger, E. (2007). Values and creativity. *Creativity Research Journal*, 19, 105-122.

Kerr, B., Gagliardi, C. (2003). Measuring creativity in research and practice. *Positive Psychological Assessment: A Handbook of Models and Measures*, 155-169.

Kreps, D. (1990). Corporate Culture and Economic Theory. Cambridge, UK: Cambridge University Press.

Li, K., Qiu, B., Shen, R. (2014). Organization capital and mergers and acquisitions. Working Paper, University of British Columbia.

Loughran, T., McDonald B. (2016). Textual analysis in accounting and finance: A survey.

Journal of Accounting Research, 54, 1187-1230.

Melián-González, S., Bulchand-Gidumal, J., González López-Valcárcel, B. (2015). New evidence of the relationship between employee satisfaction and firm economic performance. *Personnel Review*, 44, 906–929.

Moniz, A. (2016). Inferring employees' social media perceptions of corporate culture and the link to firm value. Working Paper, Erasmus University.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108, 1–28.

O'Reilly, C. 1989. Corporations, culture, and commitment: Motivation and social control in organizations. *California Management Review*, 31, 9-25.

Popadak, J. A. (2013). A corporate culture channel: How increased shareholder governance reduces firm value. Working Paper, The Wharton School.

Schwartz, S. H. (1999). A theory of cultural values and some implications for work. *Applied psychology*, 48, 23-47.

Seibert, S. E., Wang, G., Courtright, S. H. (2011). Antecedents and consequences of psychological and team empowerment in organizations: a meta-analytic review. *Journal of Applied Psychology*, 96, 981-1003.

Sørensen, J. B. (2002). The strength of corporate culture and the reliability of firm performance. *Administrative Science Quarterly*, 47, 70-91.

Spreitzer, G. M. (1996). Social structural characteristics of psychological empowerment. *Academy of Management Journal*, 39, 483-504.

Starks, L., Sun, Y. (2016). Economic Policy Uncertainty, Learning and Incentives: Theory and Evidence on Mutual Funds. Working Paper, University of Texas at Austin.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, 62, 1139-1168.

Torrance, E. P. 1965. Rewarding Creative Behavior. Englewood Cliffs, NJ: Prentice-Hall

Tottie, G. (1991). Negation in English Speech and Writing: A Study in Variation. San Diego: Academic Press.

Tremblay, A. (2018). Cultural differences, synergies and mergers and acquisitions. Working Paper, Laval University.

VandenBos, G. R. (2013). APA dictionary of clinical psychology. Washington, DC, US: American Psychological Association.

Whited, T. M., Wu, G. (2006). Financial constraints risk. *Review of Financial Studies*, 19, 531-

559.

Wright, P. M., Snell, S. A. (1998). Toward a unifying framework for exploring fit and flexibility in strategic human resource management. *Academy of Management Review*, 23, 756-772.

Zammuto, R.F., Gifford, B., Goodman, E.A. (2000). Managerial ideologies, organizational culture, and the outcomes of innovation. In N.M. Ashkanasy, C.M. Wilderoom and M.F. Peterson, (Eds.), Handbook of Organizational Culture and Climate. Sage: Thousand Oaks, CA.

Chapter 3 References

Beny, L. N. (2005). Do insider trading laws matter? Some preliminary comparative evidence. *American Law and Economics Review*, *7*(1), 144-183.

Bhattacharya, U., & Daouk, H. (2002). The world price of insider trading. *The Journal of Finance*, *57*(1), 75-108.

Bris, A. (2005). Do insider trading laws work? *European Financial Management*, *11*(3), 267-312.

Cumming, D., Johan, S., & Li, D. (2011). Exchange trading rules and stock market liquidity. *Journal of Financial Economics*, *99*(3), 651-671.

Danisewicz, P., McGowan, D., Onali, E. and Schaeck, K., Forthcoming. The real effects of regulatory enforcement actions: Evidence from US counties. *Journal of Financial Intermediation*.

Dechow, P. M., Ge, W., Larson, C. R., & Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary accounting research*, *28*(1), 17-82.

Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1996). Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary accounting research*, *13*(1), 1-36.

Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud?. *The Journal of Finance*, 65(6), 2213-2253.

Ehrlich, I. (1996). Crime, punishment, and the market for offenses. *The Journal of Economic Perspectives*, *10*(1), 43-67.

Feroz, E. H., Park, K., & Pastena, V. S. (1991). The financial and market effects of the SEC's accounting and auditing enforcement releases. *Journal of Accounting Research*, 107-142.

Fiordelisi, F., Raponi, J., and Rau P.R., 2015. Corporate culture and enforcement actions in banking, Working Paper.

Gino, F., Ayal, S., & Ariely, D. (2009). Contagion and differentiation in unethical behavior: The effect of one bad apple on the barrel. *Psychological science*, 20(3), 393-398.

Goldman, E., Peyer, U., & Stefanescu, I. (2012). Financial misrepresentation and its impact on rivals. *Financial Management*, *41*(4), 915-945.

