THREE ESSAYS ON CORPORATE FINANCIAL POLICIES

by

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A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Business Administration

Charlotte

2021

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ABSTRACT

KARLA NATALIA VILLATORO GODOY. Three Essays on Corporate Financial Policies.
(Under the direction of DR. DAVID C. MAUER)

In the first chapter ("Brand Equity and Corporate Debt Structure"), we develop measures of brand equity based on firms' portfolio of trademarks. We find that firms with higher brand equity have lower equity and asset volatility and higher cash flows. Although suggestive of greater debt capacity, we find that firms with high brand equity use less debt and shorter maturity debt. We provide evidence that the relation between brand equity and leverage is causal, using the enactment of the Federal Trademark Dilution Act in 1996, which exogenously increased the value of famous brands and significantly decreased the leverage ratio of firms with famous brands. We find that the effects of brand equity on leverage are weaker for firms with higher business risk, and stronger for firms with higher information asymmetry.

In the second chapter ("Cybersecurity Awareness and Debt Contracting"), we examine whether and by which mechanisms firms' cybersecurity awareness influences firms' cost of debt. We construct a text-based measure of firm-specific cyberawareness that captures firms' ex-ante readiness to deter potential cyber threats and handle successful cyberattacks, and test its effect on bank debt, public debt, and credit ratings. Consistent with self-disclosed cyber awareness contributing to reduce information asymmetries surrounding firms' cyber risks, we find that bank loan spreads and bond spreads are decreasing in firm's cyber awareness. We further find that greater cybersecurity awareness translates into higher credit ratings and lower covenant counts in firms' bank loans. To strengthen identification and mitigate endogeneity concerns we instrument cyberawareness using geographic cyberawareness. We continue to find significantly negative coefficients on cyberawareness in the loan spread regressions. In cross-sectional analysis, we

document a stronger effect of cybersecurity awareness on loan spread in subsamples of high default risk. Lastly increasing operating efficiency on cybersecurity awareness is consistent with creditors' positive assessment of cyber readiness. Our evidence supports the view that cybersecurity awareness creates business value through lower cost of debt.

Lastly, in the third chapter I examine the effect of liberal judge ideology as a measure of ex ante litigation risk on corporate policies. Measuring judge ideology as the probability that a three-judge panel at the federal circuit court level is dominated by democratic presidents' appointees, I find that firms facing higher ex ante litigation risk hold more cash and prefer a more flexible payout policy shrinking away from dividends in favor of stock repurchase programs. In addition, I document that firm stock return volatility, asset volatility and capital expenditures are decreasing in judge ideology. Interestingly, judge ideology is associated with higher marginal value of cash to shareholders. Cross-sectional tests show that the effect of judge ideology on cash holdings and marginal value of cash is stronger among financially constrained firms. Collectively, these findings suggest that ex ante litigation risk acts as an external governance mechanism through which shareholders can influence managers' behavior.

ACKNOWLEDGEMENTS

I am grateful to my advisor and dissertation chair David C. Mauer for close mentoring, unconditional support and feedback throughout my Ph.D. studies and dissertation. I thank Yilei Zhang for her guidance, patience, and example. I am thankful to my dissertation committee members Tao-Hsien Dolly King and Artie Zillante for their time and valuable comments.

I thank my coauthor and friend Gunratan Lonare, for great and formative teamwork. I am grateful to all my professors along the Ph.D. program, my fellow Ph.D. colleagues, and members of the Belk College of Business family. I owe thanks to Deon Ritchie for attending to my needs from day one, making my time at UNCC productive and warm. I thank Lee Perkins, Daniel Wallace, and Tim Carmichael. They facilitated my research and teaching tremendously through their outstanding technical support. I am grateful to Julie Goodliffe for her advice and mentoring during my time at UNC Charlotte. Our conversations helped me grow to the challenges and opportunities that came my way. I thank Lissa Russell-Pinson for her support in developing my writing skills and realizing the importance of reveling in the small victories. My gratitude goes to Matthew Hood, Vance Lesseig and Paul Gowens for their counseling and support. I acknowledge the steadfast support of my family, Nicolas, and friends.

To all of you - I am grateful for your kindness amid our every day interactions.

DEDICATION

To my audience of One - Deo gratias.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

This dissertation investigates the influence of intangible assets and external sources of risk on corporate financial policies. The first essay examines the relation between brand equity and corporate debt structure. Over the last decades, firms' production technology has grown increasingly dependent on intangible assets (Corrado and Hulten 2010; Lev 2018, Falato et al. 2020). Brands, with trademarks as their legal foundation are identified by firms as one of their most valuable intangible assets (Jankowski 2012). We construct measures of brand equity based on a firm's portfolio of trademarks to test the relation between brand equity and debt structure. Our results show that brand equity is negatively related to measures of business risk and positively related to measures of profitability. Following, in panel regressions controlling for firm characteristics, macroeconomic variables, and industry and year fixed effects, we find that firms with higher brand equity have significantly lower leverage and shorter debt maturity. We conduct additional tests, based on business risk, information asymmetry and brands collateralization, to better understand the mechanism(s) driving the inverse relation between brand equity and leverage. Results from this battery of tests indicate that the negative effect of brand equity on leverage is consistent with the pecking order hypothesis, whereas the debt maturity results is driven by agency cost of debt. We use the enactment of the Federal Trademark Dilution Act (FTDA) in 1996 to generate plausibly exogenous variation in the value of trademarks allowing us to identify the causal effect of brand equity on leverage through a difference-in-differences analysis. Lastly, our results are also robust to the simultaneous choice of leverage and maturity and to alternative definitions of leverage, maturity, and variations of fixed effects. Our paper contributes to the literature novel quantitative measures of brand equity available for a large sample of firms and to the understanding of the effects of an important intangible asset, brand equity, on a firm's capital structure.

The second essay investigates the relation between firms' cybersecurity awareness and debt contracting. In recent years cybersecurity has become an increasingly important source of risk for corporations. Successful cyberattacks pose risks to firms' customers, investors, capital markets, and the economy. Therefore, firms' transparency about their cybersecurity has become critical, with the SEC taking a more active role in providing guidance to U.S. corporations about cyber risk and cyber preparedness disclosures in their 10-K reports. As a result, the importance of firms' risk management measures to prepare for and minimize the likelihood of successful cyberattacks has increased (e.g., Berkman et al. 2018). We construct a firm-specific measure of cybersecurity awareness to test the relation between self-disclosed cybersecurity readiness and the cost of debt. We create our cybersecurity awareness measure using textual analysis of 10-K statements and a comprehensive dictionary of cybersecurity-related words for a large sample of U.S. firms. In cross-sectional regressions controlling for firm characteristics, macroeconomic variables, and industry fixed effects, we find that firms with higher cybersecurity awareness have significantly lower loan and bond spreads, as well as better credit ratings. These results suggest that arms-length lenders positively evaluate firms' increased preparedness to fend off potential cyberattacks. We use Instrumental Variable (IV) estimation to account for the possible endogeneity of cybersecurity awareness. Our work contributes to the emerging literature on cybersecurity readiness and firms' corporate policies by providing the first evidence that firms' self-disclosed proactive measures and investments aimed to reduce firms' vulnerability to a successful cyberattack influence firms' cost of debt. In addition, our paper complements and extends the literature examining the determinants of bank loan contracting and consistent with extant studies (Gordon et al. 2015; Berkman et al. 2018), our evidence supports the view that cybersecurity preparedness represents an intangible asset.

In the third essay, I use judge ideology as a novel measure of ex ante litigation risk that is plausibly exogenous to firm's corporate policies (Huang et al. 2019; Kubick et al. 2021) to evaluate the relation between shareholder litigation risk and corporate policies. Shareholder litigation risk has long been identified as an important source of external risk for corporations. However, much of this literature examines actual lawsuits or industry and firm characteristics to measure litigation risk (e.g., Johnson et al. 2000; Lowry and Shu 2002; Field et al. 2005; Cheng et al. 2010; Arena and Julio 2015). Such measures are directly related to firm behavior or characteristics, making the analysis based on them prone to endogeneity concerns. Using judge ideology, defined as the probability that a three-judge panel at the federal circuit court level is dominated by democratic presidents' appointees, I find that firms facing higher ex ante litigation risk hold more cash and prefer a more flexible payout policy shrinking away from dividends in favor of stock repurchase programs. In addition, I document that firm stock return volatility, asset volatility and capital expenditures are decreasing in judge ideology. Interestingly, judge ideology is associated with higher marginal value of cash to shareholders. Cross-sectional tests show that the effect of judge ideology on cash holdings and marginal value of cash is stronger among financially constrained firms. My work contributes to the literature on shareholder litigation risk and its effect on firms' corporate policies documenting evidence that suggests that ex ante litigation risk acts as an external governance mechanism through which shareholders can influence managers' behavior, with its effects being accentuated among subsamples of firms that are financially constrained.

Collectively, my dissertation contributes to the finance literature that examines the influence of intangible assets and external sources of risk on corporate financial policies, guided by theory and leveraging novel datasets and measures.

Chapter 1: Brand Equity and Corporate Debt Structure

1. Introduction

In recent decades, firms' production technology has grown increasingly dependent on intangible assets (Corrado and Hulten 2010; Lev and Gu 2016; Lev 2018, Falato et al. 2020).[1] Meanwhile, studies examining the effects of intangible assets on firm value and policy decisions have gained increasing popularity (e.g., Larkin 2013; Loumioti 2015; Mann 2018; Heath and Mace 2020). One of the most valuable intangible assets, brands, with trademarks as their legal foundation, constitute brand equity which is a significant asset class to firms (Aaker 1991; Keller 1993; Aaker 2004). Brands have important product market and policy implications because they identify and distinguish firms' products and services from those of competitors. Brand equity has been shown to contribute substantially to firm value (Rao et al. 2004; Sandner and Block 2011; Faurel et al. 2019) and to be associated with higher firm performance (Krasnikov et al. 2009; Crass et al. 2019; Heath and Mace 2020), higher credit ratings (Rego et al. 2009; Larkin 2013), and lower firm risk (Rego et al. 2009; Larkin 2013). Studies also show that brand equity plays a significant role in firms' M&A activity (Capron et al. 1999; Wiles et al. 2012; Hsu et al. 2018), financing decisions (Larkin 2013), IPO underpricing (Drivas et al. 2018; Yang and Yuan 2019), and borrowing costs (Chiu et al. 2020). In this paper, we examine the effects of brand equity on firms' leverage and debt maturity decisions.

[1] Intangible assets include intellectual property (e.g., patents, trademarks, copyrights, and trade secrets), brands, corporate reputation, franchises, and human capital. Corrado and Hulten (2010) document that the average rate of investment in intangible capital formation in the nonfarm business sector increased from 5.9% in 1948-1972 to 12.8% in 1995-2007, while investment in tangible assets decreased over the same period. Lev (2018) documents that the aggregate investment relative to gross value added in tangible assets declined continuously from 16% to 10% during 1977-2016, while the nonfarm business sector's investment in intangibles almost doubled from 8% to 15% of value added.

Brand equity is a long-lived intangible asset; and unlike growth options, brand equity is a component of asset-in-place that is built by firms over years. An important benefit of brand equity is that it may allow a firm to insulate itself from product market competition and enhance market power. Indeed, research shows that strong brands are associated with lower customer price sensitivity (Sivakumar and Raj 1997; Ailawadi 2003), higher profit margins (Stahl et al. 2012), and lower entry and exit in product markets (Heath and Mace 2020). These favorable product market effects increase the level and stability of cash flows and thereby suggest a positive relation between brand equity and leverage (Larkin 2013).

However, higher and more stable cash flows might also suggest a negative relation between brand equity and leverage. First, pecking order theory argues that firms base their financing decisions on issue costs and the use of internal funds is first on the firm's pecking order of financing sources (Myers 1984; Myers and Majluf 1984). If brands generate abundant and stable cash flows, then firms with considerable brand equity may have little need for external financing. Second, as an intangible asset brand equity may have limited contractability (Titman and Wessels 1988; Rampini and Viswanathan 2013; Falato et al. 2020). Specifically, the value of brand equity relies on discretionary future investments (e.g., advertising, product innovation, quality maintenance) and is thereby susceptible to underinvestment in financial distress (Myers, 1977). Further, brand value may be severely damaged in bankruptcy since the brand is inextricably tied to the firm as a going concern (e.g., Apple's iPhone or Nike's swoosh), and the market for more generic brands may not be liquid or deep. These considerations limit the collateral value of brands and suggest that brand equity may have limited debt capacity.

Concerning debt maturity, all else equal, long-lived assets tend to be "matched" with longer maturity liabilities. Since brand equity is clearly long-lived, this maturity-matching principle suggests that firms with substantial brand equity have longer debt maturity (Chang 1989; Stohs and Mauer 1996). From an agency cost perspective, however, creditors may prefer shorter-term debt to mitigate underinvestment incentives (Myers 1977; Child et al. 2005) or to minimize costs associated with the inalienability of brands in bankruptcy (Hart and Moore 1994).[2]

We construct measures of brand equity based on a firm's portfolio of trademarks to test the relation between brand equity and debt structure. We obtain trademark data from the United States Patent and Trademark Office (USPTO) data files and use a fuzzy matching algorithm to match the owners of trademarks with CRSP-Compustat firms. Using USPTO public records on trademark registration, renewal, and cancellation or abandonment, we dynamically construct a firm's portfolio of trademarks on a yearly basis. Our sample starts in 1982, as the USPTO data is less complete before this date (Graham et al. 2013).[3] We require a firm-year to have at least one trademark to be included in the sample and we require non-missing data for all variables in our baseline regressions.[4] Firms in finance and regulated industries are excluded. This results in a sample of 62,975 firm-year observations on 7,577 U.S. firms over the period from 1982 to 2018. Our primary measure of brand equity is calculated as the age-weighted trademark portfolio scaled by the market value of assets, where the weight of a trademark in a year is calculated as its age relative to the average age of all other active trademarks in the year.[5]

We first examine the relations between our brand equity measure and firm risk and performance. Consistent with the literature, we find that brand equity is negatively related to

[2] The latter suggests that brands are linked to the firm as a going concern and may lose value when transferred to creditors in the bankruptcy estate. Hart and Moore (1994) show that the optimal debt contract for these types of intangible assets is short-term debt.
[3] Although the sample starts in 1982, the oldest trademark in our sample (i.e., in a firm's trademark portfolio) was registered in the 19th century. Examples of some of the oldest trademarks in our sample include Coca-Cola (registered with the USPTO on 1/31/1893), Tiffany & Co. (9/5/1893), and John Deere (9/21/1897).
[4] Since debt maturity can only be calculated for firms with debt, our sample does not include firms without debt. Our results remain the same if we include all-equity firms.
[5] See Section 2 and Appendix A for a discussion of our brand equity measures.

measures of risk (e.g., stock and asset return volatility) and positively related to measures of profitability (e.g., ROA and free cash flow).[6] Thus, our trademark-based brand equity measure captures similar characteristics of other brand equity measures used in the literature, but leaves open the question of how brand equity influences debt structure. In panel regressions controlling for firm characteristics, macroeconomic variables, and industry and year fixed effects, we find that firms with higher brand equity have significantly lower leverage and shorter debt maturity. These effects are economically significant. For the average firm in the sample, a one-standard-deviation increase in brand equity decreases book leverage by 6% and increases the proportion of short-term debt by 4%. These results are robust to using firm fixed effects in lieu of industry fixed effects, and to alternative measures of leverage, maturity, and brand equity.

The negative relation between brand equity and leverage supports both the pecking order and the limited contractibility hypotheses. We conduct additional tests to better understand the mechanism(s) driving the inverse relation between brand equity and leverage. First, if pecking order behavior drives the relation, we would expect that the negative relation between brand equity and leverage is weaker when the firm has high business risk. Although the cash flow generating ability of brand equity is likely to be more valuable in high business risk settings, all else equal, high volatility suggests that the firm is likely to have to turn to external debt finance more often than when volatility is low. In contrast, the limited contractibility hypothesis suggests that creditors would be more concerned about the limited collateralizability of brand equity when business risk

[6] Using consumer surveys to measure brand equity, Rego et al. (2009) find that greater brand perception decreases measures of equity risk and Larkin (2013) finds that greater brand stature reduces cash flow volatility. Both papers find that a favorable assessment of brands improves credit ratings. Several papers measure brand equity using the stock of trademarks and explore relations between brand equity and firm risk and profitability. Crass et al. (2019), Faurel et al. (2019), and Hsu et al. (2019) find that ROA increases with the stock of trademarks, while Krasnikov et al. (2009) find that cash flows increase and cash flow volatility decreases with the stock of trademarks. In contrast, Faurel et al. (2019) find that cash flow volatility increases with the stock of trademarks. Finally, Heath and Mace (2020) find that "famous" trademarks, as measured by long-lived trademarks, boost ROA.

is high, suggesting that the negative relation between brand equity and leverage is likely to be stronger when volatility is high than when volatility is low. Consistent with the pecking order hypothesis, we find that the negative effect of brand equity on leverage is significantly weaker in riskier firms.

We also test how information asymmetry influences the relation between brand equity and leverage. Viewing the degree of information asymmetry as a measure of the information-related cost of external finance (Myers and Majluf 1984), we would expect that the relation between brand equity and leverage is much stronger, or only exists, when information asymmetry is high rather than low. Indeed, we do find that the negative relation between brand equity and leverage is only significant when information asymmetry is high rather than low. This evidence supports the pecking order hypothesis but it is not inconsistent with the limited contractability hypothesis, since the characteristics of brand equity that make it unsuitable for collateral (e.g., limited redeployability) may be accentuated in more opaque settings. However, in additional analysis, we find no evidence that having collateralizable trademarks enhances the debt capacity of brand equity. Thus, our results are most consistent with pecking order behavior driving the negative relation between brand equity and leverage.

The negative relation between brand equity and debt maturity is not inconsistent with pecking order behavior, suggesting that when firms need to raise external debt finance, they issue shorter-term debt because it is less informationally sensitive than longer-term debt. Consistent with this conjecture, we find a negative relation between brand equity and debt maturity only when there is high information asymmetry.[7] However, we cannot rule out that the negative relation

[7] Goswami et al. (1995) show that when asymmetric information is not concentrated around long- or short-term cash flows but rather is uniformly distributed, it is optimal for firms to finance with shorter-term debt.

between brand equity and debt maturity is a contracting devise used to minimize the costs arising from underinvestment and/or the inalienability of brands in bankruptcy.

Lastly, we use the enactment of the Federal Trademark Dilution Act (FTDA) in 1996 to generate plausibly exogenous variation in the value of trademarks allowing us to identify the causal effect of brand equity on leverage. As discussed in Heath and Mace (2020), the passage of the FTDA on January 16, 1996, granted federal protection for "famous" trademarks against dilution, thereby increasing the value of brand equity for firms with "famous" trademarks. Using the enactment of the FTDA as an exogenous shock to the value of brands, we find that treatment firms with "famous" brands experience a significant decrease in leverage relative to control firms without "famous" brands over the period from before to after the FTDA.[8] This treatment effect is economically significant, representing 5.5% of treated firms' average pre-treatment book leverage. Further, we use IV estimation to account for possible simultaneity bias of leverage and maturity choices, along with endogeneity of brand equity. We continue to find inverse relations between instrumented brand equity and leverage and debt maturity.

Our paper makes two primary contributions to the literature. First, we use the comprehensive USPTO trademark database to construct novel measures of brand equity that capture how brand equity varies across firms and overtime. We use these measures to test how brand equity influences capital structure, but they can also be used in a variety of other contexts.

Second, our analysis contributes to the understanding of the effects of an important intangible asset, brand equity, on a firm's capital structure. When viewed as part of the class of intangible assets, we might expect that limited contractibility would dominate the explanation for why higher brand equity is associated with lower leverage and shorter debt maturity. However, we

[8] We follow Heath and Mace (2020) and use trademark age to classify "famous" trademarks. Examples of "famous" trademarks include Rolex, Kodak, and Levi's.

argue that these results are more consistent with pecking order behavior. This highlights the recognition that a firm's intangible assets have varying and perhaps unexpected influences on firms' policy decisions.

To our knowledge, Larkin (2013) is the only other paper that examines the effect of brand equity on leverage.[9] Using a proprietary database surveying consumers' perceptions of brands, she finds that a more favorable brand "stature" increases leverage.[10] We can only speculate why Larkin (2013) finds a different effect of brand on leverage. Although consumer survey data certainly provides valuable insights about specific brands, it is difficult to distill consumer sentiment about a specific brand into a measure of brand equity for a firm that may have multiple different brands. In contrast, our brand equity measure is objective and allows us to estimate a quantitative measure of the stock of brands at any given point in time. Further, market survey data may be limited in coverage and representativeness. Larkin's sample consists of 2,572 firm-year observations of 468 large global firms from 1993 to 2009. In contrast, our sample consists of 62,975 firm-year observations of 7,577 U.S. firms that have at least one trademark in the USPTO database from 1982 to 2018. Our much larger and diversified sample might help explain why we find the opposite result for the influence of brand equity on leverage. Nevertheless, both studies serve as valuable steps to enhance our understanding of how an important intangible asset influences debt structure.

The remainder of the paper is organized as follows. Section 2 provides background on trademarks and develops testable hypotheses. Section 3 describes our data and variable construction and provides descriptive statistics. Sections 4 and 5 present the main empirical results.

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[9] Larkin (2013) does not examine how brand equity influences debt maturity.

[10] Brand stature combines product knowledge (how well consumers know the brand) and esteem (how much regard and loyalty consumers have toward the brand).

Section 6 discusses additional tests to address the endogeneity of brand equity, leverage, and maturity. Section 7 concludes. Appendix A reports variable definitions, Appendix B discusses the construction of the instrument for brand equity, and Appendix C reports additional tests.

2. Trademarks, brand equity, and testable hypotheses

In this section, we first discuss the institutional details of trademarks and brands in the U.S., the link between trademarks and brand equity, and the properties of brand equity. We then present testable predictions for the impact of brand equity on leverage and debt maturity.

2.1. Trademarks and brands

Trademarks and brands are highly intertwined (Mendonça et al. 2004; Sandner and Block 2011). According to the American Marketing Association (AMA), a brand is a "name, term, design, symbol, or any other feature or combination of them that identifies one seller's product or service as distinct from those of other sellers" and a trademark is "a legal term meaning the same as brand".[11] Similarly, the USPTO defines a trademark as "any word, name, symbol, or device or any combination thereof adopted and used by a manufacturer or merchant to identify its goods and distinguish them from those manufactured or sold by others".[12] As Peterson et al. (1999) observe, "the two terms are virtually synonymous, and what marketers term brands, lawyers term trademarks".

Trademarks provide the legal foundation upon which a brand is built (Peterson et al. 1999; Mendonça et al. 2004; Sandner and Block 2011). As such, a trademark registered with the USPTO endows its owner with a legal instrument to preserve the exclusive use of the brand, thereby protecting the firm from activities of competitors that may damage the brand. This legal protection

[11] The definitions can be found in the *AMA Dictionary of Marketing Terms* (1995).
[12] The USPTO definition follows from the United States Trademark Act of 1946.

incentivizes firms to invest in their brands because they will be able to capitalize on the returns from these investments (Landes et al. 1987; Ramello 2006). Accordingly, Sandner and Block (2011) argue that trademarks "can be seen as a proxy for the output of marketing efforts aiming to build a company and/or a product brand".