Irwin, Neil. "This is a Complete List of Wall Street CEOs Prosecuted for their Role in the Financial Crisis." *The Washington Post.* September 12, 2013.

Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008a). The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis*, *43*(03), 581-611.

Karpoff, J. M., Lee, D. S., & Martin, G. S. (2008b). The consequences to managers for financial misrepresentation. *Journal of Financial Economics*, *88*(2), 193-215.

Karpoff, J. M., Koester, A., Lee, D. S., & Martin, G. S. (2017). Proxies and databases in financial misconduct research. *The Account Review* Forthcoming

Kedia, S., & Rajgopal, S. (2009). Neighborhood matters: The impact of location on broad based stock option plans. *Journal of Financial Economics*, 92(1), 109-127.

Kedia, S., & Rajgopal, S. (2011). Do the SEC's enforcement preferences affect corporate misconduct?. *Journal of Accounting and Economics*, *51*(3), 259-278.

Kedia, S., Koh, K., & Rajgopal, S. (2015). Evidence on contagion in earnings management. *The Accounting Review*, *90*(6), 2337-2373.

Levitt, S. D. (1998). Why do increased arrest rates appear to reduce crime: deterrence, incapacitation, or measurement error?. *Economic inquiry*, *36*(3), 353-372.

Lynch, S. “Trump's SEC pick Clayton points to capital formation, not enforcement.” *Reuters January 5, 2017*. Retrieved from http://www.reuters.com/article/us-usa-trump-sec-idUSKBN14N1Y9

Malloy, C. J. (2005). The geography of equity analysis. *The Journal of Finance*, *60*(2), 719-755.

Miceli, T. J., & Segerson, K. (2007). Punishing the innocent along with the guilty: The economics of individual versus group punishment. *The Journal of Legal Studies*, *36*(1), 81-106.

Nocera, J. "Biggest Fish Face Little Risk of being Caught." *New York Times* February 25, 2011.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of financial studies*, 22(1), 435-480.

Picker, Leslie. “Donald Trump Nominates Wall Street Lawyer to Head S.E.C.” *The New York Times* January 4, 2017 retrieved from https://www.nytimes.com/2017/01/04/business/dealbook/donald-trump-sec-jay-clayton.html?_r=0

Roman, R. A. (2017). Impact of Regulatory Enforcement Actions on Corporate Borrowers’ Stock Returns and Credit Supply. Working Paper. Federal Reserve.

Robinson, M. & Bain, B. “Wall Street Cops Reined In as SEC Braces for Trump Budget Cuts.” *Bloomberg March 6, 2011.* Retrieved from https://www.bloomberg.com/news/articles/2017-03-06/wall-street-cops-reined-in-as-sec-braces-for-trump-budget-cuts

Weidner, David. "Why no Jail Time for Wall Street CEOs?" *MarketWatch* June 1, 2011.

Chapter 4: References

Aghion, P., Askenazy, P., Berman, N., Cette, G., & Eymard, L. (2012). Credit constraints and the cyclicality of R&D investment: Evidence from France. *Journal of the European Economic Association*, 10(5), 1001-1024.

Avramov, D., Li, M., & Wang, H. (2016). Risk and Corporate Policies: A Text-Based Analysis. Working paper, Hebrew University of Jerusalem.

Benston, G. J. (1973). Required disclosure and the stock market: An evaluation of the Securities Exchange Act of 1934. *The American Economic Review*, 63(1), 132-155.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1), 85-106.

Bernstein, S. (2015). Does going public affect innovation?. *The Journal of Finance*, 70(4), 1365-1403.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, 64(1), 151-185.

Brown, J. R., Martinsson, G., & Petersen, B. C. (2012). Do financing constraints matter for R&D?. *European Economic Review*, 56(8), 1512-1529.

Byard, D., Li, Y., & Yu, Y. (2011). The effect of mandatory IFRS adoption on financial analysts' information environment. *Journal of Accounting Research*, 49(1), 69-96.

Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H. M., & Steele, L. B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, 19(1), 396-455.

Chava, S., & Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. *The Journal of Finance*, 63(5), 2085-2121.

Chemmanur, T. J., & Tian, X. (2016). Do anti-takeover provisions spur corporate innovation? Working paper, Boston College.

Covas, F., & Den Haan, W. J. (2012). The role of debt and equity finance over the business cycle. *The Economic Journal*, 122(565), 1262-1286.

Cremers, M., & Sepe, S. M. (2017). Board Declassification Activism: The Financial Value of the Shareholder Rights Project. Working Paper, University of Notre Dame.

Dawling, P., & Den Haan, W. J. (2011). The cyclical behavior of debt and equity finance. The *American Economic Review*, 101(2), 877-899.

DeFond, M., Hu, X., Hung, M., & Li, S. (2011). The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting and Economics*, 51(3), 240-258.

Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97(3), 418-435.

Dutta, S., & Nezlobin, A. (2017). Information disclosure, firm growth, and the cost of capital. *Journal of Financial Economics*, 123(2), 415-431.

Eberhart, A. C., Maxwell, W. F., & Siddique, A. R. (2004). An examination of long-term abnormal stock returns and operating performance following R&D increases. *The Journal of Finance*, 59(2), 623-650.

Fazzari, S. M., Hubbard, R. G., Petersen, B. C., Blinder, A. S., & Poterba, J. M. (1988). Financing constraints and corporate investment. *Brookings papers on economic activity*, 1988(1), 141-206.

Gao, P. (2010). Disclosure quality, cost of capital, and investor welfare. *The Accounting Review*, 85(1), 1-29.

Gaulin, M. (2017). Risk Fact or Fiction: The information content of risk factor disclosures. Working Paper, Rice University.

Grossman, G. M., & Helpman, E. (1993). *Innovation and growth in the global economy*. MIT press.

Gu, F., & Li, J. Q. (2003). Disclosure of innovation activities by high-technology firms. *Asia-Pacific Journal of Accounting & Economics*, 10(2), 143-172.

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909-1940.

He, J. J., & Tian, X. (2013). The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109(3), 856-878.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1), 405-440.

Hirshleifer, D., Hsu, P. H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, 107(3), 632-654.

Holmstrom, B. (1989). Agency costs and innovation. *Journal of Economic Behavior & Organization*, 12(3), 305-327.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *the Quarterly Journal of economics*, 112(3), 663-691.

Hombert, J., & Matray, A. (2015). Can Innovation Help US Manufacturing Firms Escape Import Competition from China? Working paper, HEC Paris.

Hope, O. K., Hu, D., & Lu, H. (2016). The benefits of specific risk-factor disclosures. *Review of Accounting Studies*, 21(4), 1005-1045.

Horton, J., Serafeim, G., & Serafeim, I. (2013). Does mandatory IFRS adoption improve the information environment?. *Contemporary Accounting Research*, 30(1), 388-423.

Iliev, P. (2010). The effect of SOX Section 404: Costs, earnings quality, and stock prices. *The Journal of Finance*, 65(3), 1163-1196.

Kanodia, C., Singh, R., & Spero, A. E. (2005). Imprecision in accounting measurement: Can it be value enhancing?. *Journal of Accounting Research*, 43(3), 487-519.

Kanodia, C., & Sapra, H. (2016). A real effects perspective to accounting measurement and disclosure: Implications and insights for future research. *Journal of Accounting Research*, 54(2), 623-676.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.

Koh, P. S., & Reeb, D. M. (2015). Missing R&D. *Journal of Accounting and Economics*, 60(1), 73-94.

Kravet, T., & Muslu, V. (2013). Textual risk disclosures and investors' risk perceptions. *Review of Accounting Studies*, 18(4), 1088-1122.

Lambert, R., Leuz, C., & Verrecchia, R. E. (2007). Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research*, 45(2), 385-420.

Li, F., (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting & Economics*, 45, 221-247.

Li, X., Moshirian, F., Tian, X., & Zhang, B., (2017). The Real Effect of Financial Disclosure: International Evidence. Working Paper, London School of Economics.

Loughran, T., & McDonald, B. (2014). Measuring readability in financial disclosures. *The Journal of Finance*, 69(4), 1643-1671.

Mazzucato, M., & Tancioni, M. (2012). R&D, patents and stock return volatility. *Journal of Evolutionary Economics*, 4(22), 811-832.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187-221.

Pindyck, R. S. (1990). Irreversibility, uncertainty, and investment (No. w3307). *National Bureau of Economic Research*.

Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2006). What works in securities laws?. *The Journal of Finance*, 61(1), 1-32.

Porter, M. E. (1991). Capital disadvantage: America's failing capital investment system. *Harvard Business Review*, *70*(5), 65-82.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, 32(1), 97-180.

Whited, T. M., & Wu, G. (2006). Financial constraints risk *Review of Financial Studies*, 19(2), 531-559.

Appendices

Appendix A.1 Case Study: Airlines

When oil prices unexpectedly plunged in mid-2014 and again in 2015, most U.S. airlines posted record earnings, yet over the same period, the stock of Southwest Airlines (LUV, a firm with a flex score of 1.88) outperformed that of United Airlines (UAL, with a flex score of 1.51).[60] Such a pattern in stock prices is consistent with our interpretation that in the event of exogenous shocks, Southwest's employee flexibility allowed the firm to react more timely and adequately to changing circumstances. Southwest's operating flexibility (e.g., servicing shorter routes and flying a single type of aircraft) may explain part of the outperformance, but so does its employee flexibility, which is an integral part of Southwest's culture.

For example, a Southwest pilot who decided to hold a plane to wait for a customer rushing to a dying relative received praise from management.[61] Employee flexibility is also embodied by a 2010 story where the pilot of a re-routed flight stuck on tarmac ordered pizza for all passengers, or by the flight crew who abandoned take-off and rerouted free of charge a passenger who had just learned that her son was in a coma.[62,63] These anecdotes are not isolated in a company with a strong empowerment culture. In the words of Southwest's CMO: "[our culture is to] empower employees to make decisions. We [the management] let them use their judgment and act on situations where they can improve customer experience."[64] In contrast,

---

[60] United enters our sample in 2016; we therefore use the 2016 flex score as a proxy for United's true score in 2014 and 2015, a reasonable assumption given both Southwest's and United's relatively stable positions in Airline Quality Ratings during 2014-2016 (Bowen and Headley 2017). The sample median flex score in 2014 is 1.55.