The term "brand equity", as originally coined by Aaker (1991), is intended to convey the notion that brands, and trademarks as their legal basis, are an asset class like knowledge-based assets and real assets. Well-known corporate brands include, for example, Coca-Cola, Nike, McDonald's, and Metro-Goldwyn-Mayer's (MGM) roaring lion Leo. The importance of brands is explicitly detailed in firms' 10-K reports. For instance, in its 2019 10-K report Nike Corporation states: "Our iconic brands have worldwide recognition, and our success depends on our ability to maintain and enhance our brand image and reputation. Maintaining, promoting, and growing our brands will depend on our design and marketing efforts, including advertising and consumer campaigns, product innovation and product quality." [13] The brands owned by firms are "trademarked" with the USPTO. The number of trademarks registered with the USPTO has grown steadily at an average annual rate of roughly 5% over the last twenty years. According to the USPTO *Fiscal Year 2019 Performance and Accountability Report*, the USPTO received 375,428 trademark applications in 2000, which nearly doubled to 673,233 in 2019.

2.2. Properties of brand equity

Brand equity has four properties that potentially have significant implications for corporate financial policy. First, brand equity is a valuable asset. A brand identifies a firm's products and services in the marketplace and differentiates them from those of competitors. By reducing information asymmetry and search costs it facilitates consumers' decisions and increases consumer

[13] Nike, Inc. 2019 10-K, Item 1A. Risk Factors, p. 9.

loyalty. Branding may also create a barrier to product market competition (Heath and Mace 2020). Therefore, strong brands are expected to increase cash flows to firms and reduce cash flow volatility. Studies have documented that higher brand equity is associated with lower firm risk (Rego et al. 2009; Larkin 2013) and better firm performance (Krasnikov et al. 2009; Crass et al. 2019; Faurel et al. 2019; Hsu et al. 2019; Heath and Mace 2020).

Second, brand equity is a long-lived asset which is built over time with expenditures on advertising, promotions, market research, loyalty programs, distribution channel development, product quality, customer service efforts, and product innovation (Kirk et al. 2013). For example, in a sample of German firms, Crass et al. (2019) find that it takes on average 11 years before investments in brand equity reach maximum financial performance. As an asset class, brand equity is different from growth options, which are future investment options that management has discretion to exercise. On the contrary, brand equity is best viewed as part of assets-in-place.

Third, brand equity is a fragile asset, which must be maintained through advertising and other brand-maintenance expenditures.[14] Although the amount of expenditures varies across industries and product life cycles; ultimately, brand equity requires significant economic resources to be maintained or its value will deteriorate. For example, using new trademarks to measure brand innovation, Bereskin et al. (2020) find that a cut in advertising expenditures significantly decreases the survival rate of new brands. Since advertising and other brand-maintenance expenditures are discretionary, managers may have weakened incentives to maintain brands if the firm is in financial distress and the benefits are likely to accrue to creditors (Myers 1977).

[14] For example, in its 2019 10-K, Nike states: "Our iconic brands have worldwide recognition, and our success depends on our ability to maintain and enhance our brand image and reputation. Maintaining, promoting and growing our brands will depend on our design and marketing efforts, including advertising and consumer campaigns, product innovation and product quality." (Nike, Inc. 2019 10-K, Item 1A. Risk Factors, p. 9.)

Lastly, brand equity may have limited value as collateral because it is an intangible asset that may lose value outside the hands of the firm that built the brand. These characteristics, intangibility, inalienability, and lack of non-uniqueness, make brand equity a poor choice of collateral in debt contracts (Williamson 1988; Shleifer and Vishny 1992; Hart and Moore 1994; Benmelech and Bergman 2009; Hall and Lerner 2010; Falato et al. 2020). Although there is some evidence that intellectual assets such as patents and trademarks have been used as collateral in loan contracts (Loumioti 2015; Mann 2018; Chiu et al. 2020), Nguyen and Hille (2018) find that most trademarks are "idle assets," since banks and nonbanks typically do not accept trademarks as collateral.[15]

2.3. Hypotheses

Building on the properties of brand equity and capital structure theories, we present hypotheses on the relations between brand equity and the firm's choice of leverage and debt maturity.

2.3.1. Effect of brand equity on leverage

Product market power hypothesis. Brand equity and leverage are positively related.

Theory suggests that product market competition may lead to a higher cost of debt and lower financial leverage (Brander and Lewis 1986; Clayton 2009). Brand equity may allow a firm to insulate itself from product market competition, since a strong brand distinguishes one product from competing products. In early work, Chamberlin (1933) argues that product differentiation

[15] Using USPTO filing data from 2002 to 2015, Nguyen and Hille (2018) find that only 10% of registered trademarks serve as collateral in debt contracts. They argue that "Lenders from banks to nonbanks know that a loan against a trademark is seen as the 'fulcrum security on a tough balance sheet.' In other words, the borrowers in these situations are too risky for both banks and nonbanks. Banks would shy away from these borrowers while nonbanks may lend with very high interest rates and fees." pp. 389-390.

creates “monopolistic competition”. Consistent with enhanced market power, Sivakumar and Raj (1997) and Ailawadi et al. (2003) find that high-quality brands are associated with lower customer price sensitivity, and Stahl et al. (2012) find that higher brand equity is associated with an increase in customer acquisition, customer retention rates, and higher profit margins. And more recently, Heath and Mace (2020) find that an exogenous increase in trademark protection sharply lowered entry and exit in affected product markets. Thus, the product market power attendant to high quality brands helps to insulate a firm from competition and contributes to lower cash flow volatility and risk and higher firm performance (Rego et al. 2009; Belo et al. 2014; Larkin 2013; Crass et al. 2019; Heath and Mace 2020). Ultimately, this may enhance debt capacity and leverage.

Pecking order hypothesis. Brand equity and leverage are negatively related.

Pecking order theory argues that firms choose their financing based on issue costs (Myers 1984; Myers and Majluf 1984). Accordingly, the direct and indirect costs of issuing securities motivate managers to first choose internally generated funds, then debt and hybrid securities, and last equity issues. Since strong brands have been shown to boost profitability (Rego et al. 2009; Belo et al. 2014; Crass et al. 2019; Heath and Mace 2020), firms with substantial brand equity may finance their operations with internal capital in lieu of debt financing. This suggests that firms with high brand equity will have low leverage.

Limited contractibility hypothesis. Brand equity and leverage are negatively related.

Shleifer and Vishny (1992) and Benmelech and Bergman (2009) argue that tangibility and non-uniqueness, as originally suggested by Titman (1984) and Titman and Wessels (1988), are essential characteristics for assets that make good collateral. Brand equity possesses neither of these characteristics, since it is an intangible asset likely to have a limited secondary market value

(Hart and Moore 1994). In addition, the value of brand equity relies on discretionary future investments (e.g., advertising, quality maintenance, and product innovation), which management may choose not to make if the firm enters financial distress (Myers 1977). Thus, all else equal, creditors should be reluctant to extend credit to firms with assets heavily weighted toward brand equity, which suggests a negative relation between brand equity and leverage.

Both pecking order and limited contractibility predict an inverse relation between brand equity and leverage. Though they could be at play concurrently, we explore additional factors that affect the relation between brand equity and leverage to differentiate the two hypotheses. We first consider the effect of firm risk. In a pecking order environment, firms with higher business risk tend to have a higher probability of seeking external financing. When firms are forced to go to the capital market, debt is the preferred source of external funds. Therefore, the marginal effect of additional brand equity on leverage will be less negative in high-risk firms. In contrast, if limited contractibility is the driving force, we expect the opposite because firms with high business risk are more likely to enter financial distress and so should have less access to debt finance when business risk is high than when it is low (i.e., the relation between brand equity and leverage should be more negative when business risk is high than when it is low).

Two additional tests may highlight the relative importance of pecking order behavior or limited contractibility as explanations for a negative relation between brand equity and leverage. First, using the degree of information asymmetry as a measure of the information-related cost of external finance (Myers and Majluf 1984), we predict a stronger negative relation between brand equity and leverage when information asymmetry is high rather than low. Second, we condition the relation between brand equity and leverage on whether the firm uses any trademarks as collateral or has potentially collateralizable trademarks (based on an assessment of classes of trademarks that have historically been used as collateral). Assuming limited contractibility is a key determinant of the negative relation between brand equity and leverage, we predict that the relation should be less negative for firms with collateralized or collateralizable trademarks.

2.3.2. Effect of brand equity on debt maturity

Maturity matching hypothesis. Brand equity and the proportion of short-term debt are negatively related.

Given that brands are long-lived assets, the maturity matching principle suggests that it is optimal for firms with substantial brand equity to have longer debt maturity (Chang 1989; Stohs and Mauer 1996).

Agency cost of debt hypothesis. Brand equity and the proportion of short-term debt are positively related.

Given brand equity's limited collateral capacity, low liquidation value, and underinvestment properties, contracting mechanisms such as shortening debt maturity may be necessary to alleviate agency conflicts (Myers 1977). It is not clear whether additional factors will accentuate or mitigate the relation between brand equity and debt maturity. For example, brand-heavy firms with higher risk or facing greater information asymmetry may want to borrow longer-term but creditors may only offer shorter-term debt (Diamond 1991).

3. Data and variables

3.1. Sample construction

We obtain trademark data from the United States Patent and Trademark Office (USPTO) research datasets.[16] The USPTO Trademark Case Files dataset contains 5,370,836 trademarks

[16] https://www.uspto.gov/ip-policy/economic-research/research-datasets

registered between 1870 and 2018.[17] Requiring that trademarks have owner name information reduces the sample to 4,679,484 trademarks. We then match owner names with CRSP-Compustat firm names using a fuzzy matching algorithm and manually check the results to ensure accurate matches. We also obtain subsidiary names of public firms from Mergent Online and match trademarks registered by subsidiaries to their parent firms. This results in a sample of 462,409 trademarks registered by 13,484 unique CRSP-Compustat firms from 1870 to 2018.

We track a trademark's legal status over time using the information in the Case Files. Trademarks are either active, abandoned, expired, or transferred. For transferred trademarks, we examine transaction records in the USPTO Trademark Assignment dataset to determine the type of ownership change.[18] Considering only ownership changes that involve a transfer of ownership, we find that 30% (139,875) of the trademarks in our sample have at least one ownership transfer. The other trademarks (322,534) either have no transfer of ownership or are abandoned or expired. In our analysis, we remove a trademark from a firm's trademark portfolio when it is no longer active or its ownership is transferred to another party. Likewise, we add a trademark to the firm's trademark portfolio when it purchases the trademark from another party.

We then gather firm-year accounting data from Compustat. Excluding financials (SIC codes 6000-6999) and utilities (SIC codes 4900-4999), we require each firm-year to have at least one active trademark, and we require firm-years to have positive book assets, positive net sales,

[17] The USPTO Trademark Case Files dataset provides information on trademark applications and registrations issued by the USPTO since 1870. The information includes trademark ownership, mark characteristics, and renewal and maintenance history. See Graham et al. (2013) for more details.

[18] The USPTO Trademark Assignment dataset contains information on assignments (i.e. ownership transfers of trademarks) as well as other types of transactions that may not involve ownership transfer, such as the use of a trademark as collateral or company name changes (for details, see Graham et al., 2018). Although recording assignments with the USPTO is not mandatory, U.S. legislation and regulations provide strong incentives for buyers to record transactions to secure ownership. If a trademark purchase is not recorded with the USPTO by the new owner, the seller could sell it again to another buyer. If the second buyer records ownership with the USPTO, the first unrecorded buyer legally loses the right to use the trademark. Since the Assignment dataset starts from 1952, we collect 970,528 assignments recorded by the USPTO from 1952 to 2018.

and non-zero leverage. Requiring that firms have non-missing information on leverage, debt maturity, and control variables in our baseline regressions results in a final CRSP-Compustat-USPTO sample of 62,975 firm-year observations for 7,577 firms with 362,070 trademarks from 1982 to 2018.[19]

3.2. Brand equity

We use a firm's portfolio of active trademarks at fiscal year-end to construct brand equity measures. The number of active trademarks owned by firm i at year-end t, TM_{it}, is computed as

$$TM_{it} = TM_{it-1} + TM_{it}^{N} + TM_{it}^{A} - TM_{it}^{X} \tag{1}$$

where TM_{it-1} is the number of trademarks at the end of the prior year, TM_{it}^{N} is the number of new trademarks registered in year t, TM_{it}^{A} is the number of trademarks acquired during year t, and TM_{it}^{X} is the number of trademarks lost due to transfer, expiration, or abandonment. Since trademarks can be renewed indefinitely, we assume that the stock of trademarks does not depreciate (Sandner and Block 2011; Belo et al. 2014).[20] Further, since brand equity is built over time, we assume that individual trademarks contribute to brand equity in relation to their age. Thus, an older more established trademark is assumed to contribute more to brand equity than a newer trademark.

We compute two primary measures of brand equity. Our first measure weights each trademark in a firm's trademark portfolio based on its relative age. Thus, we compute:

$$BEREL_{it} = \frac{\sum_{j=1}^{TM_{it}} Age_{ijt}/\overline{Age}_{t}}{MVA_{it}} \tag{2}$$

[19] We start the panel in 1982 because USPTO data is largely complete starting from 1982 (Graham et al. 2013).
[20] Prior to November 16, 1989, trademarks were required to be renewed every 20 years. After that date, the renewal period was reduced to every 10 years. However, the cost to renew a trademark is negligible, amounting to $425 per class of goods or services in the registration. In contrast, patents are granted for a limited period and cannot be renewed. In general, a utility patent is granted for 20 years and a design patent is granted for 14 years.

where j denotes trademark, TM_{it} from equation (1) is the number of trademarks in firm i's portfolio at time t, Age_{ijt} is the age of firm i's trademark j at time t, $\overline{Age}_t$ is the average age of all active trademarks in our sample at time t, and MVA_{it} is the market value of firm i's assets at time t. Trademark age, Age_{ijt}, is computed as the fiscal year-end date minus the trademark's registration date. The market value of assets, MVA_{it}, is computed as the book value of assets minus the book value of equity plus the market value of equity.

Our second measure of brand equity weights each trademark in a firm's trademark portfolio by its age, expressed as a fraction of 21 years. Thus, we compute:

$$BEW21_{it} = \frac{\sum_{j=1}^{TM_{it}} \min(Age_{ijt}, 21)/21}{MVA_{it}} \tag{3}$$

Notice in (3) that the weight of trademark j is zero at registration (i.e., at registration $Age_{ijt} = 0$) and grows linearly to one when trademark age reaches 21 years. We choose a cutoff of 21 years since it reflects a trademark's renewal cycle (see footnote 20).

We scale both brand equity measures by the market value of assets to make them comparable across firms of different size. A similar size adjustment is used in papers that examine the effects of patents on firm value and policies (e.g., Hall and Learner 2010; Kogan et al. 2017). Since the value of intangible assets is reflected in market value and not book value, we scale the brand equity measures by the market value of assets. Nevertheless, our results are unchanged if we instead scale by the book value of assets. For robustness, we also measure brand equity of firm i at time t by the average age of the firm's trademark portfolio, $\overline{Age}_{it}$, the number of trademarks, TM_{it}, the measure in equation (3) using 11 years instead of 21 years, $BEW11_{it}$, and citation-weighted trademark measures, $BECite_1$ and $BECite_2$. Appendix A provides details on the construction of these measures.

3.3. Debt structure, risk, and performance variables

We analyze the impact of brand equity on firm debt structure (leverage and maturity), risk, and performance. We measure financial leverage as the ratio of long-term debt plus debt in current liabilities to the book value of total assets (*Book leverage*). For robustness, we also compute market leverage (*Market leverage*) as the ratio of long-term debt plus debt in current liabilities to the market value of assets, which is estimated as the book value of assets minus the book value of equity plus the market value of equity. Our measure of debt maturity is the proportion of total debt maturing in three years or less (*ST*3). For robustness, we similarly calculate a measure for debt maturing in five years or less (*ST*5). Since maturity can only be calculated for firms with debt in their capital structures, our sample does not include zero leverage firms. However, in unreported tests, our results are not affected by the inclusion of zero leverage firms.

We measure firm risk using stock return volatility and asset volatility. *Stock return volatility* is computed as the annualized standard deviation of daily stock returns over the fiscal year. *Asset volatility* is constructed following Schwert and Strebulaev (2014) as the standard deviation of returns on a portfolio of the firm's equity and debt over the fiscal year.[21] Firm performance is measured by the ratio of EBITDA to total book assets (*ROA*) and the ratio of free cash flow to total book assets (*FCF*). Free cash flow is computed as operating income before depreciation minus interest expense, income taxes, cash dividends, and capital expenditures.

[21] See Appendix A for details on the construction of *Asset volatility*.

3.4. Control variables

The choice of control variables follows the leverage and debt maturity literature (e.g., Barclay et al. 2003; Billett et al. 2007; Schwert and Strebulaev 2014). We include *Market-to-book*, *Size*, and *Asset beta* in both leverage and maturity regressions to control for growth options, firm size, and firm risk, respectively. In the leverage regressions, we also include *ROA*, *Asset tangibility*, and dummy variables for net operating loss carryforwards (*NOLCF*) and investment tax credits (*ITC*). The additional control variables in the maturity regressions include *Size-sq* (the square of firm size), *Asset maturity*, *Abnormal earnings*, *Term spread*, and *Rated* (dummy variable for whether the firm has an S&P long-term bond rating). Appendix A contains the definitions of all variables that we use in our empirical tests.

3.5. Descriptive statistics

Panel A of Table 1 presents descriptive statistics of main variables for the sample of 62,975 firm-year observations. All continuous variables are winsorized at the 1 and 99 percentiles of their distributions. The average (median) firm in the sample holds 29 (7) trademarks, consistent with the numbers reported in Heath and Mace (2020). The mean (median) of our brand equity measures, $BEREL$ and $BEW21$, are 0.057 (0.009) and 0.023 (0.003), respectively.

For debt structure and firm characteristics variables, the last three columns of Panel A report mean, standard deviation, and median values for the overall CRSP-Compustat sample before merging with USPTO trademark data. This much larger and more comprehensive sample included 120,020 firm-year observations for 14,330 firms over the sample period from 1982 to 2018. Asterisks on the means and medians in these columns indicate whether they are significantly different from the means and medians for our CRSP-Compustat-USPTO intersection sample. As Panel A shows, the debt structure and firm characteristics are roughly comparable in the two samples although most mean and median comparisons are statistically significantly different. Of most interest, observe that firms in our joint CRSP-Compustat-USPTO sample have lower leverage and less short-term debt, and are larger with lower risk and higher profitability than the firms in the CRSP-Compustat sample. Panel B of Table 1 reports the industry distribution of the two samples based on Fama-French 12 industry categories. Relative to the CRSP-Compustat sample, all industry categories are well represented in our final baseline sample.

Lastly, Panel C of Table 1 reports Pearson correlations between our brand equity variables and firm characteristics.[22] The brand equity variables are negatively associated with leverage and positively associated with short-term debt, suggesting that firms with more brand equity use less leverage and have a higher proportion of short-term debt. The positive (negative) associations between the brand equity variables and firm risk (performance) are unexpected given results in the prior literature (e.g., Rego et al. 2009; Larkin 2013), although we need to control for other firm characteristics before drawing any conclusions.

4. Effects of brand equity on firm risk and performance

Our empirical analysis starts with an examination of the effects of brand equity on firm risk and performance in a multivariate framework. We estimate the following regressions:

$$Risk_{it} \text{ (or } Performance_{it}) = \alpha_t + \alpha_j + \beta_1 Brand\ Equity_{it-1} + \gamma' Controls_{it-1} + \varepsilon_{it} \quad (4)$$

where i indexes firm, t indexes time, j indexes industry, and α_t and α_j are year and industry fixed effects. We measure dependent variables at time *t*, and all regressors at time $t-1$. Table 2 reports regressions where $Brand\ Equity$ is $Ln(BEREL)$ in columns (1) and (3) and $Ln(BEW21)$ in

[22] Note that we compute brand equity correlations using the natural logarithms of one plus $BEREL$ and $BEW21$, which we denote as $Ln(BEREL)$ and $Ln(BEW21)$, respectively. We use these logged brand equity measures in our subsequent regression analysis.

columns (2) and (4). In addition to coefficient estimates and their *t*-statistics (in parentheses), we report economic significance (in square brackets) for the coefficient estimates on brand equity. Economic significance is computed as the effect of a one-standard-deviation increase in brand equity on the dependent variable relative to its mean.[23]

Panel A reports the results for the firm risk regressions. The dependent variable is *Stock return volatility* in columns (1) and (2), and *Asset volatility* in columns (3) and (4). The results show that firms with more brand equity have lower risk, with the coefficient estimates statistically significant in three of the four regressions. However, the effect of brand equity on firm risk is not economically strong. A one-standard-deviation increase in $BEREL$ ($BEW21$) decreases stock return volatility by 1.45% (0.87%) and decreases asset volatility by 1.57% (0.96%).

Panel B reports results for the firm performance regressions. The dependent variable is *ROA* in columns (1) and (2), and *FCF* in columns (3) and (4). The results show that firms with more brand equity have significantly better performance. All coefficient estimates are highly statistically and economically significant. For example, using the estimates on $Ln(BEREL)$ in columns (1) and (3), a one-standard-deviation increase in the relative age-weighted trademark portfolio increases *ROA* and *FCF* relative to their sample means by roughly 10% and 32%, respectively.[24]

Overall, more brand equity is associated with higher firm profitability and only a modest reduction in risk. Although the effect of brand equity on risk is not economically strong, it is

[23] Note that the right-hand-side brand equity variable is the natural logarithm of one plus the brand equity (BE) measure (i.e., $Ln(1 + BE)$). The effect of an infinitesimal change in brand equity on the dependent variable (y) is $dy/dBE = \beta/(1 + BE)$, where β is the regression coefficient. Discretizing the change for a one-standard-deviation increase in BE, we compute the change in y relative to its mean $\bar{y}$ as $\Delta y/\bar{y} = \beta[\Delta BE/(1 + \overline{BE})][1/\bar{y}]$, where ΔBE and $\overline{BE}$ are the standard deviation and mean of BE. We use this formula to compute economic significance throughout the paper.

[24] In the *FCF* regressions, we compute economic significance by comparing the effect of a one-standard-deviation increase in brand equity to the absolute value of the sample mean of *FCF*.

important to document that brand equity is not associated with higher firm risk. These results are consistent with the "monopolistic competition" theory of brand equity (Chamberlin 1933) and more recent literature modeling the effect of brand equity on firm cash flows and risk (Belo et al. 2014; Gourio and Rudanko 2014). Our risk and profitability results are also consistent with several empirical studies in the marketing and finance literature that use different brand equity measures (e.g., Krasnikov et al. 2009; Rego et al. 2009; Larkin 2013; Crass et al. 2019; Hsu et al. 2019; Heath and Mace 2020). The relations between brand equity and firm risk and performance provide the necessary prerequisites underpinning the *Product market hypothesis*, which predicts a positive relation between brand equity and leverage. These relations also lay the foundation to support the *Pecking order hypothesis*, which argues that firms with high brand equity will use less debt.

5. Brand equity and debt structure

In this section, we first report baseline regressions examining the effects of brand equity on leverage and debt maturity. We then conduct tests to help uncover the forces driving the relations between brand equity and debt structure. Lastly, we discuss the robustness of our results.

5.1. Baseline estimates

We estimate the following regressions:

$$Book\ leverage_{it} = \alpha_t + \alpha_j + \beta_1 Brand\ Equity_{it-1} + \gamma' Controls_{it-1} + \varepsilon_{it} \quad (5)$$

$$ST3_{it} = \alpha_t + \alpha_j + \beta_2 Brand\ Equity_{it-1} + \gamma' Controls_{it-1} + \varepsilon_{it} \quad (6)$$

where i indexes firm, t indexes time, j indexes industry, $Book\ leverage$ is the ratio of long-term debt plus debt in current liabilities to the book value of total assets, $ST3$ is the proportion of total debt maturing in three years or less, and α_t and α_j are year and industry fixed effects. Columns (1)-(3) in Table 3 report leverage (*Book leverage*) regressions, and columns (4)-(6) report maturity

($ST3$) regressions. Columns (1) and (4) report regressions without brand equity, columns (2) and (5) report regressions with $Ln(BEREL)$, and columns (3) and (6) report regressions with $Ln(BEW21)$.

The leverage regressions show a strong inverse relation between brand equity and leverage. Economically, a one-standard-deviation increase in brand equity decreases leverage by 6% (column (2)) relative to mean leverage. Thus, we may rule out the *Product market hypothesis* since it predicts a positive relation between brand equity and leverage. However, both the *Pecking order hypothesis* and the *Limited contractibility hypothesis* predict the negative relation between brand equity and leverage that we see in Table 3.

The maturity regressions show that firms with more brand equity have a significantly higher proportion of short-term debt. Economically, a one-standard-deviation increase in brand equity increases the proportion of short-term debt by 4% (column (5)) relative to mean maturity. Although inconsistent with the *Maturity matching hypothesis*, the positive relation between brand equity and short-term debt is consistent with the *Agency cost of debt hypothesis*.

The effects of the control variables on leverage and maturity are consistent with prior studies (Stohs and Mauer 1996; Barclay et al. 2003; Johnson 2003; Billett et al. 2007; Schwert and Strebulaev 2014). Moreover, the coefficients are virtually the same with and without brand equity in the regressions. This indicates that the effects of brand equity on leverage and maturity are not affected by the firm characteristics in our regressions.

5.2. Subsample analysis based on firm risk and information asymmetry

Both pecking order behavior and limited contractibility can explain the negative relation between brand equity and leverage. To further explore which theory plays a primary role, we split the sample based on business risk and information asymmetry. As argued in Section 2.3, we expect the negative effect of brand equity on leverage to be weaker for firms with high business risk if pecking order behavior drives the relation because these firms are more likely to seek external debt financing in bad states when cash flows are low. In contrast, we expect the opposite if limited contractibility is the driving force because creditors should be even more sensitive to the limited collateral value of brand equity when a firm faces high business risk and thereby enhanced risk of financial distress. In addition, if pecking order behavior plays a major role explaining the negative relation between brand equity and leverage, we expect the negative relation will be stronger or only exist in firms with high information asymmetry because they face the largest adverse selection financing costs (Myers and Majluf 1984). Nevertheless, the characteristics of brand equity that make it unsuitable for collateral (e.g., limited redeployability) may be accentuated in more opaque settings. Therefore, a stronger negative relation between brand equity and leverage in firms with high information asymmetry is not inconsistent with limited contractability.

Although the positive relation between brand equity and use of short-term debt is consistent with agency cost arguments, it is unclear how business risk and information uncertainty will influence the relation. On the one hand, firms with greater business risk and/or information uncertainty should desire to borrow longer term to minimize rollover risk (Diamond 1991). Notwithstanding, creditors may only be willing to extend short-term debt (Diamond 1991; Goswami et al. 1995). Ultimately, the influence of risk and information asymmetry on the relation between brand equity and debt maturity is an empirical question.

We measure business risk using asset volatility and asset beta. These measures filter out the impact of leverage on risk, which is essential for our analysis of how risk influences the relation between brand equity and debt structure. Following the literature, we measure information asymmetry using analyst coverage, where higher analyst coverage indicates lower information asymmetry (e.g., Yu 2008; Kelly and Ljungqvist 2012; Billett et al. 2017; Kim et al. 2019). We provide details on the construction of the variables *Asset volatility*, *Asset beta*, and *Analyst coverage* in Appendix A. For the analysis, we group firms into high- and low-risk subsamples by whether the firm's risk measure is above or below the median risk for the year, and we group firms into high and low information asymmetry subsamples by whether the firm's analyst coverage is below or above the median analyst coverage for the year.

Table 4 reports regressions for leverage (Panel A) and debt maturity (Panel B). For brevity, we only report coefficient estimates on brand equity. When coefficients on brand equity are significantly different from zero in both the below and above median subsamples, we report a *p*-value from an *F*-test of the null hypothesis that the coefficient estimates are equal; otherwise we report "NA" for the *p*-value. Panel A shows that the relation between brand equity and leverage is significantly less negative (i.e., smaller in absolute value) in the above median risk group than in the below median risk group, regardless whether risk is measured by *Asset volatility* or *Asset beta*. This attenuation of the relation between brand equity and leverage as business risk increases supports the *Pecking order hypothesis* and is not consistent with the *Limited contractability hypothesis*. Regressions in subsamples grouped by analyst coverage also support the *Pecking order hypothesis*. Thus, we see at the bottom of Panel A that the coefficient on brand equity is only significant when there is a high degree of information asymmetry (i.e., below median analyst coverage).

Panel B in Table 4 shows that more brand equity is associated with shorter debt maturity in both high and low risk firms. However, this positive effect is smaller for the high-risk group, as indicated by the significantly smaller coefficient estimates on brand equity in the high-risk group in comparison to the low-risk group. Lastly, the influence of analyst coverage on the relation between brand equity and maturity is indeterminant, since the coefficient estimates in the high and low analyst coverage groups are positive and either not significantly different from zero or only marginally so. The weak results could be due to a lack of power because over 40% of our firm-year sample have missing analyst data on I/B/E/S (our source for analyst coverage).

5.3. Brand collateralization

The *Limited contractibility hypothesis* argues that the negative relation between brand equity and leverage is driven by the inability to use trademarks as collateral. Although our analysis so far strongly suggests that the negative relation between brand equity and leverage is driven by pecking order behavior, a direct test of the *Limited contractability hypothesis* is to ask whether any trademarks actually have been used as collateral, and then group firms into those with and without collateralizable trademarks to see whether the relation between brand equity and leverage is less negative for firms with collateralizable trademarks.

We use the USPTO Trademark Assignment dataset to search trademark collateral history. Over the period from 1870 to 2018, we find that only 10.8% of registered trademarks were ever used as collateral. This is consistent with Nguyen and Hille (2018) who report that only 10% of trademarks in the USPTO database during 2002 to 2015 were used as collateral. However, if we search the collateral history of the trademarks in our final CRSP-Compustat-USPTO trademark sample, we find that 28.7% of trademarks have been used as collateral.[25] Since our sample includes only publicly traded firms, the higher frequency of collateralization suggests that public firms are more likely to use trademarks for collateral than private firms.

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[25] Examples of trademarks in our sample that have been collateralized include Eastman Kodak's photographic color-screens, Nike's swoosh, and Procter and Gamble's Zest.

We create two variables to capture whether the firm has collateralizable trademarks. The variable $DCOL\_ed$ is a dummy variable equal to one if the firm has at least one collateralized trademark in its portfolio of trademarks, and zero otherwise. We define a trademark as collateralized if it has been used as collateral at any time during the previous five years, including the current year. The variable $DCOL\_able$ is a dummy variable equal to one if the firm has at least one collateralizable trademark in its portfolio of trademarks, and zero otherwise. We define a trademark as collateralizable if it belongs to a Nice class in the top one-third of Nice classes with collateralized trademarks in the USPTO database.[26] The difference between $DCOL\_ed$ and $DCOL\_able$ is that the former measures actual collateral usage while the latter measures potential collateral usage.

Panel A in Table 5 groups firm-year observations into those with $DCOL\_ed = 0$ and $DCOL\_ed = 1$. Inconsistent with the *Limited contractability hypothesis*, we find that the negative relation between brand equity and leverage is significantly more negative when the firm has collateralized trademarks ($DCOL\_ed = 1$) than when it does not ($DCOL\_ed = 0$). The effect of brand equity on the proportion of short-term debt is positive in both groups, with no statistical difference. Panel B in Table 5 groups firm-year observations into those with $DCOL\_able = 0$ and $DCOL\_able = 1$. As seen in the panel, there is no statistical difference between the effect of brand equity on leverage or maturity by whether the firm has potentially collateralizable trademarks. Overall, these results do not support the *Limited contractability hypothesis* since the relation

[26] Under the Nice classification system, trademarks are assigned to 45 goods and services classes and 3 special classes. Although trademarks are generally assigned to one class, a small number are assigned to more than one class. Using the USPTO Assignment dataset over the period from 1952 to 2018, for each class we compute the proportion of trademarks in the class that have ever been collateralized. We then sort the class proportions and choose the top one-third. These classes are then used to construct the dummy variable $DCOL\_able$. The results reported below are similar if we construct $DCOL\_able$ using the top 20% or 10% of collateralized Nice classes.

between brand equity and leverage should be less negative when the firm has collateralized or collateralizable trademarks.

5.4. Robustness checks

We perform several robustness checks of the baseline leverage and maturity specifications. These results are reported in Tables 8-11 of Appendix C. In Table 8, we use alternative measures of leverage and debt maturity. Specifically, *Market leverage*, defined as the ratio of long-term debt plus debt in current liabilities to the market value of assets, is used instead of book leverage in the leverage regressions. In the debt maturity regressions, we use the proportion of total debt maturing in five years or less ($ST5$). The baseline results are highly robust to using these alternative debt structure measures. We continue to find that more brand equity decreases leverage and increases the proportion of short-term debt.

Table 9 reports regression results using firm fixed effects to control for unobserved firm characteristics that could be correlated with brand equity and debt structure. We continue to find a robust negative relation between brand equity and leverage and a robust positive relation between brand equity and proportion of short-term debt, even though the addition of firm fixed effects emphasizes within firm variation.

In Table 10 we report leverage and maturity regressions using six alternative measures of brand equity. The measures include the average age of the firm's trademark portfolio, $\overline{Age}$, the number of trademarks, $Ln(TM)$, the age-weighted trademark portfolio with age expressed as a fraction of 11 years, $Ln(BEW11)$, the relative age-weighted trademark portfolio scaled by the book value of assets, $Ln(BEREL_{book})$, the relative citation-weighted trademark portfolio, $Ln(BECite1)$, and the relative citation-weighted trademark portfolio without adding the base weight of one for each trademark, $Ln(BECite2)$.[27] Our baseline results are robust to these alternative measures of brand equity. In all six cases, we see a negative relation between brand equity and leverage and a positive relation between brand equity and proportion short-term debt. Additionally, in unreported results we confirm that the six alternative brand equity measures are negatively related to firm risk (*Stock return volatility* and *Asset volatility*) and positively related to firm performance (*ROA* and *FCF*).

Lastly, Table 11 reports leverage and maturity regressions for firms grouped by top and bottom terciles of risk and information asymmetry. The results are very similar to those reported in Table 4, where firm groups are based on above and below median risk and performance.

6. Difference-in-differences and IV estimation

To sharpen identification of the causal relation between brand equity and debt structure, we use the enactment of the 1996 Federal Trademark Dilution Act (FTDA), which strengthened the legal protection for "famous" trademarks and thereby increased the value of brand equity. We also use the 1988 Trademark Law Revision Act (TLRA) in a placebo test, since the TLRA was virtually identical to the subsequent FTDA but did not contain the key antidilution provision of the FTDA. Lastly, we use instrumental variable (IV) methods to account for the endogeneity of debt structure and brand equity.

6.1. Federal Trademark Dilution Act of 1996

The analysis so far establishes that brand equity and debt structure are related but lacks a strong causal interpretation. Further, the relations could suffer from omitted variable bias, as unobserved firm characteristics could affect both financial policy and brand equity and thereby

[27] See Appendix A for details on the construction of these measures.

potentially bias our results. We use the enactment of the 1996 FTDA to generate plausibly exogenous variation in the value of brand equity to provide evidence that brand equity has a causal effect on debt structure.[28]

Trademark values are negatively affected by "dilution," which "is the use of a trademark in commerce sufficiently similar to a famous brand that by association it reduces, or is likely to reduce, the ability of the famous trademark to identify unique goods or services."[29] In contrast to trademark infringement, trademark dilution denotes situations in which another party uses the mark (or a similar mark) on non-competing products or services (Mermin 2000; Morrin et al. 2006). Prior to 1996, protection from trademark dilution was adjudicated at the state court level in cases of proven dilution only. The FTDA, which was signed into law on January 16, 1996, for the first time granted federal protection of famous U.S. trademarks against dilution. Further, the FTDA allowed for an expansion of trademark rights since the trademark holder was no longer required to prove actual dilution; instead, only the likelihood of dilution was enough to obtain an injunction. Because the FTDA significantly strengthened protection of trademarks and because it was a plausibly exogenous shock to the value of trademarks, we use the passage of the law to identify a causal effect of brand equity on the financial policy of treated firms.

According to the FTDA, the protection against dilution applied to "famous" trademarks. However, the act did not define the term "famous," which was left to the discretion of the courts. Following Heath and Mace (2020), we classify a trademark as famous if the trademark is registered in 1974 or earlier and is still active at the end of 1995. This definition ensures that a famous

[28] Several recent papers, including Yang and Yuan (2019), Chiu et al. (2020), and Heath and Mace (2020), use the FTDA to generate exogenous variation in the value of trademarks.
[29] Dilution comprises two principal harms: (1) blurring, which occurs when the uniqueness of a famous trademark is limited by association with another similar trademark; and (2) tarnishment, which occurs when the reputation of a famous brand is harmed through association with another similar mark (Legal Information Institute, Cornell Law School, https://www.law.cornell.edu/wex/dilution_(trademark)).

trademark is renewed at least once and has been active in commerce for at least 21 years prior to the enactment of the FTDA in January 1996.

We estimate a difference-in-differences regression model around the 1996 FTDA by grouping firms-years into treatment and control groups. A firm-year is classified as treated if the firm has a least one famous trademark at the end of 1995; otherwise the firm-year is part of the control group. Using a six-year window from 1993 to 1998, we estimate the specification:

$$Debt\ Str_{it} = \alpha_i + \alpha_{jt} + \beta FamousTM1995_i \times PostFTDA_t + \gamma' Controls_{it} + \varepsilon_{it} \qquad (7)$$

where $Debt\ Str_{it}$ denotes the debt structure of firm i at time t, α_i and α_{jt} are firm and industry-by-year fixed effects, $FamousTM1995_i$ is a dummy variable equal to one if a firm held at least one famous trademark at the end of 1995, and zero otherwise, $PostFTDA$ is a dummy variable equal to one for the post FTDA period 1996-1998, and zero for the pre-FTDA period 1993-1995, and $Controls_{it}$ is a set of firm characteristics. Industry-by-year fixed effects are based on Fama-French 49 industry categories and fiscal years.[30] The coefficient β is the difference-in-differences estimate, which captures the change in debt structure (leverage or maturity) from the pre- to post-FTDA period for treated firms net of the change for control firms.

We prefer to estimate (7) without controls because a key assumption for identification in difference-in-difference methods is that the control (or conditioning) variables are not influenced by the treatment (Lechner 2011). Thus, if any of the control variables are affected by the FTDA, then including them in (7) will bias the estimate of β (Angrist and Pischke 2008; Lechner 2011; Heath and Mace 2020). When we estimate (7) with controls, we carefully choose controls that are not expected to be influenced by FTDA. Thus, for example, in the leverage regression we include

[30] Firm and industry-by-year fixed effects adjust firms' leverage or debt maturity so that the remaining variation is within each industry-year. Results are similar if instead we use firm and year fixed effects.

Size, *Asset tangibility*, *NOLCF*, and *ITC*. Additionally, we include a control for the number of trademarks, $Ln(TM)$. Notice that we do not include control variables measuring firm profitability or risk, since these types of variables are likely to be affected by the FTDA.

Panel A in Table 6 reports the results with *Book leverage* (columns (1) and (2)) and *Market leverage* (columns (3) and (4)) as the dependent variable in specification (7).[31] The results without controls are reported in columns (1) and (3). The coefficients on $FamousTM1995 \times PostFTDA$ are negative and statistically significant, indicating a decrease in leverage for treated firms (with famous brands) relative to control firms (without famous brands) in the post-FTDA time period. The effect is economically significant, representing 5.5% (12.4%) of treated firms' average pretreatment book (market) leverage. Columns (2) and (4) show that the addition of controls has a negligible effect on the estimated treatment effect, confirming that the exogenous shock is random to treatment and control groups (Angrist and Pischke 2008; Roberts and Whited 2013; Chu 2018; Kubick et al. 2020).

The results suggest that the decrease in leverage for treated firms relative to control firms after 1995 is attributable to the 1996 FTDA. This interpretation would be challenged if treated firms' leverage is decreasing relative to control firms' leverage in the years preceding 1996. To check for non-parallel trends, we plot the yearly average residual leverage for treated and control firm groups, where residual leverage is from panel regressions of leverage with firm and industry-by-year fixed effects. Figure 1 shows that the leverage plots for both book leverage (Panel A) and market leverage (Panel B) are parallel in the pre-FTDA period. Further, notice that the plot for treated firms starts adjusting downward in 1996 while the plot for control firms follows an upward trend. Overall, the parallel trends assumption appears to be satisfied.

[31] We do not find significant results for debt maturity in the difference-in-differences analysis. To save space, the results are not reported but are available upon request.

To provide additional assurance that the results in Table 6 are not due to non-parallel trends or unobserved characteristics that affect leverage differently for firms with famous trademark versus other firms, we conduct a falsification test using the 1988 Trademark Law Revision Act (TLRA). The TLRA originally included an antidilution provision that was virtually identical to that in the FTDA, but the provision was removed from the TLRA before its passage (Denicola 1997). Panel B in Table 6 reports regression results where the placebo event year is 1988, the post-event period is 1988 to 1990, and the pre-event period is 1985 to 1987. The key interaction term is the product of a dummy variable equal to one if a firm held at least one famous trademark at the end of 1987 ($FamousTM1987$) and a dummy variable equal to one for post-event years ($PostTLRA$). As seen in the table, the difference-in-differences estimates are not significantly different from zero. This shows that the TLRA had no affect on leverage and suggests that the results for the FTDA are unlikely to be driven by unobserved trend differences between treated and control firms.

6.2. Endogeneity of leverage, debt maturity, and brand equity

The separately estimated regressions for leverage and debt maturity could have biased estimates because leverage and debt maturity are simultaneously determined. Further, brand equity is likely to be endogenous; driven by a set of decisions that are correlated with other firm policy decisions, including financial policy. We use IV estimation to address these challenges.

We follow Barclay et al. (2003) and related literature (e.g., Johnson 2003; Datta et al. 2005; Billet et al. 2007; Brockman et al 2010; Saretto and Tookes 2013) for our choice of instruments for leverage and debt maturity. Instruments for leverage include *Asset tangibility*, *ROA*, *NOLCF*, and *ITC*. These variables are suggested by the trade-off and pecking order theories of capital structure as factors that determine a firm's leverage and are not directly linked to the choice of debt maturity. We use *Asset maturity, Size-sq*, *Rated*, *Abnormal earnings*, and *Term spread* as instruments for debt maturity, since these variables are most often linked to theories of debt maturity structure (e.g., Myers 1977; Brick and Ravid 1985; Flannery 1986; Diamond 1991).

Lastly, following Chemmanur et al. (2018) and Yang and Yuan (2019), our instrument for brand equity is the average examiner leniency for the trademarks in a firm's trademark portfolio.[32] Examiner leniency for a trademark is the proportion of trademark applications approved by the examiner that evaluated the trademark. Thus, if the current year is t, the examiner leniency of trademark j applied for in year $\hat{t} \leq t$, is the proportion of trademark applications accepted by the examiner of trademark j in year $\hat{t}$. Thus, *Average leniency* for firm i in year t is the average of the examiner leniencies of the firm's trademarks.[33] Table 1 reports that the mean and median of *Average Leniency* in our sample are 0.677 and 0.621, respectively. Both statistics are consistent with the values reported in Chemmanur et al. (2018).

Although the success of an application depends largely on the quality of the trademark, examiner discretion also plays a role in determining the outcome of the application. On the margin, an application assigned to a more lenient examiner will be more likely to be approved than an application of similar quality assigned to a less lenient examiner. Therefore, *Average leniency* satisfies the relevance criterion for a valid instrument, which we also formally test. Further, the random process of examiner assignment provides confidence that *Average leniency* is related to financial policy only through its association with the trademarks that constitute the firm's brand equity (i.e., the instrument satisfies the exclusion restriction).

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[32] Constructed using USPTO trademark examiner data on application acceptance and rejection, this variable was first used in studies of patents (see, e.g., Farre-Mensa et al. 2017; Melero et al. 2017; Gaule 2018; Sampat and Williams 2019).

[33] Appendix B provides additional details on the construction of this variable.

We use GMM IV to jointly estimate leverage and maturity regressions while accounting for the endogeneity of brand equity.[34] In the first stage, we estimate regressions of leverage, maturity, and brand equity on all control variables, all instruments, and industry and year fixed effects. The predicted values of leverage, maturity, and brand equity are then used as regressors in second stage leverage and maturity regressions. We report these second-stage regressions in Table 7. As seen there, we continue to find significantly negative coefficients on brand equity in the leverage regressions and significantly positive coefficients on brand equity in the maturity (*ST*3) regressions.[35] Also note that leverage is negatively related to the proportion of short-term debt, which is consistent with results in the literature (e.g., Billett et al. 2007).

7. Conclusions

In recent decades, firms' production technology has grown increasingly dependent on intangible assets with brands among the most valuable (Jankowski 2012; Falato et al. 2020). Using data from the USPTO data files, we construct a brand equity measure based on the firm's age-weighted portfolio of trademarks, and we allow this measure to change overtime as the firm registers new trademarks, acquires trademarks, and abandons trademarks. In panel data regressions, we first establish the properties that higher brand equity decreases firm risk and increases firm performance. We then establish our primary findings that firms with higher brand equity use less leverage and shorter-term debt. These results are robust to alternative measures of leverage, debt maturity, and brand equity, and continue to hold when we control for firm fixed

[34] We use GMM estimation because tests of heteroskedasticity reject the null hypothesis of no heteroskedasticity (Pagan-Hall χ^2 tests have *p*-values < 0.0000). GMM IV estimation generates efficient estimates in the presence of heteroskedasticity of unknown form. In contrast, the conventional IV estimator with robust standard errors, although consistent, is relatively inefficient when there is heteroskedasticity.
[35] We report the statistics for under-identification and weak identification tests at the bottom of Table 7. These tests confirm that the instruments satisfy the relevance criterion.

effects. Using the enactment of the FTDA in 1996 as a natural experiment, we find that an exogenous increase in the value of famous brands causes a decrease in leverage of firms with famous brands. Our results are also robust when we account for the joint choice of leverage and maturity as well as the potential endogeneity of brand equity.

Taking into consideration various properties of brand equity as well as capital structure theories, we argue that both pecking order theory and limited contractability of brand equity may explain the negative relation between brand equity and leverage. Additional tests show that the effect of brand equity on leverage is stronger in firms with low business risk and high information asymmetry. Moreover, having collateralizable trademarks does not enhance the debt capacity of brand equity. Overall, the evidence supports pecking order behavior as the primary driver of the negative effect of brand equity on leverage. We further argue that the positive effect of brand equity on the use of short-term debt is consistent with debt contracting arguments which predict that the limited collateral value and inalienability of many iconic brands along with the incentive to underinvest in brand maintenance in financial distress encourage creditors to demand shorter-term debt.