[61] Tenney, M., Why empowering employees to be compassionate is great for business, Huffington Post, 9/6/2016.

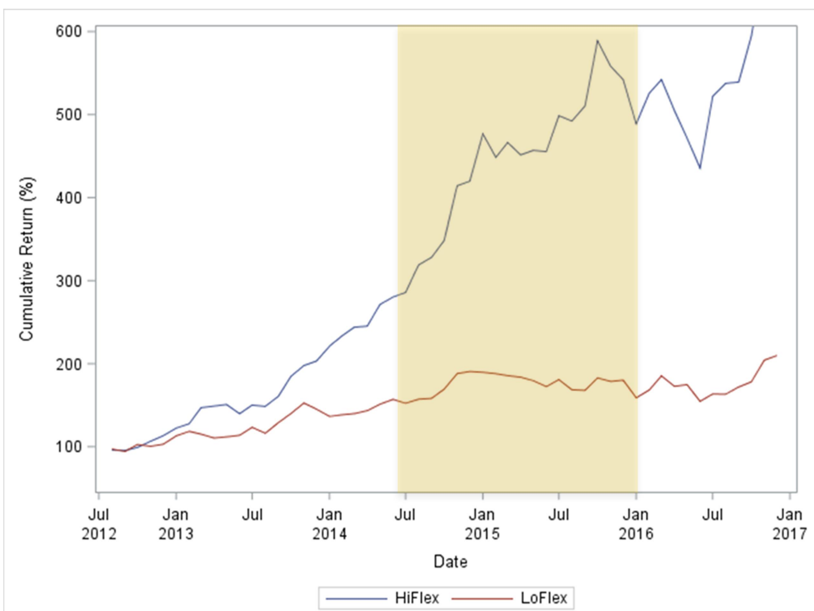
[62] Mainz, C., A pizza party on Southwest Airlines, Southwest Airlines' Community blog, 5/25/2010, https://www.southwestaircommunity.com/t5/Southwest-Stories/A-Pizza-Party-on-Southwest-Airlines/ba-p/28951.

[63] Pemberton, B., Southwest Airlines turns plane around at last minute and provides free flight home after passenger learns her son is in a coma, *Daily Mail*, 5/26/2015, http://www.dailymail.co.uk/travel/travel_news/article-3097690/Southwest-Airlines-turns-plane-minute-provides-free-flight-home-passenger-learns-son-coma.html.

[64] Kevin Krone, CMO of Southwest Airlines, quoted in SiegelGale.com, 1/29/2016, https://www.siegelgale.com/kevin-krone-cmo-of-southwest-airlines-on-conquering-complexity-for-employees-and-customers/.

referring to a highly publicized 2017 incident involving the violent removal of a passenger from an overbooked flight, United's CEO Oscar Muñoz said that rule-following was the root cause of the incident: "Our policies got in the way of our values and procedures interfered in doing what's right."[65]

The collective weight of these anecdotes amounts to significant stock performance differences between firms with high and low employee flexibility. Considering the airlines industry, we form two portfolios by splitting publicly traded airlines along their median flex score. The following figure plots the cumulative value-weighted returns of the high- and low-flex portfolios, and shows that as oil prices plummeted (starting in the second half of 2014, highlighted), high-flex airlines significantly outperformed low-flex ones.[66]



[65] Fotsch, B. and Case, J., Is your company like United Airlines? *Forbes*, 5/2/2017.
[66] Portfolios are formed at the end of June 2011, rebalanced in June of each year, and held to December 2016. The starting value of each portfolio is normalized to be 100.

Appendix A.2 Parsing the Reviews

We provide here a detailed description of the parsing method applied to reviews. We retrieve reviews from a career insight website and convert the reviews into raw text. We use a text parsing software to convert all characters into lowercase characters and contractions into full-form expressions (for example, “don’t” into “do not”). We remove punctuation and stop words, using Python’s Natural Language Tool Kit’s list of stop words.[67] We keep negation words (no, not, neither, none, nobody, nowhere, nor, never) in the text, to make adjustments for semantical negation possible. To account for the grammatical declinations of words, we lemmatize words in the remaining text with Python’s Natural Language Tool Kit’s English Lemmatizer algorithm.