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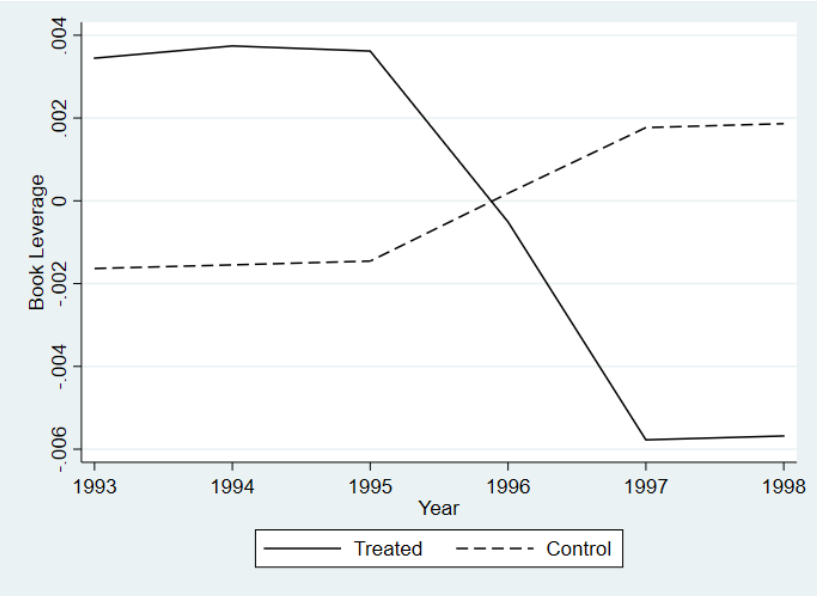
Figures

Panel A. Effect of FTDA on Book Leverage



Panel B. Effect of FTDA on Market Leverage

Figure 1.1. Effect of the 1996 Federal Trademark Dilution Act on leverage ratios
The figure displays yearly average residuals from panel regressions of leverage on firm and industry-by-year fixed effects for treated and control firm groups. The Federal Trademark Dilution Act (FTDA) strengthened the legal protection for famous trademarks against dilution. The FTDA was signed into law on January 16, 1996. Treated firms have at least one famous trademark at the end of 1995 and control firms do not have any famous trademarks. Panel A (B) reports yearly average residuals from *Book (Market) Leverage* regressions.

Tables

Table 1.1. Descriptive statistics and correlations

Panel A reports descriptive statistics of main variables for the baseline sample, corresponding to 62,975 firm-year observations over the 1982 to 2018 period. For comparison, the last three columns report descriptive statistics of corresponding variables for the overall Compustat sample (including the baseline sample). Asterisks on the mean and median values in these columns indicate whether they are significantly different from the corresponding values for our baseline USPTO-Compustat intersection sample. Both samples exclude financial and regulated firms, and require firm-years to have positive assets, positive sales, non-missing leverage and maturity variables, and non-missing control variables in the baseline regressions. The baseline sample further requires firm-years to have at least one active trademark. The sample period for debt structure (dependent) variables is 1983 to 2018, while for all other (independent) variables the sample period is 1982 to 2017. All variables are defined in Appendices A and B. Panel B reports the sample distribution by Fama-French 12 industry categories. Since we exclude financial and utility firms, there are only 10 Fama-French industry categories reported in Panel B. Panel C reports Pearson correlation coefficients for the main variables. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Descriptive statistics: Baseline sample and Compustat sample

	Baseline sample (Obs. = 62,975)			Compustat sample (Obs. = 120,020)		
Variable	Mean	Std. dev.	Obs.	Mean	Std. dev.	Median
<u>Debt structure variables</u>						
Book leverage	0.251	0.198	62,975	0.271***	0.210	0.239***
Market leverage	0.181	0.161	62,971	0.201***	0.174	0.159***
*ST*3	0.489	0.364	62,975	0.509***	0.366	0.464***
*ST*5	0.647	0.350	62,974	0.659***	0.351	0.763***
<u>Brand equity variables</u>						
TM	29.163	64.807	62,975			
BEREL	0.057	0.143	62,975			
Ln(*BEREL*)	0.049	0.108	62,975			
*BEW*21	0.023	0.057	62,975			
*Ln(BEW*21*)*	0.021	0.050	62,975			
DCOL_ed	0.229		62,974			
DCOL_able	0.313		62,975			
Average leniency	0.677	0.144	62,975			
<u>Firm characteristics</u>						
Stock return volatility	0.549	0.329	62,901	0.606***	0.374	0.504***
Asset volatility	0.422	0.252	62,901	0.453***	0.281	0.364***
ROA	0.082	0.184	62,975	0.059***	0.214	0.108***
FCF	–0.033	0.189	62,937	–0.058***	0.216	0.006***
Assets ($M)	4333	12855	62,975	3306***	9977	307***
Sales ($M)	3847	10645	62,975	2875***	8350	303***
Ln(Sales)	6.182	2.221	62,975	5.685***	2.363	5.712***
Asset tangibility	0.276	0.207	62,975	0.309***	0.235	0.247***
Market-to-book	1.955	1.452	62,975	1.942*	1.541	1.437***
Advertising	0.015	0.036	62,975	0.013	0.032	0.000***
R&D	0.050	0.094	62,975	0.041	0.088	0.000***
Asset maturity	8.544	7.964	62,975	9.541***	10.000	6.310***
Asset beta	0.925	0.614	62,975	0.889***	0.666	0.779***
Rated	0.277		62,975	0.227***		

Table 1.1 – *continued*

Variable	Mean	Std. dev.	Obs.	Mean	Std. dev.	Median
Abnormal earnings	0.017	0.262	62,975	0.018	0.333	0.003***
NOLCF	0.408		62,975	0.396***		
ITC	0.202		62,975	0.168***		
Analyst coverage	8.225	7.508	35,496	7.464***	7.078	4.917***
Macroeconomic variables						
Term spread	0.018	0.012	62,975			

Panel A. Descriptive statistics for baseline sample only: complete distribution						
Baseline sample (Obs. = 62,975)						
Variable	Mean	Std. dev.	1st quartile	Median	3rd quartile	Obs.
Debt structure variables						
Book leverage	0.251	0.198	0.095	0.221	0.358	62,975
Market leverage	0.181	0.161	0.050	0.141	0.268	62,971
ST3	0.489	0.364	0.154	0.428	0.888	62,975
ST5	0.647	0.350	0.357	0.727	1.000	62,974
Brand equity variables						
TM	29.163	64.807	3.000	7.000	23.000	62,975
BEREL	0.057	0.143	0.002	0.009	0.041	62,975
Ln(BEREL)	0.049	0.108	0.002	0.009	0.040	62,975
BEW21	0.023	0.057	0.001	0.003	0.016	62,975
Ln(BEW21)	0.021	0.050	0.001	0.003	0.015	62,975
DCOL_ed	0.229					62,974
DCOL_able	0.313					62,975
Average leniency	0.677	0.144	0.565	0.621	0.785	62,975
Firm characteristics						
Stock return volatility	0.549	0.329	0.318	0.457	0.678	62,901
Asset volatility	0.422	0.252	0.247	0.346	0.518	62,901
ROA	0.082	0.184	0.058	0.119	0.173	62,975
FCF	–0.033	0.189	–0.042	0.018	0.055	62,937
Assets ($M)	4333	12855	103	456	2195	62,975
Sales ($M)	3847	10645	107	500	2227	62,975
Ln(Sales)	6.182	2.221	4.673	6.215	7.708	62,975
Asset tangibility	0.276	0.207	0.113	0.225	0.387	62,975
Market-to-book	1.955	1.452	1.116	1.478	2.193	62,975
Advertising	0.015	0.036	0.000	0.000	0.013	62,975
R&D	0.050	0.094	0.000	0.009	0.061	62,975
Asset maturity	8.544	7.964	3.101	6.027	11.255	62,975
Asset beta	0.925	0.614	0.546	0.820	1.191	62,975
Rated	0.277					62,975
Abnormal earnings	0.017	0.262	–0.029	0.004	0.033	62,975
NOLCF	0.408					62,975
ITC	0.202					62,975

Table 1.1 – *continued*

Variable	Mean	Std. dev.	1st quartile	Median	3rd quartile	Obs.
Analyst coverage	8.225	7.508	2.500	5.583	11.750	35,496
Macroeconomic variables						
Term spread	0.018	0.012	0.008	0.019	0.028	62,975

Panel B. Sample distribution by Fama-French 12 industries

Fama-French industry code	Baseline sample Obs.	Baseline sample %	Compustat Obs.	Compustat %
1. Consumer Nondurables	5,171	8.21	9,288	7.74
2. Consumer Durables	2,597	4.12	4,267	3.56
3. Manufacturing	10,761	17.09	18,608	15.50
4. Oil, Gas, and Coal Extraction and Products	1,998	3.17	7,804	6.50
5. Chemicals and Allied Products	2,510	3.99	3,948	3.29
6. Business Equipment	14,743	23.41	23,855	19.88
7. Telephone and Television Transmission	1,994	3.17	4,721	3.93
9. Wholesale, Retail, and Some Services	8,081	12.83	16,184	13.48
10. Healthcare, Medical Equipment, and Drugs	8,171	12.97	13,468	11.22
12. Other	6,949	11.03	17,877	14.90

Panel C. Pearson Correlations

	1	2	3	4	5	6	7
1 *Book lev*	1.000						
2 *ST*3	–0.277***	1					
3 *Ln(BEREL*	–0.058***	0.134***	1				
4 *Ln(BEW*21)	–0.046***	0.128***	0.982***	1			
5 *Stock ret vol*	0.081***	0.273***	0.118***	0.119***	1		
6 *Asset vol*	–0.272***	0.339***	0.100***	0.097***	0.841***	1	
7 *ROA*	–0.061***	–0.179***	–0.030***	–0.026***	–0.454***	–0.463***	1
8 *FCF*	–0.127***	–0.131***	–0.003	–0.005	–0.400***	–0.400***	0.914***

Table 1.2. Effect of brand equity on firm risk and performance

The table reports OLS regressions of firm risk and performance on brand equity, controls, and industry and year fixed effects. In Panel A the dependent variable is *Stock return volatility* in columns (1) and (2) and *Asset volatility* in columns (3) and (4). In Panel B the dependent variable is *ROA* (EBITDA scaled by total assets) in columns (1) and (2) and *FCF* (free cash flow scaled by total assets) in columns (3) and (4). The brand equity variable is identified at the top of each column. Industry fixed effects are based on Fama-French 49 industry categories. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. The economic significance of the coefficient estimates on brand equity are reported in square brackets. They measure the effect of a one-standard-deviation increase in brand equity on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Firm risk

	Dependent var. = *Stock return volatility*		Dependent var. = *Asset volatility*	
	(1)	(2)	(3)	(4)
Brand equity:	*Ln(BEREL)*	*Ln(BEW21)*	*Ln(BEREL)*	*Ln(BEW21)*
Brand equity	–0.059**	–0.085	–0.049**	–0.073*
	(–2.22)	(–1.43)	(–2.51)	(–1.70)
	[–1.45%]	[–0.87%]	[–1.57%]	[–0.96%]
Ln(Assets)	–0.079***	–0.078***	–0.058***	–0.057***
	(–65.15)	(–65.19)	(–63.05)	(–63.02)
Stock return	–0.059***	–0.059***	–0.023***	–0.023***
	(–26.94)	(–26.93)	(–14.58)	(–14.57)
Sales growth	0.047***	0.048***	0.040***	0.041***
	(11.22)	(11.36)	(12.27)	(12.40)
Market-to-book	–0.006***	–0.006***	0.016***	0.016***
	(–4.44)	(–4.25)	(13.92)	(14.12)
Book leverage	0.257***	0.258***	–0.163***	–0.163***
	(22.68)	(22.72)	(–23.90)	(–23.82)
Industry stock return volatility	0.048***	0.048***	0.030***	0.030***
	(26.34)	(26.39)	(24.36)	(24.40)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.478	0.478	0.529	0.529
Observations	59,984	59,984	59.984	59,984

Table 1.2 – *continued*

Panel B. Firm performance				
	Dependent var. = *ROA*		Dependent var. = *FCF*	
	(1)	(2)	(3)	(4)
Brand equity:	*Ln(BEREL)*	*Ln(BEW21)*	*Ln(BEREL)*	*Ln(BEW21)*
Brand equity	0.060***	0.121***	0.077***	0.162***
	(4.49)	(4.23)	(6.66)	(6.63)
	[9.89%]	[8.22%]	[31.56%]	[27.35%]
Ln(Assets)	0.032***	0.032***	0.028***	0.027***
	(29.20)	(29.18)	(27.94)	(27.91)
Stock return	0.057***	0.057***	0.050***	0.050***
	(28.77)	(28.77)	(25.28)	(25.29)
Sales growth	–0.058***	–0.058***	–0.055***	–0.056***
	(–13.15)	(–13.19)	(–12.64)	(–12.68)
Market-to-book	–0.009***	–0.009***	–0.020***	–0.020***
	(–4.34)	(–4.39)	(–10.59)	(–10.65)
Book leverage	–0.041***	–0.041***	–0.065***	–0.066***
	(–4.77)	(–4.82)	(–8.11)	(–8.17)
Industry stock	–0.008***	–0.008***	–0.005***	–0.005***
return volatility	(–6.68)	(–6.73)	(–4.71)	(–4.78)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.290	0.290	0.245	0.245
Observations	60,025	60,025	60,025	60,025

Table 1.3. Baseline leverage and maturity regressions

The table reports OLS regressions of leverage and debt maturity (*ST*3) on brand equity, controls, and industry and year fixed effects. Columns (1)-(3) report leverage regressions, where *Book leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the book value of total assets. Columns (4)-(6) report maturity regressions, where *ST*3 is defined as the proportion of total debt maturing in three years or less. Columns (1) and (4) report regressions without brand equity. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. The economic significance of the coefficient estimates on brand equity are reported in square brackets. They measure the effect of a one-standard-deviation increase in brand equity on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

	Dependent variable = *Book leverage*			Dependent variable = *ST*3		
	(1)	(2)	(3)	(4)	(5)	(6)
Brand equity:	*N/A*	*Ln(BEREL)*	*Ln(BEW*21*)*	*N/A*	*Ln(BEREL)*	*Ln(BEW*21*)*
Brand equity		–0.110***	–0.183***		0.135***	0.265***
		(–6.50)	(–4.98)		(4.80)	(4.46)
		[–5.92%]	[–4.06%]		[3.73%]	[3.02%]
Market-to-book	–0.004***	–0.005***	–0.005***	–0.005***	–0.003*	–0.003*
	(–2.75)	(–3.63)	(–3.38)	(–2.66)	(–1.71)	(–1.83)
Asset tangibility	0.151***	0.148***	0.148***			
	(11.11)	(10.90)	(10.92)			
Asset maturity				–0.002***	–0.003***	–0.003***
				(–7.26)	(–7.55)	(–7.46)
ROA	–0.168***	–0.164***	–0.165***			
	(–14.55)	(–14.20)	(–14.29)			
Size	0.008***	0.006***	0.006***	–0.097***	–0.093***	–0.094***
	(7.58)	(5.58)	(6.07)	(–19.81)	(–18.89)	(–18.88)
Size-sq				0.006***	0.006***	0.006***
				(14.62)	(14.32)	(14.27)
Asset beta	–0.052***	–0.053***	–0.053***	0.002	0.004	0.004
	(–27.33)	(–28.27)	(–28.02)	(0.54)	(1.27)	(1.16)
NOLCF	0.031***	0.031***	0.031***			
	(8.67)	(8.71)	(8.73)			
ITC	–0.027***	–0.027***	–0.027***			
	(–7.27)	(–7.41)	(–7.38)			
Rated				–0.205***	–0.204***	–0.205***
				(–30.74)	(–30.67)	(–30.72)
Abnormal earnings				–0.011**	–0.011**	–0.011**
				(–2.14)	(–2.27)	(–2.27)
Term spread				–0.109	–0.120	–0.123
				(–0.33)	(–0.36)	(–0.37)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.166	0.169	0.167	0.192	0.193	0.193
Observations	62,975	62,975	62,975	62,975	62,975	62,975

Table 1.4. Effect of brand equity on debt structure grouping sample by risk and information asymmetry

The table reports results for leverage (Panel A) and maturity (Panel B) regressions for sub-samples grouped by asset volatility, asset beta, and analyst coverage. Subsamples of lower risk (lower asset volatility, lower asset beta) and lower information asymmetry (higher analyst coverage) are reported in the left columns, and subsamples of higher risk and higher information asymmetry are reported in the right columns. For brevity, we only report coefficient estimates on brand equity. For each grouping, the table reports *p*-values from tests of the null hypothesis that the coefficient estimates on brand equity are equal. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Dependent variable is *Book leverage*

	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW21)*	
Asset volatility	Below median	Above median	Below median	Above median
Brand Equity	–0.189***	–0.062***	–0.347***	–0.095**
	(–7.47)	(–3.53)	(–6.39)	(–2.46)
p-value	[0.000]		[0.000]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.177	0.141	0.175	0.141
Observations	31,477	31,494	31,477	31,494
Asset beta	Below median	Above median	Below median	Above median
Brand Equity	–0.132***	–0.091***	–0.229***	–0.155***
	(–6.59)	(–5.54)	(–5.24)	(–4.41)
p-value	[0.029]		[0.071]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.140	0.140	0.138	0.139
Observations	31,479	31,496	31,479	31,496
Analyst coverage	Above median	Below median	Above median	Below median
Brand Equity	–0.074	–0.146***	–0.131	–0.290***
	(–1.21)	(–4.77)	(–0.95)	(–4.35)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.245	0.194	0.245	0.193
Observations	17,764	17,732	17,764	17,732

Table 1.4 – *Continued*

Panel B. Dependent variable is *ST*3				
	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW*21*)*	
Asset volatility	Below median	Above median	Below median	Above median
Brand Equity	0.147***	0.096***	0.278***	0.198***
	(3.63)	(3.08)	(3.19)	(3.00)
p-value	[0.000]		[0.000]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.160	0.135	0.160	0.135
Observations	31,477	31,494	31,477	31,494
Asset beta	Below median	Above median	Below median	Above median
Brand Equity	0.142***	0.117***	0.282***	0.230***
	(4.43)	(3.50)	(4.11)	(3.28)
p-value	[0.071]		[0.090]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.212	0.177	0.211	0.177
Observations	31,479	31,496	31,479	31,496
Analyst coverage	Above median	Below median	Above median	Below median
Brand Equity	0.131	0.093*	0.207	0.188
	(1.11)	(1.76)	(0.81)	(1.60)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.133	0.152	0.133	0.152
Observations	17,764	17,732	17,764	17,732

Table 1.5. Collateralization of trademarks

We define a trademark as collateralized if it has been used as collateral at any time during the previous five years, including the current year. We define a trademark as collateralizable if it belongs to a Nice class in the top one-third of Nice classes with collateralized trademarks in the USPTO database. Panel A reports results of leverage and maturity regressions for subsamples of firms with and without collateralized trademarks. Panel B reports results of leverage and maturity regressions for subsamples of firms with and without collateralizable trademarks. The dummy variable *DCOL_ed* (*DCOL_able*) equals 1 for firms with at least one collateralized (collateralizable) trademark in the trademark portfolio, and zero otherwise. For brevity, we only report coefficient estimates on brand equity. For each grouping, the table reports *p*-values (in square brackets) from tests of the null hypothesis that the coefficient estimates on brand equity are equal. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Subsample regressions grouping by whether the firm has collateralized trademarks

Dependent variable = *Book leverage*				
	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW21)*	
	DCOL_ed = 0	*DCOL_ed* = 1	*DCOL_ed* = 0	*DCOL_ed* = 1
Brand Equity	–0.103***	–0.194***	–0.162***	–0.407***
	(–5.98)	(–6.00)	(–4.32)	(–5.49)
p-value	[0.002]		[0.001]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.175	0.183	0.173	0.182
Observations	48,528	14,446	48,528	14,446
Dependent variable = *ST*3				
	DCOL_ed = 0	*DCOL_ed* = 1	*DCOL_ed* = 0	*DCOL_ed* = 1
Brand Equity	0.114***	0.207***	0.225***	0.433***
	(3.79)	(3.61)	(3.61)	(3.26)
p-value	[0.129]		[0.134]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.182	0.226	0.182	0.226
Observations	48,528	14,446	48,528	14,446

Table 1.5 – *Continued*

Panel B. Subsample regressions grouping by whether the firm has collateralizable trademarks				
Dependent variable = *Book leverage*				
	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW*21*)*	
	DCOL_able = 0	*DCOL_able* = 1	*DCOL_able* = 0	*DCOL_able* = 1
Brand Equity	–0.111***	–0.147***	–0.183***	–0.254***
	(–5.49)	(–5.15)	(–4.16)	(–4.02)
p-value	[0.308]		[0.351]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.173	0.167	0.172	0.164
Observations	43,281	19,694	43,281	19,694
Dependent variable = *ST*3				
	DCOL_able = 0	*DCOL_able* = 1	*DCOL_able* = 0	*DCOL_able* = 1
Brand Equity	0.132***	0.167***	0.265***	0.311***
	(3.48)	(4.01)	(3.36)	(3.42)
p-value	[0.523]		[0.697]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.184	0.194	0.184	0.193
Observations	43,281	19,694	43,281	19,694

Table 1.6. Difference-in-differences estimation

Panel A reports difference-in-differences (DID) estimates of the effect of the 1996 Federal Trademark Dilution Act (FTDA) on firm leverage. The FTDA strengthened the legal protection for famous trademarks against dilution. The regressions are estimated over 1993 to 1998. *FamousTM1995* is a dummy variable that equals one if the firm held at least one famous trademark at the end of 1995, and zero otherwise. Following Heath and Mace (2020), we classify a trademark as famous if the trademark is registered in 1974 or earlier and is still active at the end of 1995. This definition ensures that a famous trademark is renewed at least once and has been active in commerce for at least 21 years prior to the enactment of the FTDA in January 1996. *PostFTDA* is a dummy variable that equals one in years 1996 to 1998, and zero in years 1993 to 1995. Economic significance, which compares the DID estimate to the average pre-treatment leverage of treated firms, is reported at the bottom of Panel A. Panel B reports DID results for a placebo test using the 1988 Trademark Law Revision Act (TLRA). The TLRA was virtually identical to the FTDA except it did not include the key antidilution provision. The sample runs from 1985 to 1990. *FamousTM1987* is a dummy variable that equals one if the firm held at least one famous trademark at the end of 1987, and zero otherwise. *PostTLRA* is a dummy variable that equals one in years 1988 to 1990, and zero in years 1985 to 1987. In each panel, columns (1) and (3) report results without control variables and columns (2) and (4) report results with control variables (*Size*, *Asset tangibility*, *NOLCF*, *ITC*, and *Ln(TM)*). All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Effect of the Federal Trademark Dilution Act of 1996 on leverage

	Dependent variable = *Book leverage*		Dependent variable = *Market leverage*	
	(1)	(2)	(3)	(4)
*FamousTM*1995 × *PostFTDA*	–0.013**	–0.012**	–0.021***	–0.020***
	(–2.33)	(–2.03)	(–4.25)	(–3.92)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry ×Year FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.757	0.758	0.761	0.763
Observations	11,274	11,267	11,274	11,267
Economic Significance	–5.49%	–5.06%	–12.35%	–11.76%

Panel B. Placebo test: Effect of the Trademark Law Revision Act of 1988 on leverage

	Dependent variable = *Book leverage*		Dependent variable = *Market leverage*	
	(1)	(2)	(3)	(4)
*FamousTM*1987 × *PostTLRA*	0.004	0.006	–0.003	–0.002
	(0.62)	(0.77)	(–0.43)	(–0.36)
Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry ×Year FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.722	0.726	0.736	0.740
Observations	9,085	9,076	9,084	9,075

Table 1.7. GMM IV estimation of leverage and maturity regressions

The table reports the second stage of two-stage GMM IV regressions where leverage, maturity, and brand equity are treated as endogenous variables. We use trademark examiner leniency (*Average leniency*) as the instrumental variable for brand equity. All variables are defined in Appendix A. Details on the construction of *Average leniency* are provided in Appendix B. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. We report the *p*-value of the Kleibergen-Paap rk LM χ^2-statistic (underidentification test) and the *F*-statistic of the Kleibergen-Paap rk Wald test (weak instruments test), where the significance of the latter is based on Stock-Yogo critical values. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dependent variable:	*Book leverage*	*ST*3	*Book leverage*	*ST*3
	(1)	(2)	(3)	(4)
Brand equity:	*Ln(BEREL)*		*Ln(BEW*21*)*	
*Predicted ST*3	–0.630***		–0.630***	
	(–21.89)		(–21.89)	
Predicted Book leverage		–0.284***		–0.273***
		(–4.78)		(–4.53)
Predicted Brand equity	–0.210***	0.199**	–0.514***	0.515**
	(–3.16)	(2.33)	(–3.29)	(2.53)
Market-to-book	–0.008***	–0.003	–0.008***	–0.003
	(–4.70)	(–1.44)	(–4.77)	(–1.24)
Asset tangibility	0.014		0.013	
	(0.91)		(0.82)	
Asset maturity		–0.002***		–0.002***
		(–6.26)		(–6.27)
ROA	–0.140***		–0.139***	
	(–10.57)		(–10.46)	
Size	–0.027***	–0.088***	–0.027***	–0.086***
	(–11.72)	(–17.15)	(–11.70)	(–16.44)
Size-sq		0.005***		0.005***
		(12.12)		(11.99)
Asset beta	–0.055***	–0.010**	–0.055***	–0.009*
	(–22.04)	(–2.10)	(–22.04)	(–1.90)
NOLCF	0.032***		0.032***	
	(7.89)		(7.96)	
ITC	–0.037***		–0.038***	
	(–8.33)		(–8.35)	
Rated		–0.163***		–0.165***
		(–15.83)		(–15.76)
Abnormal earnings		–0.017***		–0.017***
		(–3.31)		(–3.32)
Term spread		–0.153		–0.163
		(–0.47)		(–0.50)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	62,975	62,975	62,975	62,975
Underidentification test *p*-value	0.000	0.000	0.000	0.000
Kleibergen-Paap Wald rk *F*-stat	175.60***	96.63***	175.27***	87.74***

Appendix A. Variable definitions

Name	Definition (data source)
Brand equity variables	
TM	The cumulative number of trademarks the firm holds at the end of the fiscal year. (USPTO)
$BEREL$	The relative age-weighted trademark portfolio at the end of the fiscal year. The measure is computed as $$BEREL_{it} = \frac{\sum_{j=1}^{TM_{it}} Age_{ijt}/\overline{Age}_t}{MVA_{it}}$$ where j denotes trademark, TM_{it} is the number of trademarks in firm i's portfolio at the end of fiscal year t, Age_{ijt} is the age of firm i's trademark j at the end of fiscal year t, $\overline{Age}_t$ is the average age of all active trademarks in our sample at the end of fiscal year t, and MVA_{it} is the market value of firm i's assets at the end of fiscal year t. Trademark age, Age_{ijt}, is computed as the fiscal year-end date minus the trademark's registration date. The market value of assets, MVA_{it}, is computed as the book value of assets minus the book value of equity plus the market value of equity. (USPTO/Compustat)
$Ln(BEREL)$	The natural logarithm of one plus $BEREL$. (USPTO/Compustat)
$BEW21$	The age-weighted trademark portfolio where age is expressed as a fraction of 21 years. The measure is computed as $$BEW21_{it} = \frac{\sum_{j=1}^{TM_{it}} \min(Age_{ijt}, 21)/21}{MVA_{it}}$$ where the weight of trademark j is zero at registration (i.e., at registration $Age_{ijt} = 0$) and grows linearly to one when trademark age reaches 21 years. The cutoff of 21 years reflects one trademark renewal cycle. The market value of assets, MVA_{it}, is computed as the book value of assets minus the book value of equity plus the market value of equity. (USPTO/Compustat)
$Ln(BEW21)$	The natural logarithm of one plus $BEW21$. (USPTO/Compustat)
$DCOL\_ed$	A dummy variable equal to one if the firm has at least one collateralized trademark in its portfolio of trademarks, and zero otherwise. We define a trademark as collateralized if it has been used as collateral at any time during the previous five years, including the current year. (USPTO/Compustat)
$DCOL\_able$	A dummy variable equal to one if the firm has at least one collateralizable trademark in its portfolio of trademarks, and zero otherwise. We define a trademark as collateralizable if it belongs to a Nice class in the top one-third

	of Nice classes with collateralized trademarks in the USPTO database. Using the USPTO Assignment dataset over the period from 1952 to 2018, for each Nice class we compute the proportion of trademarks in the class that have ever been collateralized. We then sort the Nice class proportions and choose the top one-third. (USPTO/Compustat)
FamousTM1995	A dummy variable equal to one if a firm held at least one famous trademark at the end of 1995, and zero otherwise. A trademark is classified as famous if it was registered in 1974 or earlier. (USPTO/Compustat)
FamousTM1987	A dummy variable equal to one if a firm held at least one famous trademark at the end of 1987, and zero otherwise. A trademark is classified as famous if it was registered in 1966 or earlier. (USPTO/Compustat)
Average Leniency	The average examiner leniency for the trademarks in a firm's trademark portfolio. Examiner leniency for a trademark is the proportion of trademark applications approved by the examiner that evaluated the firm's trademark. Thus, if the current year is t, the examiner leniency of trademark j applied for in year $\hat{t} \leq t$, is the proportion of trademark applications accepted by the examiner of trademark j in year $\hat{t}$. Details of variable construction are provided in Appendix B. (USPTO/ Compustat)

Brand equity variables for robustness

$\overline{Age}$	The average age of the trademarks in the firm's trademark portfolio, computed as the sum of the ages of trademarks divided by the number of trademarks. (USPTO/Compustat)
$Ln(TM)$	The natural logarithm of one plus the number of trademarks in the firm's trademark portfolio. (USPTO/Compustat)
$BEW11$	The same as $BEW21$, except using an 11-year cutoff. (USPTO/Compustat)
$Ln(BEW11)$	The natural logarithm of one plus $BEW11$. (USPTO/Compustat)
$BEREL_{book}$	The same as $BEREL$, except use the book value of assets as a scaler. (USPTO/Compustat)
$Ln(BEREL_{book})$	The natural logarithm of one plus $BEREL_{book}$. (USPTO/Compustat)
$BECite1$	The relative citation-weighted trademark portfolio at the end of the fiscal year. The measure is computed as $$BECite1_{it} = \frac{\sum_{j=1}^{TM_{it}}\left(1 + Cite_{ijt}/\overline{Cite}_t\right)}{MVA_{it}}$$ where j denotes trademark, TM_{it} is the number of trademarks in firm i's portfolio at the end of fiscal year t, $Cite_{ijt}$ is the number of citations trademark j has received through the end of fiscal year t, $\overline{Cite}_t$ is the average citations received by all trademarks in the sample filed in the same year as trademark i through the end of fiscal year t, and MVA_{it} is the market value of firm i's assets at the end of fiscal year t. The market value

	of assets, MVA_{it}, is computed as the book value of assets minus the book value of equity plus the market value of equity. (USPTO/Compustat)
$Ln(BECite1)$	The natural logarithm of one plus $BECite1$. (USPTO/Compustat)
$BECite2$	The same as $BECite1$, except we do not add 1 to the relative trademark citation weight. (USPTO/Compustat)
$Ln(BECite2)$	The natural logarithm of one plus $BECite2$. (USPTO/Compustat)

Debt structure variables

Book leverage	The ratio of long-term debt plus debt in current liabilities to the book value of total assets. (Compustat)
Market leverage	The ratio of long-term debt plus debt in current liabilities to the market value of assets, where the market value of assets is computed as the book value of assets minus the book value of equity plus the market value of equity. (Compustat)
*ST*3	The proportion of total debt maturing in three years or less. (Compustat)
*ST*5	The proportion of total debt maturing in five years or less. (Compustat)

Firm variables

Stock return volatility	The annualized standard deviation of daily stock returns over the fiscal year. (CRSP)
Asset volatility	The unleveraged annualized asset volatility is calculated following Schwert and Strebulaev (2014), as the square root of $\sigma_A^2 = (1-W)^2\sigma_E^2 + W^2\sigma_D^2 + 2W(1-W)\sigma_E\sigma_D\rho_{ED}$, where W is the ratio of the book value of debt to the sum of the book value of debt and market value of equity, σ_E is equity volatility, estimated as the standard deviation of excess returns over the trailing 12-month window, σ_D is debt volatility, estimated as $\sigma_D = -0.02 + 0.38W$, and ρ_{ED} is the correlation between equity and debt returns, estimated as $\rho_{ED} = -0.13 + 0.72W$. (Compustat/CRSP)
ROA	The ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to total book assets. (Compustat)
FCF	The ratio of free cash flow to total book assets, where free cash flow is computed as operating income before depreciation minus interest expense, income taxes, cash dividends, and capital expenditures. (Compustat)
Ln(Assets)	The natural logarithm of the book value of assets in millions of constant 2018 dollars. (Compustat)
Size	The natural logarithm of net sales in millions of constant 2018 dollars. (Compustat)
Size-sq	The square of *Size*. (Compustat)
Asset tangibility	The ratio of net property, plant, and equipment to total assets. (Compustat)

Market-to-book	The ratio of the market value of assets to the book value of assets, where the market value of assets is computed as the book value of assets minus the book value of equity plus the market value of equity. (Compustat)
Advertising	The ratio of annual advertising expenditures to the book value of assets. (Compustat)
R&D	The ratio of annual research and development expenditures to the book value of assets. (Compustat)
Asset maturity	The book value-weighted average of the maturities of current assets (CA) and gross property, plant, and equipment (PPE). The maturity of CA is CA divided by cost of goods sold. The maturity of PPE is PPE divided by annual depreciation expense. (Compustat)
Asset beta	Following Schwert and Strebulaev (2014), the asset beta in fiscal year t is computed as $Asset\ beta = (1 - W) \times Equity\ beta + W \times Debt\ beta$, where W is the ratio of the book value of debt (debt in current liabilities plus long-term debt) to the sum of the book value of debt and market value of equity, debt beta is computed as $Debt\ beta = -0.09 + 0.63 \times W$, and $Equity\ beta$ is the sum of the estimated beta coefficients ($\beta_0 + \beta_1 + \cdots + \beta_5$) from the regression: $r_{i,d} - r_{f,d} = \sum_{j=0}^{5} \beta_{i,j}(r_{m,d-j} - r_{f,d-j}) + \varepsilon_{i,d}$, which is estimated using daily stock returns during fiscal year $t - 1$. In the regression specification, i denotes firm, d denotes day, f denotes risk-free, and m denotes market. (Compustat/CRSP)
Rated	Dummy variable equal to one if the firm has a Standard and Poor's long-term bond rating, and zero otherwise. (Compustat)
Abnormal earnings	The year-over-year change in operating earnings per share divided by the previous year's stock price. (Compustat)
NOLCF	Dummy variable equal to one if the firm has net operating loss carryforwards, and zero otherwise. (Compustat)
ITC	Dummy variable equal to one if the firm has investment tax credits, and zero otherwise. (Compustat)
Stock return	One-year cumulative stock return computed over the fiscal year. (CRSP)
Sales growth	The average annual sales growth over fiscal years $t - 4$ through $t - 1$. (Compustat)
Ind. Stk. Rtn. Vol.	The average volatility of firms within a firm's Fama-French 49 industry based on daily stock return over the prior fiscal year. (Compustat/CRSP)
Analyst coverage	The average across months of a firm's fiscal year of the number of analysts providing earnings forecasts. (I/B/E/S)
Macroeconomic variable	
Term spread	The difference between the 10-year constant maturity U.S. Treasury yield and the 3-month constant maturity U.S. Treasury yield. (FRB)

Appendix B. Construction of the average leniency instrument for brand equity

We start with the 9,124,761 trademark applications recorded in the USPTO Case Files dataset over 1870 to 2018. Excluding recording errors, applications that were later cancelled, and applications with missing application date, results in a sample of 8,107,988 trademark applications. Each application is randomly assigned by the USPTO to an examining attorney, who either approves (hence the trademark is granted and registered) or rejects the trademark.[36]

The USPTO records the name of the examiner for each trademark application. Our sample of 8,107,988 applications correspond to 16,727 examiner-year observations of 1,272 unique examiners, where the year is based on the trademark application date. For each examiner k, we record the number of trademark applications assigned to her in year $\hat{t}$, denoted $Application_{k\hat{t}}$, and the number of these applications that are ultimately approved, denoted $Grant_{k\hat{t}}$. Note that approval may occur in the application year, $\hat{t}$, or a subsequent year.

The following example illustrates how $Application_{k\hat{t}}$ and $Grant_{k\hat{t}}$ are estimated. In 1996, examiner Abrams (that is, $k = Abrams$, $\hat{t} = 1996$) was assigned 418 trademark applications. Thus, $Application_{Abrams,1996} = 418$. Abrams eventually approved 197 of the 418 applications, so $Grant_{Abrams,1996} = 197$.[37] In this way, we construct a sample of examiners with four variables: examiner name k, trademark application year $\hat{t}$, $Application_{k\hat{t}}$ and $Grant_{k\hat{t}}$.

Our baseline sample includes 296,935 unique trademarks, which is merged with the examiner sample by the application year. For each trademark j applied for in year $\hat{t}$ and assigned to examiner k, we calculate $Examiner\ leniency$ as the proportion of trademark applications approved by the examiner:

[36] We refer to the newest version of the Trademark Case Files dataset in 2020 to collect the status of trademarks applied in recent years.
[37] The 197 trademarks were granted and registered over 1996-2002, with approvals of 1, 89, 67, 21, 9, 4, and 6, in years 1996, 1997, 1998, 1999, 2000, 2001, and 2002, respectively.

$$Examiner\ leniency_{jk\hat{t}} = \frac{Grant_{k\hat{t}} - 1}{Application_{k\hat{t}} - 1}$$

where we exclude trademark j from the computation by subtracting one from $Application_{k\hat{t}}$ and $Grant_{k\hat{t}}$. We than compute the average leniency for each firm-year in the sample, $Average\ leniency_{it}$, as the average of $Examiner\ leniency_{jk\hat{t}}$ for all trademarks in firm i's trademark portfolio in year t.

The Pearson correlations between the instrument $Average\ leniency$ and the two base case brand equity variables $\ln(BEREL)$ and $\ln(BEW21)$ are 0.31 and 0.34, respectively. In contrast, the correlations between $Average\ leniency$ and *Book leverage* and *ST*3 are 0.02 and –0.01 respectively.

Appendix C. Additional Tests

Table 1.8. Baseline regressions with market leverage and maturity (ST5) as dependent variables

The table reports OLS regressions of market leverage and debt maturity (*ST*5) on brand equity, controls, and industry and year fixed effects. Columns (1) and (2) report leverage regressions, where *Market leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the market value of assets (book value of assets minus book value of equity plus market value of equity). Columns (3) and (4) report maturity regressions, where *ST5* is defined as the proportion of total debt maturing in five years or less. Columns (1) and (3) report regressions without brand equity. Columns (2) and (4) report regressions using the brand equity measure *Ln(BEREL)*. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

	Dependent variable = *Market leverage*		Dependent variable = *ST*5	
	(1)	(2)	(3)	(4)
Ln(BEREL)		–0.059***		0.089***
		(–4.08)		(3.34)
Market-to-book	–0.030***	–0.031***	–0.006***	–0.005***
	(–39.18)	(–38.99)	(–3.49)	(–2.82)
Asset tangibility	0.122***	0.120***		
	(11.45)	(11.26)		
Asset maturity			–0.002***	–0.002***
			(–6.08)	(–6.25)
ROA	–0.106***	–0.103***		
	(–15.63)	(–15.29)		
Size	0.002***	0.001	–0.045***	–0.043***
	(2.58)	(1.29)	(–9.14)	(–8.60)
Size-sq			0.002***	0.002***
			(4.53)	(4.34)
Asset beta	–0.039***	–0.040***	–0.001	0.000
	(–30.16)	(–30.74)	(–0.47)	(0.02)
NOLCF	0.020***	0.020***		
	(7.78)	(7.80)		
ITC	–0.021***	–0.021***		
	(–8.26)	(–8.36)		
Rated			–0.178***	–0.178***
			(–23.95)	(–23.90)
Abnormal earnings			0.002	0.001
			(0.34)	(0.24)
Term spread			0.070	0.063
			(0.22)	(0.19)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.273	0.274	0.139	0.139
Observations	62,971	62,971	62,974	62,974

Table 1.9. Baseline leverage and maturity (ST3) regressions with firm fixed effects

The table reports OLS regressions of leverage and debt maturity (*ST*3) on brand equity, controls, and firm and year fixed effects. Columns (1) and (2) report leverage regressions, where *Book leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the book value of total assets. Columns (3) and (4) report maturity regressions, where *ST3* is defined as the proportion of total debt maturing in three years or less. Columns (1) and (3) report regressions without brand equity. Columns (2) and (4) report regressions using the brand equity measure *Ln(BEREL)*. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

	Dependent variable = *Book leverage*		Dependent variable = *ST*3	
	(1)	(2)	(3)	(4)
Ln(BEREL)		–0.093***		0.157***
		(–4.50)		(4.09)
Market-to-book	–0.004***	–0.005***	–0.005**	–0.003
	(–3.23)	(–3.93)	(–2.35)	(–1.46)
Asset tangibility	0.082***	0.083***		
	(4.92)	(5.04)		
Asset maturity			0.001	0.000
			(1.13)	(0.71)
ROA	–0.171***	–0.172***		
	(–14.93)	(–15.03)		
Size	0.013***	0.011***	–0.034***	–0.032***
	(4.83)	(4.08)	(–3.87)	(–3.57)
Size-sq			0.001	0.001
			(1.49)	(1.54)
Asset beta	–0.023***	–0.023***	–0.003	–0.003
	(–16.03)	(–16.34)	(–1.23)	(–1.00)
NOLCF	0.010***	0.010***		
	(3.58)	(3.66)		
ITC	–0.006*	–0.006*		
	(–1.78)	(–1.82)		
Rated			–0.105***	–0.104***
			(–14.19)	(–14.01)
Abnormal earnings			–0.016***	–0.017***
			(–3.38)	(–3.59)
Term spread			–0.066	–0.059
			(–0.21)	(–0.19)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.629	0.630	0.418	0.419
Observations	61,835	61,835	61,835	61,835

Table 1.10. Baseline regressions with alternative brand equity variables

The table reports OLS regressions for leverage (Panel A) and debt maturity (Panel B) using alternative measures of brand equity with controls, and industry and year fixed effects. The brand equity measure is identified at the top of each column. The brand equity measures are the average age of the trademark portfolio, $\overline{Age}$ (column (1)); the natural logarithm of one plus the number of trademarks in the firm's trademark portfolio, $Ln(TM)$ (column (2)); the natural logarithm of the age-weighted trademark portfolio with an 11-year cut-off, $Ln(BEW11)$ (column (3); the natural logarithm of the relative age-weighted trademark portfolio scaled by the book value of assets, $Ln(BEREL_{book})$ (column (4)), and the natural logarithm of the relative citation-weighted trademark portfolio scaled by the market value of assets, $Ln(BECite1)$ (column (5)). All variables are defined in Appendix A. To save space, we only report coefficient estimates on brand equity variables. T-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Dependent variable = *Book leverage*

	(1)	(2)	(3)	(4)	(5)
Brand equity:	Age	$Ln(TM)$	$Ln(BEW11)$	$Ln(BEREL_{book})$	$Ln(BECite1)$
Brand equity	–0.013***	–0.073***	–0.141***	–0.082***	–0.073***
	(–4.06)	(–4.19)	(–5.35)	(–5.99)	(–6.62)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.167	0.168	0.168	0.167	0.169
Observations	62,975	62,975	62,975	62,975	62,975

Panel B. Dependent variable = *ST3*

	(1)	(2)	(3)	(4)	(5)
Brand equity:	Age	$Ln(TM)$	$Ln(BEW11)$	$Ln(BEREL_{book})$	$Ln(BECite1)$
Brand equity	0.009*	0.024	0.216***	0.113***	0.118***
	(1.95)	(1.01)	(5.26)	(5.10)	(6.90)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R-sq	0.192	0.193	0.192	0.193	0.194
Observations	62,975	62,975	62,975	62,975	62,975

Table 1.11. Effect of brand equity on debt structure grouping sample by top and bottom terciles of risk and information asymmetry

The table reports results for leverage (Panel A) and maturity (Panel B) regressions for samples grouped by asset volatility, asset beta, and analyst coverage. The setup is the same as in Table 4 of the paper, except that in this table we split our sample into terciles and compare top and bottom terciles in each case. Subsamples of lower risk (lower asset volatility, lower asset beta) and lower information asymmetry (higher analyst coverage) are reported in the left columns, and subsamples of higher risk and higher information asymmetry are reported in the right columns of each pair. For brevity, we only report coefficient estimates on brand equity. For each grouping, the table reports *p*-values from tests of the null hypothesis that the coefficient estimates on brand equity are equal. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Dependent variable = *Book leverage*

	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW21)*	
Asset volatility	Bottom tercile	Top tercile	Bottom tercile	Top tercile
Brand Equity	–0.192***	–0.036**	–0.357***	–0.048
	(–6.89)	(–2.01)	(–5.96)	(–1.26)
p-value	[0.000]		NA	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.185	0.125	0.182	0.125
Observations	20,981	20,989	20,981	20,989
Asset beta	Bottom tercile	Top tercile	Bottom tercile	Top tercile
Brand Equity	–0.131***	–0.085***	–0.230***	–0.142***
	(–6.32)	(–4.71)	(–5.06)	(–3.69)
p-value	[0.043]		[0.076]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. R-sq	0.155	0.129	0.153	0.128
Observations	20,982	20,992	20,982	20,992
Analyst coverage	Top tercile	Bottom tercile	Top tercile	Bottom tercile
Brand Equity	–0.128***	–0.148***	–0.217**	–0.307***
	(–2.82)	(–4.68)	(–2.14)	(–4.44)
p-value	[0.004]		[0.071]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.229	0.196	0.228	0.195
Observations	11,836	11,835	11,836	11,835

Table 1.11– *Continued*

Panel B. Dependent variable = *ST*3				
	Brand Equity = *Ln(BEREL)*		Brand Equity = *Ln(BEW*21*)*	
Asset volatility	Bottom tercile	Top tercile	Bottom tercile	Top tercile
Brand Equity	0.142***	0.089***	0.268***	0.183**
	(3.17)	(2.64)	(2.72)	(2.57)
p-value	[0.000]		[0.000]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.154	0.106	0.154	0.106
Observations	20,981	20,989	20,981	20,989
Asset beta	Bottom tercile	Top tercile	Bottom tercile	Top tercile
Brand Equity	0.142***	0.108***	0.284***	0.193**
	(4.17)	(2.90)	(3.87)	(2.45)
p-value	[0.075]		[0.055]	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.223	0.164	0.222	0.164
Observations	20,982	20,992	20,982	20,992
Analyst coverage	Top tercile	Bottom tercile	Top tercile	Bottom tercile
Brand Equity	0.016	0.092*	0.029	0.188
	(0.20)	(1.65)	(0.17)	(1.53)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.158	0.144	0.158	0.144
Observations	11,836	11,835	11,836	11,835

Chapter 2: Cybersecurity Awareness and Debt Contracting

1. Introduction

In recent years, cybersecurity events have become one of the major sources of risk for corporations (e.g., Securities and Exchange Commission (SEC) 2018; Global Risks Report from the World Economic Forum 2019; Ashraf and Sunder, 2020; Kamiya et al. 2020). The number, severity, and economic cost of successful cyberattacks have been on the rise. The IBM/Ponemon 2020 Cost of a Data Breach Study (hereafter IBM/Ponemon 2020) estimates the average cost of a data breach for U.S. companies at $8.64 million. At the same time, the global average cost of a data breach increased roughly 10% over the past seven years.[38] Successful cyberattacks pose risks to firms' customers, investors, capital markets, and the economy. Therefore, firms' transparency about their cybersecurity has become critical, with the SEC taking a more active role in providing guidance to U.S. corporations about cyber risk and cyber preparedness disclosures in their 10-K reports.[39] As a result, the importance of firms' risk management measures to prepare for and minimize the likelihood of successful cyberattacks has increased (e.g., Berkman et al. 2018). In this paper, we investigate the relation between firms' cybersecurity awareness and firms' cost of debt and credit ratings.