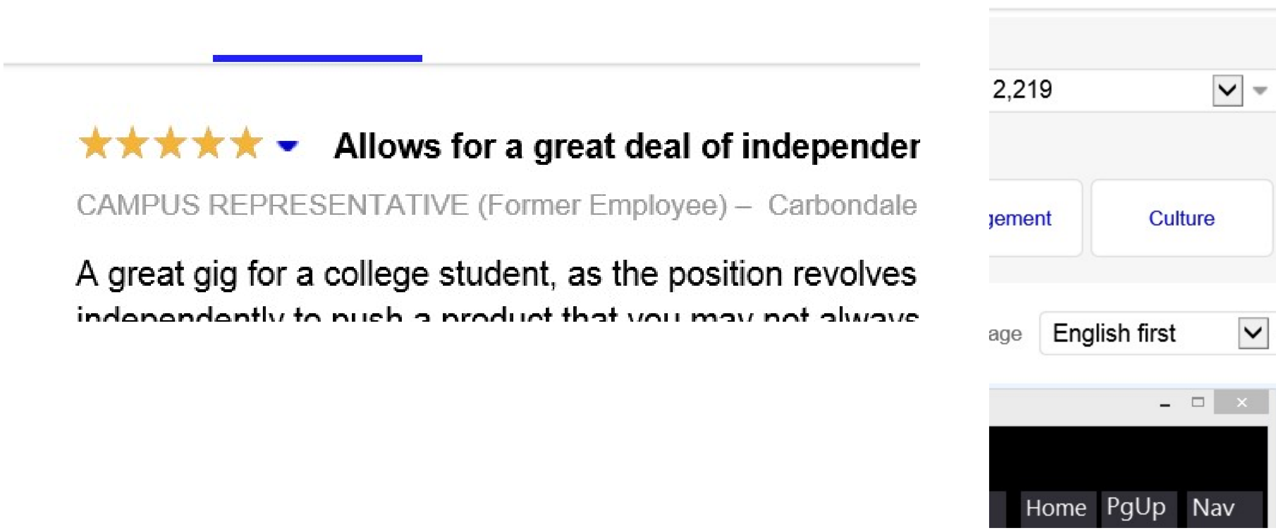
We follow Tetlock (2007) and compute the frequency of the lexical fields’ words in the parsed reviews, net of the frequencies of the negated form of each word. Appendix A.6 lists the words included in our lexical field. Finally, in Appendix A.7 we report the top 5 firms that have the highest *Flex* scores each year in our sample.

[67] The list of stop words that I used contains the following words: through, itself, any, to, our, and, theirs, because, few, some, of, how, have, same, on, above, who, or, were, only, my, more, while, from, such, up, was, whom, having, each, at, me, they, yourself, these, about, again, against, should, down, them, then, myself, those, do, you, out, all, the, does, during, your, an, am, him, into, ourselves, where, own, by, his, as, what, very, we, there, but, their, them, did, doing, can, just, being, its, yours, herself, has, is, than, below, are, if, why, hers, had, in, s, himself, before, this, she, will, been, it, once, I, yourselves, for, a, her, both, further, when, under, now, over, between, with, that, until, after, be, so.

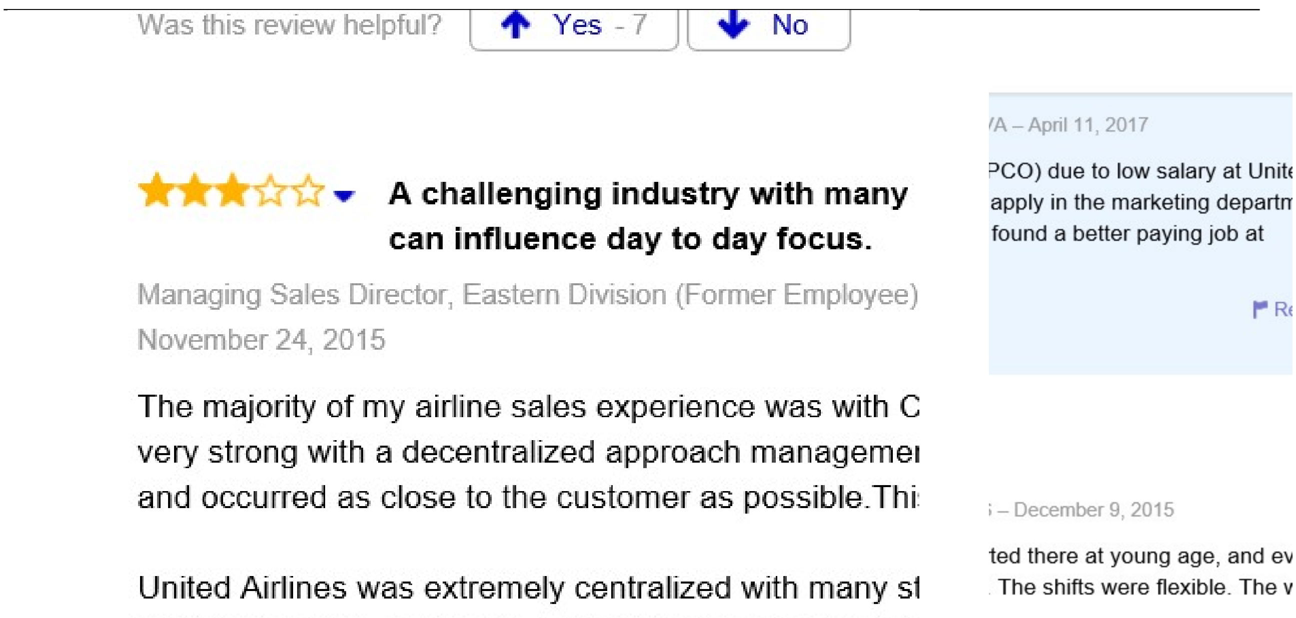
Appendix A.3 Sample Reviews

This figure shows three examples of reviews retrieved from the career intelligence website we use. Each review includes a title (bolded), details about the reviewer (pale grey), and a free-form review (black text, not bolded). The upper left corner of each reviews has a drop-down menu (not shown) with the detailed ratings on the following categories: job/work life balance, compensation benefits, job satisfaction, management, and job culture. Finally, the right column has firm-level statistics of overall employee satisfaction and satisfaction for the categories of job/work life balance, compensation benefits, job satisfaction, management, and job culture.