Researchers have recognized the importance of studying the implications of successful cyberattacks on firm policy and value. Kamiya et al. (2020) document that successful data breaches may adversely affect the stock price of the target and firms in the targeted industry. Further, their

[38] The Cost of Data Breach Study (CDBS) is sponsored by IBM Security and conducted by Ponemon Institute. The 2020 study covers a sample of 524 organizations that experienced data breaches between 08/2019 and 04/2020 across 17 countries. Global average cost is estimated based on the complete sample. The global average cost of a data breach increased from $ 3.50 million in 2014 to $ 3.86 million in 2020.

[39] See "Commission Statement and Guidance on Public Company Cybersecurity Disclosures" (https://www.sec.gov/rules/interp/2018/22-10459.pdf).

study shows that after a successful data breach targeted firms report lower sales growth and a reduction in risk-taking incentives for management. Garg (2020) finds that firms and industry peers increase cash holdings after a cyberattack, Huang and Wang (2021) find a positive association between a cybersecurity breach and firms' cost of privately placed debt, and Iyer et al. (2020) document that bondholders lose approximately 2% of wealth within one month after a successful cyberattack. However, studies that focus on the effects of a firm's proactive efforts to manage cyber risk and an increased cybersecurity awareness on firms' financial policies remain scarce. IBM/Ponemon 2020 reports that various cybersecurity preparedness measures translated into average cost savings ranging from $2 million for companies with an *Incident Response* (IR) team to $ 3.58 million for fully deployed security automation. Gordon et al. (2010) document a positive relation between voluntary disclosures concerning information security and positive abnormal returns. Building on Gordon et al. (2010), Berkman et al. (2018) propose a measure of firm-specific cybersecurity awareness and show that the market positively values cybersecurity awareness. They posit that firms with more extensive disclosures in their 10-K statements are more likely to divulge information concerning the firm's risk management strategies to mitigate cybersecurity risks rather than providing details regarding their vulnerabilities and/or a roadmap for cyber thieves to capitalize on them. Our study extends this nascent stream of research and examines the relation between a firm-specific cybersecurity awareness measure and firms' cost of debt. This issue demands attention because the literature has established the importance of firms' risk assessment by creditors as one of the main determinants of the cost of debt (e.g., Graham et al. 2008; Valta 2012).

Firms' business models have become increasingly dependent on intangible assets such as customer lists that include detailed sensitive information, R&D, trade secrets, and proprietary databases shared with partners along the supply chain, among others. (e.g., Lev 2018; Falato et al. 2020). In this context, increased cybersecurity awareness may contribute to preserve the integrity of these intangible assets and allow firms to use them more efficiently. Financial investors assess firms' tangible and intangible assets and form expectations about their future performance (Sandner and Block, 2011). As such, more cybersecurity preparedness may lead creditors to expect a more suitable cyber risk management and higher firm productivity. By increasing information transparency through voluntary disclosures on cybersecurity risk, firms may also mitigate potential litigation costs in the event of suffering a cyberattack (Francis et al. 1994; Gordon et al. 2010). These benefits of cybersecurity awareness may lead to a lower cost of debt for firms.

On the other hand, higher cybersecurity awareness may make investors more alert about cyber risks in general and the business exposure to them. In turn, this could cause creditors to be more cautious concerning potential consequences of a successful cyberattack, leading them to revise the borrower's risk upward, and ultimately lead to more costly debt contracts. Overall, we expect that the terms at which bank lenders are willing to contract with the firm (i.e., loan spread and loan non-price features) will be affected by our cybersecurity awareness measure, with the direction of the relation being an empirical question.

We construct a firm-specific measure of cybersecurity awareness to test the relation between self-disclosed cybersecurity readiness and the cost of debt. We construct our cybersecurity awareness measure using textual analysis of 10-K statements and a comprehensive dictionary of cybersecurity-related words for a large sample of U.S. firms. Our sample starts in 2005 because in this year the Securities and Exchange Commission (SEC) mandated firms to include a ''Risk Factor'' section in their annual statements to discuss different forms of risks (Campbell et al. 2014). This new section also triggers firms to discuss the risk related to cybersecurity incidence and measures they have taken to protect themselves against such cyberattacks. Our cybersecurity awareness variable results in a sample of 31,784 firm-year observations (excluding financial and utility firms) over the period from 2005 to 2016.

We merge our firm-year sample with loans in the DealScan database for our main tests. The resulting cross-sectional loan sample of 11,747 includes price and non-price features of loans made to firms during the calendar year 2005 through 2016. We focus our analysis on bank loans because the close bank-borrower relationship suggests that loan price and no-price contract features (e.g., number of covenants, secured loans) should be particularly responsive to cybersecurity awareness. In cross-sectional regressions controlling for firm characteristics, macroeconomic variables, and industry fixed effects, we find that firms with higher cybersecurity awareness have significantly lower loan spreads. Specifically, a one-standard deviation increase in cyberawareness decreases the loan spread by 5.4 bps, or 2.19% of the average loan spread in the sample. These results suggest that arms-length lenders positively evaluate firms' increased preparedness to fend off potential cyberattacks. We use IV estimation to account for the possible endogeneity of cybersecurity awareness.

Next, we examine how cybersecurity awareness influences firms' credit ratings. Our focus on credit ratings captures a broad assessment of how debt markets view cybersecurity awareness. We find that credit ratings improve as a function of cybersecurity awareness. The effect is statistically strong, with the coefficient estimates ranging from 0.726 to 0.772. In terms of economic significance, a one-standard deviation increase in Cyberawareness increases the long-term S&P bond rating of the mean firm in the sample by more than two-thirds of a notch. Thus, cyberawareness increases the long-term S&P bond rating of the mean firms in the sample from BB + to about BBB–.

With the empirical evidence showing the debt markets price firms' cyberawareness, we next investigate the effect of cyber readiness on the cost of public debt. We find that cyberawareness has a significantly negative relation with bond spread. A one-standard deviation increase in Cyberawareness decreases the bond spread by 5.4 bps, or 2.27% of the average bond spread in the sample. Overall, our results indicate that cyberawareness decreases spreads on both bank and public debt.

Subsequently we explore whether cybersecurity awareness has any effect on loan contract terms. We examine the relation between cyberawareness and loan maturity, number covenants, the use of performance pricing provisions, and whether loans are secured. We find no significant effect of cybersecurity awareness on these non-price loan features, with the exception of covenant count. However, the result is not economically strong, with a one-standard-deviation increase in cyberawareness associated with a decrease in the number of covenants by 0.04 (3.18%). We conclude that, in general, non-price loan features are unaffected by firms self-disclose cyberawareness.

Consistent with creditors assessing higher cybersecurity awareness as a way for firms to protect the integrity of their intangible assets and operate more efficiently, we find that higher cybersecurity awareness is associated with higher levels of firm operating efficiency. Results show that firms with higher cyberawareness have higher profitability, lower probability of reporting a loss, and lower costs per employee. These findings are consistent with those of Gordon et al. (2010) who finds positive abnormal returns after firms voluntarily disclosing information on cybersecurity. The higher operating efficiency results are also in line with the higher firm market-valuations reported by Berkman et al. (2018).

Our paper makes several contributions to the literature. First, we contribute to the emerging literature on cybersecurity readiness (e.g., Gordon et al. 2010; Gordon et al. 2015; Berkman et al. 2018) and firms' corporate policies by providing the first evidence that firms' self-disclosed proactive measures and investments aimed to reduce firms' vulnerability to a successful cyberattack influence firms credit ratings, and the cost of private and public debt. Although cybersecurity awareness requires the commitment of firms' resources, our analysis shows that the debt marks, and particularly arms-lengths creditors see with good eyes higher awareness, allowing firms to enjoy more favorable bank loan terms. Evidence indicating that operating performance is increasing in cyberawareness suggests that detailed disclosures on cyber risk readiness topics, leads creditors to expect proper cyber risk management, lower risk, and higher productivity.

Second, our paper complements and extends the literature examining the determinants of bank loan contracting. Graham et al. (2008) examine corporate misreporting and financial restatement, Valta (2012) examines product market competition, Campello and Gao (2017) examine customer concentration, and Kubick et al. (2020) examine industry tournament incentives. The empirical analysis in our paper contributes to this literature by showing that cybersecurity awareness, as measured by a firm-specific text-based metric available over time, is negatively related to bank loan spreads and covenant counts.

Third, consistent with extant studies (Gordon et al. 2015; Berkman et al. 2018), our evidence supports the view that cybersecurity preparedness represents an intangible asset. Firms with more extensive disclosures in their 10-K statements are more likely to divulge information concerning the firm's risk management strategies to mitigate cybersecurity risks, rather than providing a roadmap about their vulnerabilities. As such, our work contributes to the stream of literature that explores the association between non-GAAP measures with firms' value and policies

(Aboody and Lev 1998; Gordon et al. 2010, Gordon et al. 2015; Berkman et al. 2018). We expand this literature showing how cybersecurity awareness influences firms' financial costs. Lastly, the evidence we document informs the regulatory discussion regarding mandated disclosures of cybersecurity issues, providing evidence of positive effects associated with more detailed disclosure.

The remainder of the paper is organized as follows. Section 2 discusses how cybersecurity awareness can influence debt contracting. Section 3 describes our sample and variable construction and provides descriptive statistics. Section 4 and 5 presents the empirical results. Section 6 concludes.

2. Background and predictions

There has been a noticeable increase in the attention paid by research in financial economics on the real effects of cybersecurity and related issues on firms' corporate policies and outcomes. Kamiya et al. (2020) document that successful data breaches may adversely affect the stock price of the target and firms in the targeted industry. Further, their study shows that after a successful data breach targeted firms report lower sales growth and a reduction in risk-taking incentives for management. In contemporaneous work, Huang and Wang (2021) find a positive association between a cybersecurity breach and firms' cost of privately placed debt, and Iyer et al. (2020) document that bondholders lose approximately 2% of wealth within one month after a successful cyberattack. Nevertheless, studies that focus on the effects of a firm's proactive efforts to manage cyber risk and an increased cybersecurity awareness on firms' financial policies remain scarce, with a few exceptions. Gordon et al. (2010) document a positive relation between voluntary disclosures concerning information security and positive abnormal returns. Berkman et al. (2018)

propose a measure of firm-specific cybersecurity awareness and show that the market positively values cybersecurity awareness as measured by higher market value of firms. Firms with more extensive disclosures in their 10-K statements are more likely to divulge information concerning the firm's risk management strategies to mitigate cybersecurity risks rather than providing details regarding their vulnerabilities and/or a roadmap for cyber thieves to capitalize on them (Gordon et al. 2010; Gordon et al. 2015; Berkman et al. 2018).

Not surprisingly, the increase in cyberattacks over time coincides with firms' business models becoming increasingly dependent on intangible assets such as customer lists that include detailed sensitive information, R&D, trade secrets, and proprietary databases shared with partners along the supply chain, among others. (Lev, 2018; Falato et al. 2020). In this context, increased cybersecurity awareness should contribute to preserve the integrity of these intangible assets and allow firms to use them more efficiently.

Financial investors assess firms' tangible and intangible assets and form expectations about their future performance (Sandner and Block, 2011). As such, more cybersecurity preparedness may lead creditors to expect a more suitable cyber risk management and higher firm productivity. By increasing information transparency through voluntary disclosures on cybersecurity risk, firms may also mitigate potential litigation costs in the event of suffering a cyberattack (Francis et al. 1994; Gordon et al. 2010). These benefits of cybersecurity awareness may lead to a lower cost of debt for firms.

On the other hand, higher cybersecurity awareness may make investors more alert about cyber risks in general and the business exposure to them. In turn, this could cause creditors to be more cautious concerning potential consequences of a successful cyberattack, leading them to revise the borrower's risk upward, and ultimately lead to more costly debt contracts. Overall, we expect that the terms at which creditors are willing to contract with the firm will be affected by our cybersecurity awareness measure, with the direction of the relation being an empirical question.

3. Data and variables

Our sample starts with Compustat and CRSP databases for fiscal years 2005 to 2016. Annual firm-level accounting data and stock prices data come from Compustat and CRSP, respectively. The sample starts in 2005 because in this year the Securities and Exchange Commission (SEC) mandated firms to include a ‘‘Risk Factor’’ section in their Form 10-K to discuss different forms of risks (Campbell et al. 2014). This new section also causes firms to discuss the risk related to cybersecurity incidence and measures they have taken to protect themselves against such cyberattacks. Following conventions in the literature, we exclude financial firms (SIC codes 6000-6999) and regulated utilities (SIC codes 4900-4999) and require firm-years to have positive book assets. This results in a sample of 31,784 firm-year observations over the period from 2005 to 2016.

Our loan sample is constructed from the intersection of the Cyberawareness-Compustat sample and the DealScan database maintained by the Loan Pricing Corporation (LPC). We require that loans be U.S. dollar-denominated with US-based syndication to keep them in our sample. Further, we require information on whether the loan facility is secured by collateral. We match the bank loan data with Compustat data using the DealScan–Compustat link file maintained by Michael Roberts (Chava and Roberts, 2008). To ensure we match loan characteristics with firm financial data probably available to lenders during loan underwriting, we follow the matching procedure in Bharath et al. (2011). Specifically, we merge our Cyberawareness-Compustat data to DealScan loan data by calendar year if the loan’s start date is six months or more after the calendar month of the firm's fiscal year-end. Otherwise, we merge Cyberawareness-Compustat data for the previous fiscal year to the loan. The resulting cross-sectional loan sample includes 11,747 observations on price and non-price features of loans made to firms during the calendar year 2005 through the beginning of the calendar year 2016.

Our next ample consists of the S&P long-term domestic issuer credit ratings. These ratings span from AAA (highest rating) to D (lowest rating, debt in payment default). For our analysis, we transform these credit ratings to numeric values ranging from 1 (rating D) to 22 (rating AAA). To be included in the sample, a firm also must have available information for the vector of control variables. After matching, the sample for credit-rating analysis includes 9,280 firm-year observations over the period 2005 to 2016.

Lastly, we have our public debt sample, based on the newly issued corporate bonds from Mergent Fixed Income Securities Database (FISD) database. For each bond issue, FISD provides detailed information, including the cost of bond in terms of spread, the issue date, yield to maturity (YTM), maturity, proceeds, and ratings. As before, we require that firms have the necessary information on the set of control variables. The resulting cross-sectional bond issue sample includes 4,411 observations from 2005 through 2016.

3.1. Cybersecurity awareness variable

Gordon et al. (2010) use the occurrence of any 24 cybersecurity-related keywords in firms' 10-Ks to identify whether a firm uses protection against information theft. We start from Gordon et al.'s (2010) keywords list to construct our cyberawareness measure. We then supplement this list with the glossary of common cybersecurity terminology from the National Initiative for

Cybersecurity Careers and Studies (NICCS).[40] Subsequently, we initially search 10-K statements of over 300 firms, representative across all Compustat industries for occurrences of this comprehensive set of keywords. We manually read the surrounding sentences and context to understand how firms use these keywords and validate that they indeed refer to cyberawareness. After carefully reading the cyber-related discussion from this comprehensive subsample of firms, we note the following distribution of firms' cyberawareness. We observe that 69% of the firms discuss their cybersecurity in the "Risk Factors" (or Item 1A) section, 12% discuss cybersecurity in the "Management's Discussion and Analysis" (MD&A or Item 7) section, and 19% of firm discuss it under the "Business Description" (or Item 1) section of their 10-K statements. Based on our manual reading, we construct three different keyword lists reported in Appendix B, that we have high confidence capture firms' self-disclosure of cyber readiness. Using an automated script, we then search for these keyword lists in the three relevant 10-K sections (i.e., Item 1A, Item 7, and Item 1) for our full sample.

To rule out the possibility of capturing false positive cyber-related keywords hits in other 10-K sections, we first conduct our automated search for our three lists of keywords in *Risk Factors* section. If our search produces zero hits in the *Risk Factors* section, we then continue our search in *MD&A* and *Business Description* sections. In brief, we follow three steps to construct our cybersecurity awareness measure.

Step 1: For each of these three sections in 10-K, we:

[40] The National Initiative for Cybersecurity Careers and Studies is accessible through https://niccs.cisa.gov/about-niccs/cybersecurity-glossary.

A) Count the number of occurrences where one of the keywords from both List 1 and List 2 coincide within three surrounding words.[41]

B) Count the number of occurrences of keywords from List 3.

C) Take summation of the above two counts from A and B and denote the sum as cyber-related counts.

Step 2: We define our *Cyber awareness* variable as the cyber-related counts from *Step 1.C* divided by the total number of words in the respective section (Item 1, 1A, or 7) multiplied by 100.

Step 3: Impute *Cyber awareness* variable as zero when no cybersecurity awareness discussion occurs in any of the three sections (Item 1, 1A, or 7) of 10-K statement.

3.2. Debt contracting variables

We use a variety of measures to capture different dimensions of debt contracting. For our bank loan analysis, we use the cost of bank debt as the primary outcome variable. Following the literature (e.g., Graham et al. 2008; Bharath et al. 2011), we measure loan cost with the All-In-Spread-Drawn (AISD) from the DealScan database. This variable, which we denote as Loan spread, is the total (fees and interest) annual spread paid in basis points over LIBOR (or LIBOR equivalent) for each dollar drawn down from a loan facility. We use the natural logarithm of this variable in our regression analysis, *Ln*(*Loan spread*).

To examine whether cybersecurity awareness is associated with public debt ratings, we use the Standard & Poor's long-term domestic issuer credit ratings. These ratings span from AAA (highest rating) to D (lowest rating, debt in payment default). We transform these credit ratings to

[41] We require the combination within three words to avoid false positive hits. The results are similar if we increase our window size up to 10 words. The use of similar boundaries is a standard practice in the literature using text-based measures (e.g., Hope et al. 2016; Dyer et al. 2017).

numeric values ranging from 1 (rating D) to 22 (rating AAA) and use this coded variable, *Credit rating*, for our analysis.

We examine several non-price features of loans, including loan maturity, covenant count, performance-pricing provision, and secured loans. The variable, *Maturity* is the maturity of the loan in months; *Covenant count* is the number of covenants in the loan package; *Secured* is a dummy variable equal to one if the loan is secured by collateral; and *Performance pricing* a dummy variable equal to one if the loan facility has a performance pricing feature and zero otherwise. *Covenant count* ranges from zero to 13 and includes up to eight different financial covenants along with the covenants: minimum net worth, dividend restriction, asset sale sweep, debt issuance sweep, and equity issuance sweep.

In our analysis of bond spreads, we define *Bond spread* as the difference between the yield to maturity of a corporate bond and the yield to maturity of its duration equivalent Treasury bond, measured in basis points.

3.3. Instrumental variables

The influence of geographically proximate firms on various aspects of a firm is well documented in the finance literature, as well as its use to strengthen causal identifications (e.g., Bouwman 2012; Kedia and Rajgopal 2009). Further, in the cyber-related literature, Jamilov et al. (2021) show that cyber risk exposure and the sentiment towards cyber threats are geographically clustered among firms. We follow the above literature, and use the yearly average of the cybersecurity awareness measure of firms in different industries that are headquartered within a 250-km radius of firm *i*, *Geo cyber awareness*, as our instrument for firm *i*'s cyberawareness. We expect the average cybersecurity awareness of geographically close firms to be positively associated with the firm's cybersecurity awareness. Further, to construct our instrumental variable for firm *i* we require the exclusion of firms from the same industry. As such, this instrument is more likely to satisfy the exclusion condition. Additionally, our IV estimation approach rules out any biases using industry-adjusted instruments (Gormley and Matsa, 2014).

3.4. Performance variables

We follow Bennett et al. (2020) and Loderer et al. (2017) in our choice of measures to examine the effect of cyberawareness on firm operating productivity. We define *ROA* as the ratio of operating income before depreciation to total book assets. Costs per employee, *COGS/employee*, is the cost of goods sold (COGS) scaled by employees, as calculated in Loderer et al. (2017). Lastly, *Loss*, is a dummy variable equal to one if a firm's net income is negative.

3.5. Descriptive statistics

Panel A of Table 1 presents sample descriptive statistics of main variables. All continuous variables are winsorized at the 1 and 99 percentiles of their distributions. The average (median) *Cyber awareness* is 0.098 (0.037). Figure 1 plots the time series of our cybersecurity awareness measure. As shown in the figure, the mean (median) of cybersecurity awareness across firms reports an increasing trend over time. Noticeably, the trend spikes in 2011 when the SEC formally issued guidance on disclosure concerning cybersecurity risks, cyber incidents, and cyber readiness. The average *Bog index* is 86, and the average *Uncertainty* is 1.575. The average (median) leverage and profitability ratios are 0.211 (0.164) and 0.054 (0.105), respectively, which are comparable with other values reported in the literature (e.g., Mauer et al. 2021).

The average loan spread over LIBOR is 248 basis points, which is comparable with recent estimates reported in the literature (e.g., Kubick et al. 2020a 2020b, 2020c). The average loan maturity is approximately 54 months, and the average loan contains one covenant. Approximately 58% of the sample loans are secured, and 38% contain a performance pricing provision. The average bond spread over the yield to maturity of its duration equivalent Treasury bond is 240 basis points, and the average bond maturity is 128 months. Both statistics are comparable with other reports in the literature (e.g., Jiang et al. 2018).

Panel B of Table 1 reports Pearson correlations between our cyber awareness measure and main variables in the sample. Cyber awareness measure is negatively associated with loan spread and firm risk (*Stock return* and *Asset volatility*), suggesting that firms with more cyber awareness contract bank loans at lower rates and have lower risk. The positive correlation between cyber awareness and firm profitability and stock returns suggests that heavy-cyber awareness firms have better performance. However, note that it is necessary to control for firm, debt contracting, and macroeconomic characteristics before drawing any conclusions.

Table 2 reports the proportion of firms disclosing cyber awareness across Fama-French 49 industries categories as well as mean and median values of the measure. As expected, given the bulk of consumers' lists with sensible information, R&D, trade secrets, and other valuable intangible assets used by firms, the top 10 industries with the highest cybersecurity awareness include Computers, Business Services, Communication, Electronic Equipment, Pharmaceutical Products, Transportation, Retail, Medical Equipment, Candy & Soda, and Healthcare.

4. Cybersecurity awareness and debt contracting

In this section, we report regressions of our main test, documenting the effect of cybersecurity awareness on loan spread. Next, we report results for instrumental variable (IV) estimation to mitigate endogeneity concerns and strengthen identification. We also report multivariate estimates on how cybersecurity awareness influences credit rating, bond spread, and non-price loan features.

4.1. Cybersecurity awareness and bank loan spreads

To examine the effect of firm-specific cybersecurity awareness on bank loan spreads, we estimate the following OLS specification using a cross-sectional sample of firm-loans:

$$\begin{aligned} Ln(Loan\ spread)_{i,t} &= \alpha + \beta_1 Cyber\ awareness_{i,t-1} + \beta_2 Textual\ based\ controls_{i,t-1} \\ &+ \delta_1 Firm\ characteristics_{i,t-1} + \delta_2 Loan\ characteristics_{i,t-1} \\ &+ \delta_3 Macro\ controls_t + \delta_4 Industry\ FE + \epsilon_{i,t.} \end{aligned} \tag{1}$$

In specification (1), the dependent variable is the natural logarithm of the all-in-spread-drawn (*Loan spread*). The key right-hand-side variable is *Cyber awareness*. The subscript *i* indexes firm and *t* indexes year. Following Ertugrul et al. (2017) and Bonsall and Miller (2017), we also include four textual based measures to control for the complexity of 10-K statement (*Bog index*), uncertainty tone (*Uncertainty*), positive tone (*Tone*), and length of 10-K disclosure (*Word count*), respectively.[42] Following the loan contracting literature (e.g., Graham et al. 2008, Campello and Gao 2017; Kubick et al. 2020a,b), we control for firm characteristics, loan characteristics, and macroeconomic conditions. Firm characteristics include firm size, market-to-book, leverage, profitability, asset maturity, capital investment, cash flow volatility, and the modified Altman's (1968) *Z*-score. Industry fixed effects are based on Fama-French 49 industry categories. The right-hand-side variables with subscript *t–1* are measured using information prior to the loan contract.

For loan controls, we include the natural logarithm of loan maturity, whether the loan is secured, number of covenants, whether the loan has a performance pricing provision, the natural logarithm of the number of banks in the loan syndicate, the natural logarithm of the loan amount, and loan type (e.g., term loan, revolver loan, bridge loan, general-purpose loan, takeover/recap loan, and working capital loan). Along with loan characteristics, we also control for whether the

[42] See appendix A for variables definitions.

firms' debt has a Standard & Poor's long-term debt rating. For macroeconomic controls, we include default spread, term spread, and post-crisis dummy. All variables are defined in Appendix A.

Table 3 reports estimations of equation (1). Column (1) reports estimates from a regression that includes only *Cyber awareness*, firm-level controls, macroeconomic-level controls, and industry fixed effects. We see that the loan spread is significantly decreasing in *Cyber awareness*. Specifically, a one-standard-deviation increase in firm cyber awareness decreases loan spreads by 2.24% of the average loan spread in the sample. Including control variables for text-based characteristics of 10-K and loan characteristics (columns 2-4) has a robust effect on the magnitude of the coefficient estimate on *Cyber awareness*. The influence of cybersecurity awareness on loan spreads remains statistically and economically meaningful. Specifically, in the full specification in column (4), a one-standard-deviation increase in *Cyber awareness* decreases the loan spread by 5.4 bps, or 2.19% of the average loan spread.[43] Overall, these regressions support the prediction that firm-specific cybersecurity awareness decreases loan spreads.

4.2. Instrumental variable approach for the effect of cybersecurity awareness on loan spreads

The effect of cybersecurity awareness on loan spreads could suffer from endogeneity problems. For example, unobservable firm heterogeneity, such as firms' information environment, could be correlated with both cybersecurity awareness and loan spreads and could cause omitted variable bias. To address endogeneity challenges, we use instrumental variable (IV) analysis. A valid instrument for *Cyber awareness* needs to satisfy two conditions. First, the relevance condition requires that the instrument and the endogenous variable be correlated after controlling

[43] Given that the coefficient on *Cyber awareness* is 0.146 and *Cyber awareness* has a standard deviation of 0.15, a one standard deviation increase in *Cyber awareness* would decrease the loan spread by 2.19% (= 0.146× 0.15).

for all exogenous variables in the model. Second, the exclusion condition requires that the instrument be uncorrelated with the error term of the second-stage regression (Angrist and Pischke 2008).

The influence of geographically proximate peers on multiple aspects of a firm is well documented in the finance literature, as well as its use to strengthen causal identifications. Bouwman (2012) and Coles et al. (2018) document that CEO pay of a firm in consideration is related to the pay of its geographically proximate CEOs, and Coles et al. (2018) exploits this as an identification strategy. Similarly, Kedia and Rajgopal (2009) posit that competition for employees causes firms to grant more stock options to rank-and-file workers when a higher proportion of geographically close firms grant more options, and John et al. (2011) document the impact of geography on agency costs and payout policy. In the cyber-related literature, Jamilov et al. (2021) show that cyber risk exposure and the sentiment towards cyber threats are geographically clustered among firms. Anecdotal evidence from business news press and security firms' guidance also lends strong support to the stylized fact that there is a positive correlation between a firm's cyber awareness and that of corporations in their geographic proximity (e.g., Valli et al. 2014; Perlroth 2014; Brice 2020; Taggart n.d.)

Building upon this background, we use the yearly average of the cybersecurity awareness measure of firms in different industries that are headquartered within a 250-km radius of firm *i*, *Geo cyber awareness*, as our instrument for firm *i*'s *Cyber awareness*. We expect the average cybersecurity awareness measure of geographically close firms to be positively associated with firm's *i* cybersecurity awareness. Since our instrumental variable is constructed from firms outside the industry to which the firm of interest belongs, this instrument is more likely to satisfy the exclusion condition. Additionally, our IV estimation approach rules out biases originated from using industry-adjusted instruments (Gormley and Matsa, 2014).

Table 4 reports the results of our IV estimation. Column (1) reports the first stage results, where we regress *Cyber awareness* on the *Geo cyber awareness* instrumental variable, all control variables from specification (1), and industry fixed effects. The predicted value of cyber awareness is then used as regressor in a second stage loan spread regression. The significantly positive coefficient on *Geo cyber awareness* and the underidentification test *p*-value indicate that our instrument satisfies the relevance condition. We report the second stage regressions in Table 4 column (2). We continue to find a significantly negative coefficient on Predicted *Cyber awareness* in the loan spread regressions.[44]

4.3. Cybersecurity awareness and credit rating

To examine the effect of cybersecurity awareness on credit ratings, we estimate the following OLS specification:

$$\begin{aligned} Credit\ rating_{i,t} &= \alpha + \beta_1 Cyber\ awareness_{i,t-1} + \beta_2 Textual\ based\ controls_{i,t-1} \\ &+ \delta_1 Firm\ characteristics_{i,t-1} + \delta_2 Macro\ controls_t + \delta_3 Industry\ FE \\ &+ \epsilon_{i,t.} \end{aligned} \tag{2}$$

In specification (2), the dependent variable, *Credit rating*, is the Standard & Poor's long-term debt rating, coded from 1 (D) to 22 (AAA), with higher values corresponding to better ratings (e.g., Anderson et al. 2004; Jiang et al. 2018). Text-based controls, firm characteristics, macro controls, and industry fixed effects are the same as in specification (1).

The regression results are reported in Table 5. Column (1) presents the ordinary least squares (OLS) regression results with *Cyber awareness* and firm controls; column (2) reports the

[44] We report the statistics for under-identification and weak identification tests at the bottom of Table 7. These tests confirm that the instruments satisfy the relevance criterion.

result of the regression when controlling for *Bog index*; and column (3) presents results for the full specification. In all three specifications, the coefficient on the variable of interest *Cyber awareness* is significantly positive. These results indicate that all else equal, firms with higher cybersecurity awareness receive higher credit ratings. The effect is statistically strong, with the coefficient estimates ranging from 0.726 to 0.772. In terms of economic significance, a one-standard deviation increase in *Cyber awareness* increases the long-term S&P bond rating of the mean firm in the sample by more than two-thirds of a notch. The average firm in the sample has a credit rating close to 12, which corresponds to a credit rating of BB+. Thus, cyberawareness increases the long-term S&P bond rating of the mean firms in the sample from BB + to about BBB– .[45]

4.4. Cybersecurity awareness and bond spreads

In this section, we examine the effect of cybersecurity awareness on bond spreads by estimating the following OLS specification:

$$\begin{aligned} Ln(Bond\ spread)_{i,t} &= \alpha + \beta_1 Cyber\ awareness_{i,t-1} + \beta_2 Textual\ based\ controls_{i,t-1} \\ &+ \delta_1 Firm\ characteristics_{i,t-1} + \delta_2 Bond\ characteristics_{i,t-1} \\ &+ \delta_3 Macro\ controls_t + \delta_3 Industry\ FE + \epsilon_{i,t.} \end{aligned} \tag{3}$$

In specification (3), the dependent variable, *Bond spreads*, is the difference between the yield to maturity of a corporate bond and the yield to maturity of its duration equivalent Treasury bond, measured in basis points. Text-based controls, firm characteristics, macro controls, and industry fixed effects are the same as in specification (1). Following the literature (e.g., Klock et al. 2005; Borisova et al. 2015; Jiang et al. 2018), we also control for bond characteristics, including the natural logarithm of bond amount (*Amount*), the natural logarithm of bond maturity in months

[45] In the full specification in (3), a one-standard-deviation increase in *Cyber awareness* improves Credit rating by approximately 0.11 (i.e., = 0.727 * 0.150). The magnitude of the economic impact of cybersecurity awareness is smaller than that of *Market-to-book* (moving from the first to the third quartile of Market-to-book increases credit rating by 1.34), *Leverage* (1.01), and *ROA* (0.54).

(*Maturity*), an indicator variable whether the bond is subordinated (*Subordinated dummy*), puttable (*Puttable dummy*), or callable (*Callable dummy*), respectively.

Table 6 reports the results. Column (1) reports estimates from a regression that includes only *Cyber awareness*, firm-level controls, macroeconomic-level controls, and industry fixed effects. We add bond characteristics in column (2) and textual-based controls in column (3). As seen in all the columns, the coefficient on *Cyber awareness* variable is significantly negative at the 10% significance level. Although the statistical significance is low, this analysis suggests that public debt markets react to firms self-disclosed cyber readiness, leading to bond spread being significantly decreasing in *Cyber awareness*. The impact of cybersecurity awareness on bond spreads is also economically meaningful. For example, in the full specification in column (3), a one-standard-deviation increase in *Cyber awareness* decreases the bond spread by 5.4 bps, or 2.27% of the average bond spread.[46] Overall, these regressions support the prediction that firm-specific cybersecurity awareness decreases bond spreads.

4.5. Cybersecurity awareness and non-price loan features

This section examines whether firm-specific cybersecurity awareness affects non-price features of loans, including loan maturity, covenant count, performance pricing, and security. We estimate the following model:

$$\begin{aligned} Loan\ feature_{i,t} &= \alpha + \beta_1 Cyber\ awareness_{i,t-1} + \beta_2 Textual\ based\ controls_{i,t-1} \\ &+ \delta_1 Firm\ characteristics_{i,t-1} + \delta_2 Loan\ characteristics_{i,t-1} \\ &+ \delta_3 Macro\ controls_t + \delta_4 Industry\ FE + \epsilon_{i,t.} \end{aligned} \tag{4}$$

The controls in equation (4) are the same as in the loan spread equation (1): 10-K's textual characteristics, firm characteristics, loan characteristics, macro controls, and industry fixed effects.

[46] Given that the coefficient on *Cyber awareness* is 0.151 and *Cyber awareness* has a standard deviation of 0.15, a one standard deviation increase in *Cyber awareness* would decrease the bond spread by 2.27% (= 0.151× 0.15).

Table 7 reports the results. The dependent variables in columns (1) – (4) are the natural logarithm of loan's maturity in months, a count of the number of covenants in the loan, a dummy variable equal to one if the loan has a performance pricing provision, and a dummy variable equal to one if the loan facility is secured by collateral, respectively. The results show that the coefficient estimate on *Cyber awareness* is statistically significant only in the *Covenant count* regression in column (2). It suggests that loans issued to firms with higher cybersecurity awareness include fewer covenants. The effect is marginally economically significant, a one-standard-deviation increase in *Cyber awareness* decreases the number of covenants by 0.04 (3.18%).

5. Mechanisms: Default risk and operating efficiency

Thus far the results in section 4 show that all else equal, higher cybersecurity awareness improves debt contracting terms, as measured by lower loan spread, better credit rating, and lower bond spread. To further identify the potential mechanisms driving the relations between cybersecurity awareness and cost of debt, we examine the role of firm's default risk in moderating our baseline result as well as the effect of cyberawareness on operating efficiency.

5.1. Cybersecurity awareness and default risk

This section investigates how default risk modulates the effect of cyber awareness on bank loan spreads. We examine how the negative relation between cyberawareness and loan spread varies across firms with different levels of default risk. We hypothesize that the effects of cyber readiness on debt contract terms should be stronger for firms that have a higher likelihood of default because for those firms being better prepared to deal with the risk of a cyberattack would, all else equal, reduce the odds of such firms having to default on their debt service. In other words, higher cyberawareness reduces their likelihood of default.

We use three measures of default risk: Altman Z-score, Merton model expected default frequency (Merton EDF), and a Naïve model expected default frequency (Naïve EDF). *Z-Score* is the modified Altman (1968) Z-score, where a below-median value indicates a higher likelihood of default. *Merton EDF* is computed following the Merton (1974) bond pricing model, and *Naïve EDF* is computed based on the "simplified" Merton model probability of default following Bharath and Shumway (2008). Higher default frequency corresponds to a higher probability of default. The above-median values of Merton EDF and naïve EDF indicate a higher likelihood of default. Appendix C offer construction details for both EDF measures.

We group firms into high and low default risk by whether a firm's default risk measure is above or below the yearly median and estimate our baseline specification (equation (1)) for each of them. Table 8 reports high and low default risk subsample regressions. For brevity, we only report coefficient estimates on cyber awareness. To formally test the equality of coefficients on cyber awareness in the subsample regressions, we apply a Chow test and report the *p*-values in the table. The tests indicate that the coefficients are significantly different across all high and low default risk sub-groups. Consistent with our expectation, the results show that the negative effect of cyber readiness on loan spreads is significantly stronger for firm with high default risk (i.e., firms with below-median Z-score and above median EDF).

Thus far the results in section 4 show that all else equal, higher cybersecurity awareness improves debt contracting terms, as measured by lower loan spread, better credit rating, and lower bond spread. In this section we conduct additional tests to identify potential mechanisms behind these results. First, we hypothesize that the effects of cyber readiness on debt contract terms should be stronger for firms that have a higher likelihood of default because being better prepared to deal with the risk of a cyberattack would, all else equal, protect this high-risk firms more from defaulting on their debt service.

5.2. Cybersecurity awareness and operating efficiency

We now examine the impact of cyber awareness on operating efficiency. Investment in cybersecurity awareness equips firms with better protection of their intangible assets and operating network against potential attacks. We hypothesize that the positive valuation the debt market assigns to borrowers with higher *Cyber awareness* is in part driven by creditors expectation that such preventive investments have a positive effect on firm operating efficiency. We follow Bennett et al. (2020) and Loderer et al. (2017) to explore this mechanism. We define *ROA* as the ratio of operating income before depreciation to total book assets. Costs per employee, *COGS/employee*, is the cost of goods sold (COGS) scaled by employees, as calculated in Loderer et al. (2017). Lastly, *Loss* is a dummy variable equal to one if a firm's net income is negative. We expect to observe a positive (negative) effect of cyber readiness on *ROA* (*COGS/employee* and *Loss*).

Table 9 reports the results, where all models are OLS regressions except for models (3) and (4) which are probit regressions. Consistent with our expectations, we find that profitability is increasing in *Cyber awareness*, whereas the probability of reporting a loss and costs per employee, are decreasing in *Cyber awareness.* Columns (1), (3), and (5) report results from a regression that includes only *Cyber awareness*, industry, and year fixed effects. We report full specifications that add controls for firm characteristics and textual based variables in columns (2), (4), and (6). In terms of economic significance, a one-standard-deviation increase in *Cyber awareness* increases *ROA* by 3% for the average firm in the sample. For the average costs per employee estimates, a one-standard-deviation increase in *Cyber awareness* decreases *COGS/Employee* by 2.2% for the average firm in the sample.[47] Lastly, for our *Loss* models we report marginal effects, computed as the probability of paying dividends for a one-unit change in an independent variable, holding all other variables at their means. As seen the table, the propensity to report a loss is decreasing in *Cyber awareness*. The marginal effect in column (4) shows that a one-unit increase in *Cyber awareness* decreases the probability of a loss by 4.7% holding the rest of the variables at their means. Overall, the results suggest that improved firm operating efficiency is one of the mechanisms through which cyber awareness leads to better debt contracting terms for borrowing firms.

6. Conclusions

The increasing threat of costly cyberattacks on corporations has prompted concern among regulators, corporations, and society at large about firms' cybersecurity awareness. In response regulators such as the SEC have issued increasing guidelines and regulation pertaining how firms should disclose cyber risk and cyber readiness to investors. In parallel, cybersecurity awareness has become one of the key concerns for executive teams, leading firms to investing in information technologies and human resources to protect themselves against cyberattack and conduct efficient damage control in the event of a successful attack. The costs from any successful cyberattack is lower when firms have ex ante risk management policies in place (Kamiya et al. 2020). Also, firms providing disclosures on such cyber risk in their annual statements could reduce litigation risk ex post the attack. In this paper, we exploit a textual-based measure of firm-specific cybersecurity awareness discussed in annual statements constructed to capture preventive measures taken by

[47] In unreported robustness tests, we also estimate firm productivity regressions using the Cyberawareness-Compustat-Loan sample. Results are consistent with those reported in Table 8. We also estimate firm productivity regressions with two alternative dependent variables, a firm's sales scaled by book value (*Sales/BV*) and a firm's sales scaled by the value of assets in place (*Sales/VAIP*) as calculated in Loderer et al. (2016). We find no significant results when using these two alternative proxies of operating efficiency.

firms against any cyberattack. Using this measure, we examine how creditors perceive the preventive measures taken by firms against cyberattacks and how they embed this risk perception in debt contracting.

We find that cybersecurity awareness reduces bank loan spreads. This result is robust to using an instrumental variable approach where we instrument firm-specific cyberawareness with the yearly average of the cybersecurity awareness measure of geographically proximate firms. We also document that all else equal, higher cybersecurity awareness is associated with better credit ratings, lower bond spreads, and lower covenant counts in bank loans. These results suggest that creditors positively evaluate firms' precautionary measures to manage cyber risk. Consistent with the view that cyberawareness likely protects firms' intangible assets and allows them to operate more efficiently, we document higher profitability lower probability of reporting a loss, and lower costs per employee as mechanisms through which cybersecurity awareness affects firm outcomes and contribute to explain the improvement in debt contracting terms. The latter results are consistent with extant literature that shows firms with higher cyberawareness observe higher stock returns and market value.

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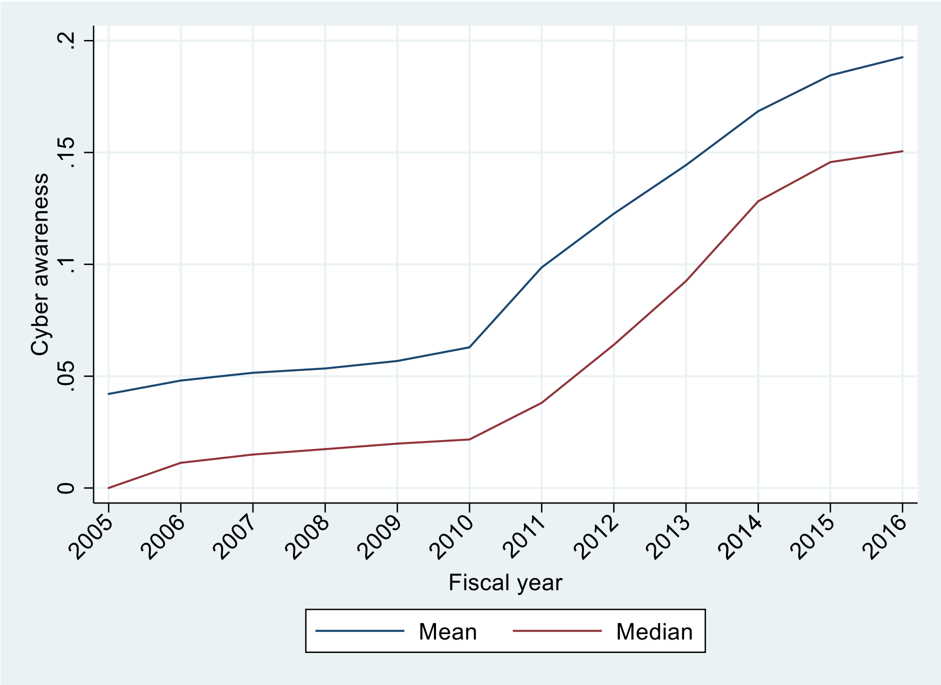
Figures

Figure 2.1. Time Trend of cybersecurity awareness

The figure displays yearly average and median of cybersecurity awareness measure from fiscal year 2005 to 2016.



Tables

Table 2.1. Descriptive statistics and correlations

Panel A reports descriptive statistics over the 2005 to 2016 period. Financial services firms and utility firms are excluded from the sample. All the variables are defined in Appendix A. Panel B reports Pearson correlation coefficients for the main variables. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. All continuous variables are winsorized at the 1% and 99% levels of the distribution.