Panel A: Apple

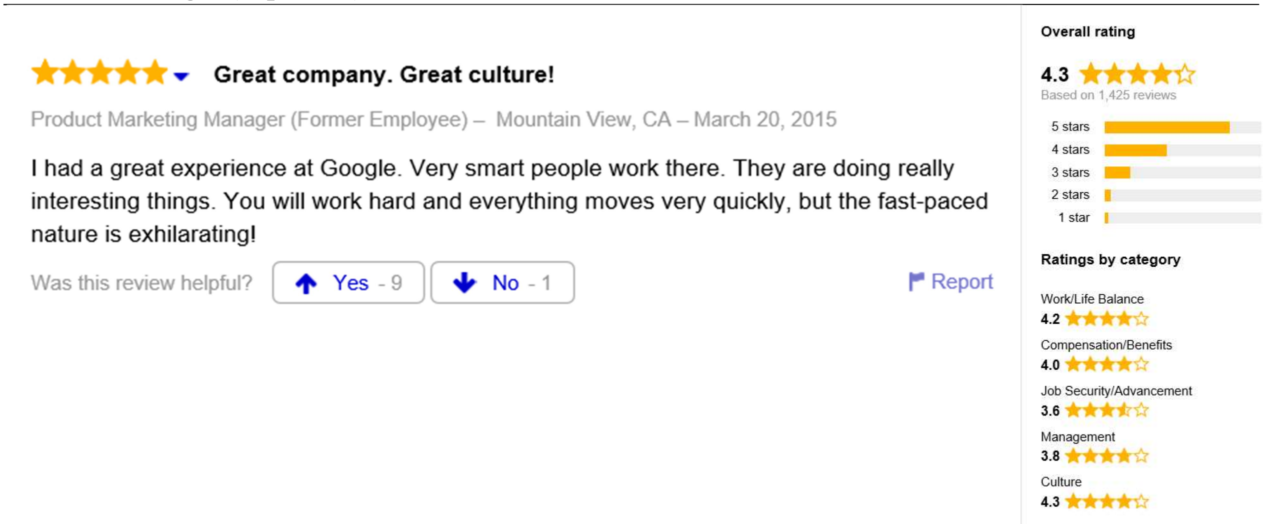


Panel B: United Airlines



Appendix A.3 (Continued). Sample Reviews

Panel C: Google (Alphabet)



Appendix A.4 Variable Definitions

Variable	Definition
Age	Age of firm calculated as the current year less the first year the firm appears in Compustat.
AT	Total assets at end of fiscal year.
BC	Indicator variable that is equal to 1 if the firm is on the "100 Best Companies to Work for" list in year t, and zero otherwise.
Beta	CAPM beta estimated by regressing monthly firm returns over a 60-month rolling window.
BM	Ratio of book equity / market capitalization, measured at the end of financial year.
Cash	Cash and short-term investments scaled by previous year total assets.
CEOtenure	The number of years the CEO has been CEO of the company.
DA	Ratio of short and long-term debt to total assets.
Ex_ret	Excess stock returns over risk free rate.
Flex	The average *Flex_rev* for each firm over the past 12 months.
Flex_net	Similar to *Flex*, but the number of flexibility words is reduced by 1 each time a flexibility word in the review is in the vicinity (within 3 words) of a negation word.
Flex_rev	The review level flexibility score, calculated as follows. Each online company review is textually analyzed to get a count of the "flexibility" words that are in the flexibility lexical field. The "flexibility" word count is scaled by the total length of the review (*len_review*) to get a flex ratio of the review (*flex_rev*).
GP	Gross Profit ($Sale - COGS / AT_{t-1}$), in percentages.
HiFlex	Indicator variable that equals 1 if the firm's *Flex* is above the median *Flex* for that year.
HiETKLD	Indicator variable that equals 1 if the firm's employee treatment score in year *t* is above the full-sample median. Calculated as per Bae, Kang, Wang (2011) except the retirement benefits and employee health and safety indicators were discontinued before the sample period begins. Firms with all missing ratings were assigned a rating of 0.
HiUncert	An indicator variable that equals 1 if the Economic Policy Uncertainty Index of Baker, Bloom and Davis (2016) is above the 10-year rolling median.
Len_review	Length of a job review in words.
MEfyr	Market capitalization of the firm at the end of the financial year.
MEjun	Market capitalization of the firm at the end of June.
Mkt_rf	Excess market return over risk-free rate.
OK	Organizational capital, calculated following Eisfeldt and Papanikolaou (2013) except that it includes financial firms and firms with any financial year-end.
$Return_{-x,-y}$	Cumulative return from month *t-x* to month *t-y*.
RDA	R&D expenditures scaled by assets
Star rating	Mean of 5 numerical ratings (job, work, life balance; compensation/benefits; job security; management; job culture) in each review. Each individual rating is out of 5, with 1 being the lowest and 5 being the highest.
UnionMemb	Percentage of unionized employees in the firm's state (Hirsch and Macpherson 2003)
UnionReviews	Firm-level average frequency of union-related words (union, unionized, unionization, etc.) in employee reviews

Appendix A.5 The FlexJobs' List of Most Flexible and Popular Companies, 2016

	Flex Score	Above Median *Flex*		*Flex* Score	Above Median *Flex*

Company Name	(%)	(Yes=1)	Company Name	(%)	(Yes=1)
Google	3.9	1	Dell	*	*
Salesforce	*	*	McKinsey & Co	*	*
Facebook	2.8	1	Deloitte	*	*
Apple	1.7	1	Box	*	*
Amazon	1.7	1	McKesson	*	*
Uber	*	*	Goldman Sachs	1.6	0
Microsoft	2.1	1	JLL	1.9	1
Tesla	*	*	Edelman	*	*
Twitter	*	*	Estee Lauder	1.9	1
Airbnb	*	*	Starbucks	2.1	1
Netflix	1.2	0	Splink	*	*
Stryker	2.7	1	Viacom	2.3	1
Visa	1.2	0	Live Nation	1.8	1
Adobe	2.6	1	HBO	*	*
Workday	*	*	Leidos	*	*
Pandora	*	*	Fox	*	*
Under Armour	2.1	1	Cisco	1.9	1
Tableau	*	*	Yelp	*	*
Coca-Cola	2.2	1	Morgan Stanley	1.9	1
Epsilon	*	*			

The ranking of job flexibility is based on job popularity data from LinkedIn and FlexJobs' own database on flexible job options. The list is available at: https://www.flexjobs.com/blog/post/flexible-popular-companies-job-seekers/.
This table shows that approximately 84% of firms on the FlexJobs list of most flexible firms where data is available are above the median *flex* score (1.63%) in our 2016 sample.
* indicates the firm is private, is not an S&P1500 firm, or has incomplete data in our sample.

Appendix A.6 Lexical Field

acclimate, acclimatize, accommodate, adapt, adjust, begin, bring, catalyze, change, create, correct, cultivate, develop, discontinue, dream, educate, elaborate, encourage, engender, entrepreneur, envision, establish, experiment, fantasy, fashion, father, flexible, foster, freedom, future, generate, give, grow, idea, inaugurate, induce, initiation, innovation, institute, intellectual, introduce, invoke, launch, learn, make, new, nourish, nurture, oriented, original, pioneer, pioneer, prediction, produce, promote, prompt, radical, risk, see, spawn, start, tailor, thought, trend, unafraid, venture, vision.
This table presents the non-stemmed lexical fields used to compute employee flexibility (flex scores) by matching these fields to the lemmatized reviews. The initial lexical field is from Fiordelisi and Ricci (2014) and is extended using WordNet's thesaurus.

Appendix A.7 Firms with the Highest Employee Flexibility Scores Each Year

Year	*Flex (%)*	Company Name
2016	6.9	CIMAREX ENERGY CO
2016	5.9	OFG BANCORP
2016	5.4	VERIFONE SYSTEMS INC
2016	5.3	SIGNATURE BANK/NY
2016	5.1	INTL FCSTONE INC
2015	7.3	UNITED INSURANCE HOLDINGS CO
2015	5.4	STRATASYS LTD
2015	5.2	CADENCE DESIGN SYSTEMS INC
2015	4.8	TELEDYNE TECHNOLOGIES INC
2015	4.7	BANC OF CALIFORNIA INC
2014	7.2	FEDERATED INVESTORS INC
2014	7.2	LIFEPOINT HEALTH INC
2014	5.8	EW SCRIPPS
2014	5.4	AKAMAI TECHNOLOGIES INC
2014	5.2	MERCURY GENERAL CORP
2013	6.5	HOLOGIC INC
2013	6.2	INTERSIL CORP
2013	5.6	TIVO CORP
2013	5.5	NEWFIELD EXPLORATION CO
2013	5.5	PIONEER NATURAL RESOURCES CO
2012	6.4	SUSQUEHANNA BANCSHARES INC
2012	6.2	BASIC ENERGY SERVICES INC
2012	5.7	SCIENTIFIC GAMES CORP
2012	5.2	EQUITY RESIDENTIAL
2012	5.0	AMERICAN ELECTRIC POWER CO
2011	2.0	DIRECTV
2011	1.7	MCDONALD'S CORP
2011	1.7	AT&T INC
2011	1.5	VERIZON COMMUNICATIONS INC
2011	1.4	WAL-MART STORES INC

This table shows the top 5 firms by the *flex* score each year at the end of June with more than 5 reviews in total. *Flex* is defined in Appendix A.4. (We do not show firms with the lowest flex scores because there are quite many firms with zero or close to zero flex scores.)

Appendix C.1 Variable Definitions

Variable	Definition
Post2005	Indicator variable set to 1 if the year is > 2005. 0 otherwise
Post2008	Indicator variable set to 1 if the year is > 2008. 0 otherwise
AT	Total assets (AT) in millions
ATLo	ATLo is an indicator variable set to 1 if the firm's total assets (AT) is in the bottom tercile for that year. It is set to 0 otherwise.
Avgrisk	Aggregate mean of all risk disclosure scores as measured using the word dictionary from Campbell, Chen, Dhaliwal, Lu, and Steele (2014). Risk disclosure scores are scaled by the total number of words in the 10-K.
Beta	*Beta* measured over the financial year using daily data.
BigN	An indicator variable if a firm uses a Big 4/5 auditor.
BM	Book equity (CEQ) to market equity (PRCC_F * CSHO) ratio
CAPXA	The capital expenditures (CAPX) of a firm as a percentage of total assets (AT)
DA	Debt (DLTT + DLC) as a percentage of total assets (AT)
DNI	Net income before extraordinary items scaled by market capitalization (t-1)
Firmage	Number of years the firm has been in Compustat
Fnpats0	Number of patents filed that calendar year
Fnpats	Log (number of patents filed that calendar year +1)
Fnpats_3	Cumulative *Fnpats* from years t to t+2
Fyear	Financial year
HHI	The Herfindahl-Hirschman Index calculated using firm sales of Compustat firms in the same 2-digit SIC industries
HHI^2	The square of the HHI index to account for any nonlinearities
Idio	Idiosyncratic risk disclosure score as measured using the word dictionary from Campbell, Chen, Dhaliwal, Lu, and Steele (2014). Risk disclosure scores are scaled by the total number of words in the 10-K.
IO	The percentage of shares owned by institutional investors. Set to 100% maximum.
IVOL	Idiosyncratic volatility measured over the financial year using daily data and the FF3 factors.
KZHi	*KZHi* is an indicator variable set to 1 if the firm's Kaplan-Zingales score is greater than the sample median for that year. It is set to 0 otherwise.
LogAT	Log of total assets (AT)
LogAnalyst	Log of the number of analysts covering the firm at the end of the financial year
LogLength	The log of the number of words in the firm's 10-K for the most recent fiscal year
Othrisk	Average of risk disclosure scores excluding idiosyncratic and systematic risks as measured using the word dictionary from Campbell, Chen, Dhaliwal, Lu, and Steele (2014). These risks include legal, tax, and financial. Risk scores are scaled by the total number of disclosure words in the 10-K.
Q	(Market Capitalization – Book Value Common Equity + Book Total Assets) / Book Total Assets
Q_CAPXAHi	An indicator variable set to 1 if the firm's investment sensitivity is greater than the median. Set to 0 if below the median

Recession	An indicator variable set to 1 if the US is in recession as defined by the NBER and 0 otherwise.
Ret0_12	Cumulative stock return from month t-0 to t-12
ROA	Net income (NI) as a percentage of total assets (AT)
RD	R&D expenditures as a percentage of lagged total assets. If R&D expenditures are missing, the value is set to 0
RDC	R&D capitalized over years t-4 to t at the following rate ($RD_t + 0.8\ RD_{t-1} + 0.6\ RD_{t-2} + 0.4\ RD_{t-3} + 0.2\ RD_{t-4}$ (Eberhart, Maxwell, and Siddique 2004)
RDMiss	Indicator variable set to 1 if R&D value is missing
Skew_Ret	The skewness of stock returns over the past financial year using daily data
SM	Indicator variable set to 1 if the firm has less than $50 million in revenues
SpreadHi	An indicator variable set to 1 if the firm's average bid-ask spread over the past year is above median. It is set to 0 otherwise.
Syst	Systematic risk disclosure score as measured using the word dictionary from Campbell, Chen, Dhaliwal, Lu, and Steele (2014). Risk disclosure scores are scaled by the total number of words in the 10-K.
TANG	Property, Plant, and Equipment (PPENT) as a percentage of total assets (AT)
TCW0	Truncated and citation-weighted patent filings. Patents were truncation-adjusted and citation-weighted by the methodology described in Kogan, Papanikolaou, Seru and Stoffman (2016)
TCW	Log (*TCW0* +1).
TCW_3	Cumulative *TCW* from t to t+2.
Turn	Mean daily share turnover over the past year.
*{risk} * Post2005*	Interaction of {risk} variable with Post2005
*{risk} * Post2008*	Interaction of {risk} variable with Post2008
*{risk} * SM*	Interaction of {risk} variable with SM
*{risk} *Post2008*SM*	Interaction of {risk} variable with Post2008 and SM
WWHi	*WWHi* is an indicator variable set to 1 if the firm's Whited-Wu score is in the top tercile for that year. It is set to 0 otherwise.
All variables are winsorized at the 1%/99% level except for *FirmAge* and indicator variables.	