Panel A. Descriptive statistics						
	Mean	Std. dev.	P25	Median	P75	Obs.
Key independent variable						
Cyber awareness	0.098	0.150	0.000	0.037	0.146	31,784
10-K text-based readability variables						
Bog index	86.045	6.485	81.000	86.000	90.000	31,784
Uncertainty	1.575	0.271	1.390	1.579	1.765	31,784
Tone	-0.927	0.429	-1.202	-0.914	-0.636	31,784
Ln(Word count)	10.599	0.429	10.334	10.598	10.868	31,784
Instrumental variables						
Geo cyber awareness	0.089	0.056	0.045	0.066	0.131	30,589
Firm characteristics						
Total assets ($000,000)	2,932	7,892	111	455	1,864	31,784
Market-to-book	2.054	1.533	1.130	1.552	2.366	31,784
Leverage	0.211	0.217	0.007	0.164	0.333	31,784
ROA	0.054	0.223	0.034	0.105	0.161	31,784
Cash	0.220	0.231	0.044	0.135	0.321	31,784
Sales growth	29.686	92.524	1.959	9.482	22.553	31,784
Stock returns	0.107	0.551	-0.229	0.040	0.326	31,784
Returns vol	0.144	0.190	0.041	0.079	0.163	31,784
Asset vol	0.421	0.235	0.258	0.360	0.514	31,784
R&D	0.503	2.785	0.000	0.005	0.091	31,784
Asset maturity	8.185	7.315	3.303	5.912	10.640	31,644
Capital invest	0.243	0.235	0.065	0.155	0.348	31,770
Cash flow volatility	0.068	0.078	0.025	0.043	0.077	31,770
Z score	0.444	4.105	0.211	1.435	2.418	31,148
Rated dummy	0.292					31,784
Credit rating	11.844	3.306	9	11	14	9,280
COGS/employee	198.195	345.242	1.978	68.281	198.681	31,770
Loss	0.330					31,770
Bank loan variables						
Loan spread (bps)	247.840	161.330	150.000	200.000	300.000	11,747
Maturity (months)	53.961	18.274	48.000	60.000	60.000	11,747
Secured	0.584					11,747
Covenant count	1.211	1.230	0.000	1.000	2.000	11,747
Performance pricing	0.380	0.485	0.000	0.000	1.000	11,747
Ln(No. of banks)	1.916	0.718	1.386	1.946	2.398	11,747
Ln(Amount)	5.388	1.440	4.500	5.521	6.397	11,747
Term loan	0.353					11,747
Revolver loan	0.620					11,747

Table 2.1- *Continued*

	Mean	Std. dev.	P25	Median	P75	Obs.
Bridge loan	0.023					11,747
General purpose loan	0.564					11,747
Takeover/recap loan	0.105					11,747
Working capital loan	0.144					11,747
<u>Bond variables</u>						
Bond spread	240.103	202.841	98.514	165.767	326.572	4,411
Maturity	128.332	99.377	61.000	97.000	121.000	4,411
Ln(Amount)	6.233	0.755	5.704	6.215	6.745	4,411
Subordinated dummy	0.003					4,411
Puttable dummy	0.007					4,411
Callable dummy	0.866					4,411
<u>Macroeconomic variables</u>						
Default spread (%)	1.197	0.611	0.900	1.080	1.320	11,747
Term spread (%)	2.395	1.101	2.200	2.340	3.000	11,747
Post-crisis dummy	0.723					11,747

Panel B. Pearson correlations

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	*Cyber awareness*	1.00					
(2)	*Loan spread*	-0.04***	1.00				
(3)	*Returns vol*	-0.14***	0.26***	1.00			
(4)	*Asset vol*	-0.15***	0.22***	0.76***	1.00		
(5)	*R&D*	-0.06***	0.00	0.16***	0.25***	1.00	
(6)	*Total assets*	0.14***	-0.24***	-0.37***	-0.59***	-0.19***	1.00
(7)	*Market-to-book*	0.05***	-0.17***	-0.02***	0.16***	0.20***	-0.20***
(8)	*Leverage*	-0.03***	0.20***	0.05***	-0.30***	-0.07***	0.31***
(9)	*ROA*	0.10***	-0.22***	-0.41***	-0.50***	-0.45***	0.44***
(10)	*Cash*	-0.02**	0.00	0.11***	0.38***	0.38***	-0.38***
(11)	*Sales growth*	-0.07***	-0.01	0.14***	0.19***	0.15***	-0.14***
(12)	*Stock returns*	0.02***	-0.05***	-0.24***	-0.15***	-0.03***	0.06***

Panel B. Pearson correlations

		(7)	(8)	(9)	(10)	(11)
(7)	*Market-to-book*	1.00				
(8)	*Leverage*	-0.14***	1.00			
(9)	*ROA*	-0.20***	0.05***	1.00		
(10)	*Cash*	0.43***	-0.36***	-0.46***	1.00	
(11)	*Sales growth*	0.19***	-0.02**	-0.25***	0.21***	1.00
(12)	*Stock returns*	0.26***	-0.04***	0.17***	0.01*	-0.02***

Table 2.2. Cybersecurity awareness distribution by Fama-French 49 industries

The table reports the sample distribution of cybersecurity awareness measure by Fama-French 49 industry categories. The sample period runs from fiscal year 2005 to 2016.

Fama-French industry	Obs.	% of firms disclosing cyber awareness	*Cyber awareness* Mean	*Cyber awareness* Median
Agriculture	101	38%	0.090	0.000
Aircraft	204	53%	0.110	0.016
Almost Nothing	195	65%	0.098	0.031
Apparel	467	62%	0.093	0.037
Automobiles and Trucks	596	48%	0.065	0.000
Beer & Liquor	114	47%	0.056	0.000
Business Services	4,508	86%	0.165	0.130
Business Supplies	401	46%	0.066	0.000
Candy & Soda	116	68%	0.070	0.028
Chemicals	849	60%	0.085	0.021
Coal	138	61%	0.028	0.012
Communication	996	85%	0.143	0.107
Computers	1,256	94%	0.146	0.098
Construction	489	44%	0.046	0.000
Construction Materials	645	35%	0.052	0.000
Consumer Goods	511	58%	0.112	0.025
Defense	105	63%	0.122	0.038
Electrical Equipment	651	54%	0.065	0.020
Electronic Equipment	2,391	82%	0.085	0.040
Entertainment	499	57%	0.096	0.022
Fabricated Products	89	49%	0.054	0.000
Food Products	612	45%	0.119	0.000
Healthcare	690	67%	0.080	0.031
Machinery	1,197	53%	0.073	0.021
Measuring and Control Equipment	849	63%	0.079	0.026
Medical Equipment	1,330	71%	0.052	0.025
Non-Metallic and Industrial Metal Mining	175	35%	0.046	0.000
Personal Services	462	66%	0.121	0.069
Petroleum and Natural Gas	1,887	43%	0.050	0.000
Pharmaceutical Products	2,800	78%	0.045	0.023
Precious Metals	80	38%	0.065	0.000
Printing and Publishing	246	50%	0.112	0.000
Recreation	232	65%	0.065	0.025
Restaurants, Hotels, Motels	688	61%	0.080	0.038
Retail	1,947	75%	0.165	0.123
Rubber and Plastic Products	196	48%	0.064	0.000
Shipbuilding, Railroad Equipment	107	52%	0.062	0.036
Shipping Containers	91	54%	0.133	0.110
Steel Works Etc.	435	42%	0.052	0.000
Textiles	95	45%	0.046	0.000
Tobacco Products	56	46%	0.026	0.000
Transportation	1,046	76%	0.135	0.082
Wholesale	1,242	59%	0.099	0.032

Table 2.3. Cybersecurity awareness and loan spreads

The table reports OLS regressions of bank loan spread on cybersecurity awareness, firm and loan characteristics, and macroeconomic controls, and industry fixed effects. The dependent variable is the natural logarithm of the all-in-spread drawn from the DealScan database, which is the amount the firm pays in basis points above LIBOR (or LIBOR equivalent) plus any additional fees for each dollar drawn down for the loan facility. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. The economic significance of the coefficient estimates on cyberawareness are reported in square brackets. They measure the effect of a one-standard-deviation increase in cyberawareness on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dependent variable =	Ln(*Loan spread*)			
	(1)	(2)	(3)	(4)
Cyber awareness	-0.149***	-0.141***	-0.138***	-0.146***
	(-2.60)	(-3.41)	(-3.30)	(-3.55)
	[–2.24%]	[–2.12%]	[–2.07%]	[–2.19%]
Bog index			0.002*	0.001
			(1.73)	(0.44)
Uncertainty				-0.019
				(-0.69)
Tone				-0.114***
				(-6.51)
Ln(*Word count*)				0.050**
				(2.33)
Ln(*Total assets*)	-0.139***	-0.040***	-0.041***	-0.049***
	(-17.99)	(-5.45)	(-5.60)	(-6.47)
Market-to-book	-0.098***	-0.062***	-0.062***	-0.061***
	(-8.14)	(-6.96)	(-6.93)	(-6.86)
Leverage	0.511***	0.290***	0.282***	0.284***
	(10.64)	(7.46)	(7.28)	(7.38)
ROA	-0.818***	-0.680***	-0.664***	-0.605***
	(-5.53)	(-6.35)	(-6.28)	(-5.81)
Asset maturity	-0.007***	-0.003**	-0.003**	-0.003*
	(-2.99)	(-2.07)	(-1.99)	(-1.72)
Capital invest	-0.006	0.052	0.057	0.050
	(-0.07)	(0.82)	(0.90)	(0.82)
Cash flow volatility	1.473***	1.463***	1.463***	1.251***
	(5.23)	(6.77)	(6.74)	(5.82)
Z score	-0.075***	-0.042***	-0.041***	-0.036***
	(-7.82)	(-6.04)	(-5.87)	(-5.07)
Rated dummy		0.012	0.013	0.017
		(0.74)	(0.82)	(1.07)
Ln(*Maturity*)		0.099***	0.098***	0.098***
		(5.97)	(5.96)	(6.08)
Secured		0.336***	0.334***	0.326***
		(24.16)	(23.98)	(23.56)
Covenant count		-0.012**	-0.012**	-0.011**
		(-2.14)	(-2.09)	(-2.03)
Performance pricing		-0.137***	-0.136***	-0.134***
		(-10.59)	(-10.55)	(-10.47)
Ln(*No. of banks*)		-0.037***	-0.037***	-0.036***

Table 2.3-- *Continued*

Dependent variable =	Ln(*Loan spread)*			
	(1)	(2)	(3)	(4)
		(-3.26)	(-3.28)	(-3.19)
Ln(*Amount*)		-0.105***	-0.105***	-0.105***
		(-14.17)	(-14.24)	(-14.36)
Term loan		0.055	0.051	0.037
		(0.69)	(0.65)	(0.48)
Revolver loan		-0.223***	-0.225***	-0.239***
		(-2.83)	(-2.86)	(-3.07)
Bridge loan		0.357***	0.352***	0.338***
		(3.76)	(3.71)	(3.60)
General purpose loan		-0.289***	-0.289***	-0.286***
		(-17.64)	(-17.65)	(-17.59)
Takeover/recap loan		-0.050**	-0.051**	-0.044**
		(-2.24)	(-2.29)	(-1.96)
Working capital loan		-0.297***	-0.298***	-0.295***
		(-14.20)	(-14.27)	(-14.25)
Default spread	0.060***	0.076***	0.075***	0.071***
	(4.13)	(6.88)	(6.83)	(6.37)
Term spread	0.062***	0.068***	0.069***	0.073***
	(7.28)	(10.21)	(10.25)	(10.78)
Post-crisis dummy	0.384***	0.435***	0.429***	0.398***
	(13.72)	(19.88)	(19.17)	(17.51)
Industry FE	Yes	Yes	Yes	Yes
Observations	11,747	11,747	11,747	11,747
Adj. *R*-sq	0.372	0.595	0.595	0.600

Table 2.4. IV estimation of cybersecurity awareness and loan spreads

The table reports the results of two-stage IV regressions where cyberawareness is treated as endogenous variable. Column (1) reports first-stage results where we use *Geo cyber awareness* as the instrumental variable for cyberawareness. *Geo cyber awareness* is defined as the average cybersecurity awareness of firms in a different industry that are headquartered within a 250-km radius of the firm. Column (2) reports second-stage results where the dependent variable is the natural logarithm of the all-in-spread drawn from the DealScan database, which is the amount the firm pays in basis points above LIBOR (or LIBOR equivalent) plus any additional fees for each dollar drawn down for the loan facility. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. We report the *p*-value of the Kleibergen-Paap rk LM χ^2-statistic (underidentification test) and the *F*-statistic of the Kleibergen-Paap rk Wald test (weak instruments test), where the significance of the latter is based on Stock-Yogo critical values. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

	First-stage	Second-stage
	(1)	(2)
Dependent variable =	*Cyber awareness*	Ln(*Loan spread*)
Predicted *Cyber awareness*		-1.187***
		(-4.34)
Geo cyber awareness (IV)	0.722***	
	(5.33)	
Bog index	-0.001**	-0.001
	(-2.06)	(-0.45)
Uncertainty	-0.016	-0.047
	(-1.51)	(-1.62)
Tone	-0.002	-0.119***
	(-0.30)	(-6.28)
Ln(Word count)	-0.003	0.055**
	(-0.37)	(2.31)
Ln(Total assets)	0.009***	-0.041***
	(3.55)	(-4.82)
Market-to-book	0.012***	-0.044***
	(4.41)	(-4.20)
Leverage	-0.031*	0.264***
	(-1.95)	(6.01)
ROA	0.049	-0.578***
	(1.52)	(-5.29)
Asset maturity	-0.001*	-0.003*
	(-1.77)	(-1.96)
Capital invest	-0.043**	0.012
	(-2.41)	(0.19)
Cash flow volatility	-0.010	1.085***
	(-0.14)	(4.71)
Z score	0.003	-0.029***
	(1.36)	(-3.79)
Rated dummy	0.001	0.007
	(0.09)	(0.44)
Ln(Maturity)	-0.003	0.092***
	(-0.79)	(5.51)
Secured	0.003	0.333***
	(0.74)	(22.22)
Covenant count	-0.003**	-0.015**

Table 2.4 -- *Continued*

	First-stage	Second-stage
	(1)	(2)
Dependent variable =	Cyber awareness	Ln(Loan spread)
	(-2.10)	(-2.52)
Performance pricing	0.003	-0.131***
	(0.70)	(-9.44)
Ln(No. of banks)	-0.008**	-0.040***
	(-2.48)	(-3.29)
Ln(Amount)	0.002	-0.102***
	(1.24)	(-12.91)
Loan-type and loan-purpose FE	Yes	Yes
Macroeconomic controls	Yes	Yes
Industry FE	Yes	Yes
Observations	11,362	11,362
Underidentification test *p*-value	0.000	
Kleibergen-Paap rk *F*- statistic		110.88***

Table 2.5. Cybersecurity awareness and credit ratings

The table reports OLS regressions of credit ratings on cybersecurity awareness, firm controls, macroeconomic controls, and industry fixed effects. The dependent variable is the Standard and Poor's long-term debt rating, *Credit rating*, coded from 1 (D) to 22 (AAA). All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dependent var. =		*Credit rating*	
	(1)	(2)	(3)
Cyber awareness	0.772***	0.726***	0.727***
	(3.84)	(3.56)	(3.41)
Bog index		-0.050***	-0.016*
		(-5.22)	(-1.67)
Uncertainty			-69.266***
			(-3.46)
Tone			68.219***
			(5.62)
Ln(Word count)			-1.113***
			(-8.21)
Ln(Total assets)	1.369***	1.397***	1.441***
	(27.37)	(28.14)	(29.87)
Market-to-book	1.072***	1.036***	0.936***
	(11.58)	(11.53)	(12.39)
Leverage	-2.328***	-2.182***	-2.169***
	(-8.29)	(-8.09)	(-7.81)
ROA	0.786	0.633	1.549*
	(0.78)	(0.64)	(1.79)
Asset maturity	0.019	0.019*	0.019*
	(1.59)	(1.72)	(1.80)
Capital invest	-0.339	-0.447	-0.499
	(-0.92)	(-1.23)	(-1.45)
Cash flow volatility	-5.498***	-5.230***	-5.587***
	(-3.07)	(-2.90)	(-3.33)
Z score	0.447***	0.433***	0.396***
	(6.57)	(6.28)	(5.90)
Default spread	0.189***	0.205***	0.299***
	(7.24)	(7.50)	(10.31)
Term spread	0.052**	0.034	-0.002
	(2.45)	(1.57)	(-0.10)
Post-crisis dummy	-0.280***	-0.147*	0.246***
	(-3.24)	(-1.66)	(2.64)
Industry FE	Yes	Yes	Yes
Observations	10,095	9,744	9,577
Adj. R-sq	0.665	0.672	0.696

Table 2.6. Cybersecurity awareness and bond spreads

This table reports the results of OLS regressions of bond spread on cybersecurity awareness, firm and bond characteristics, macroeconomic controls, and industry fixed effects. The dependent variable is the natural logarithm of the difference between the yield to maturity of a corporate bond and the yield to maturity of its duration equivalent Treasury bond. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. The economic significance of the coefficient estimates on cyberawareness are reported in square brackets. They measure the effect of a one-standard-deviation increase in cyberawareness on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dependent variable =	Ln(*Bond spread*)		
	(1)	(2)	(3)
Cyber awareness	-0.164*	-0.153*	-0.151*
	(-1.87)	(-1.68)	(-1.72)
	[–2.46%]	[–2.30%]	[–2.27%]
Bog index			0.003
			(0.79)
Uncertainty			-1.456
			(-0.25)
Tone			0.519
			(0.13)
Ln(Word count)			0.087**
			(1.97)
Ln(Total assets)	-0.205***	-0.262***	-0.269***
	(-16.55)	(-18.66)	(-18.01)
Market-to-book	-0.243***	-0.251***	-0.248***
	(-9.75)	(-11.37)	(-11.73)
Leverage	0.834***	0.806***	0.778***
	(8.25)	(8.56)	(8.07)
ROA	0.394	-0.021	0.030
	(1.54)	(-0.09)	(0.13)
Asset maturity	0.001	-0.002	-0.002
	(0.17)	(-0.40)	(-0.54)
Capital invest	-0.100	-0.024	0.049
	(-0.68)	(-0.18)	(0.35)
Cash flow volatility	1.557***	2.046***	1.915***
	(2.65)	(3.59)	(3.35)
Z score	-0.035	-0.035*	-0.034
	(-1.56)	(-1.68)	(-1.63)
Ln(Amount)		0.145***	0.139***
		(5.77)	(5.54)
Ln(Maturity)		0.196***	0.189***
		(8.89)	(8.19)
Subordinated dummy		-0.014	-0.036
		(-0.05)	(-0.12)
Puttable dummy		-1.074***	-1.011***
		(-6.02)	(-6.03)
Callable dummy		0.302***	0.320***
		(4.72)	(4.74)
Default spread	0.194***	0.205***	0.197***
	(7.56)	(8.56)	(8.13)
Term spread	0.071***	0.077***	0.080***
	(5.03)	(5.70)	(5.27)
Post-crisis dummy	-0.006	0.001	-0.041
	(-0.12)	(0.03)	(-0.90)
Industry FE	Yes	Yes	Yes

Table 2.6 --*Continued*

Dependent variable =	Ln(*Bond spread*)		
	(1)	(2)	(3)
Observations	4,410	4,410	4,152
Adj. *R*-sq	0.464	0.536	0.541

Table 2.7. Cybersecurity awareness and non-price loans

The table reports regressions of non-price features of loans on cybersecurity awareness, firm and loan characteristics, macroeconomic controls, and industry fixed effects. The dependent variables in regressions (1)-(4) are the natural logarithm of loan maturity in months, a count of the number of covenants in the loan facility, a dummy variable for whether the loan has a performance pricing provision, and a dummy variable if the loan is secured by collateral, respectively. Column (1) reports OLS regression, column (2) repots Poisson regression, and columns (3) and (4) report marginal effects of probit regressions. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dep var =	Ln(*Maturity*)	*Covenant count*	*Performance pricing*	*Secured*
	(1)	(2)	(3)	(4)
Cyber awareness	-0.009	-0.257***	0.028	0.178
	(-0.24)	(-2.62)	(0.22)	(1.12)
Bog index	0.001	-0.003	-0.005	0.005
	(1.01)	(-1.00)	(-1.30)	(1.07)
Uncertainty	0.079***	-0.079	0.005	0.052
	(3.16)	(-1.38)	(0.06)	(0.50)
Tone	-0.004	-0.012	0.050	-0.219***
	(-0.29)	(-0.35)	(0.97)	(-3.37)
Ln(Word count)	-0.007	-0.045	-0.031	0.285***
	(-0.37)	(-1.01)	(-0.50)	(3.49)
Ln(Total assets)	-0.056***	-0.137***	-0.013	-0.241***
	(-7.78)	(-8.19)	(-0.63)	(-8.57)
Market-to-book	-0.026***	-0.054***	0.049**	-0.112***
	(-3.46)	(-3.46)	(2.30)	(-3.77)
Leverage	-0.109***	-0.082	-0.775***	1.327***
	(-3.05)	(-0.89)	(-6.51)	(8.43)
ROA	0.604***	0.895***	0.211	-2.050***
	(5.85)	(4.47)	(0.69)	(-5.15)
Asset maturity	0.000	-0.001	-0.004	-0.023***
	(0.14)	(-0.39)	(-0.97)	(-4.05)
Capital invest	-0.062	0.055	0.165	0.411**
	(-1.40)	(0.52)	(1.11)	(2.08)
Cash flow volatility	-1.288***	-0.756*	-0.368	4.559***
	(-5.14)	(-1.66)	(-0.59)	(5.60)
Z score	-0.004	-0.023	0.007	-0.054*
	(-0.62)	(-1.64)	(0.32)	(-1.87)
Rated dummy	0.013	-0.067*	0.076	0.143**
	(0.88)	(-1.73)	(1.49)	(2.25)
Ln(Maturity)		-0.145***	0.034	0.538***
		(-5.22)	(0.85)	(12.47)
Secured	0.148***	0.384***	0.095**	
	(12.01)	(11.78)	(2.27)	
Covenant count	-0.026***		0.457***	0.312***
	(-5.12)		(26.09)	(13.69)
Performance pricing	0.013	0.709***		0.060
	(1.12)	(24.22)		(1.40)
Ln(No. of banks)	0.103***	0.191***	0.549***	-0.407***
	(9.09)	(7.86)	(16.10)	(-10.53)

Table 2.7 --*Continued*

Dep var =	Ln(*Maturity*)	*Covenant count*	*Performance pricing*	*Secured*
	(1)	(2)	(3)	(4)
Ln(Amount)	0.055***	0.010	0.048***	0.052**
	(8.53)	(0.73)	(2.96)	(2.56)
Term loan	0.097	0.182	-0.079	0.535**
	(1.11)	(1.53)	(-0.46)	(2.28)
Revolver loan	-0.034	0.150	0.297*	0.249
	(-0.39)	(1.27)	(1.72)	(1.07)
Bridge loan	-1.263***	-0.316**	0.289	-0.569**
	(-13.15)	(-2.08)	(1.40)	(-2.00)
General purpose loan	-0.005	0.203***	-0.084*	-0.634***
	(-0.32)	(4.92)	(-1.68)	(-10.52)
Takeover/recap loan	-0.012	0.302***	0.163**	-0.048
	(-0.62)	(6.02)	(2.17)	(-0.55)
Working capital loan	-0.061***	0.459***	0.395***	-0.554***
	(-2.78)	(10.60)	(6.20)	(-7.50)
Default spread	-0.041***	-0.008	0.006	-0.090***
	(-3.67)	(-0.46)	(0.18)	(-2.62)
Term spread	-0.072***	0.015	0.085***	0.082***
	(-9.97)	(1.04)	(3.81)	(3.77)
Post-crisis dummy	0.078***	-0.115***	-0.442***	-0.347***
	(4.05)	(-2.79)	(-6.95)	(-5.09)
Industry FE	Yes	Yes	Yes	Yes
Observations	11,747	11,747	11,747	11,747
Adj. *R*-sq	0.290			
Pseudo *R*-sq		0.131	0.267	0.280

Table 2.8. Effect of cybersecurity awareness on loan spreads grouping sample by default risk

The table reports OLS regressions of loan spread on cybersecurity awareness, firm characteristics, textual controls, macroeconomic controls, and industry and year fixed effects for sub-samples grouped by default risk. The sample is grouped in two subsamples based on whether a firm has below or above sample-year median Altman Z-score (ZSCORE), Merton model expected default frequency (MEDF), and Naïve model expected default frequency (NEDF) at the beginning of a fiscal year. ZSCORE is the modified Altman (1968) Z-score, where a below-median value indicates a higher likelihood of default (High default risk). MEDF is computed following the Merton (1974) bond pricing model, and NEDF is computed based on the "simplified" Merton model probability of default following Bharath and Shumway (2008). The above-median values of MEDF and NEDF indicate a higher likelihood of default (High default risk). . Subsamples of low default risk are reported in the left columns, and sub samples of high default risk are reported in the right columns. For brevity, we only report coefficient estimates on cybersecurity awareness. For each grouping, the table reports *p*-values from tests of the null hypothesis that the coefficient estimates on cyberawareness are equal. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

	Z-Score		Merton EDF		Naïve EDF	
Default risk =	Low default risk	High default risk	Low default risk	High default risk	Low default risk	High default risk
Cyber awareness	–0.0489**	-0.145***	–0.036*	–0.116***	–0.039*	–0.116***
	(–2.07)	(-4.25)	(–1.89)	(–2.46)	(–1.98)	(–2.46)
p-value	[0.011]		[0.041]		[0.053]	
Text controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,896	5,861	5,195	5,143	5,194	5,142
Adj. *R*-sq	0.548	0.601	0.532	0.599	0.534	0.589

Table 2.9. Cybersecurity awareness and operating efficiency

The table reports regressions of operating efficiency on cybersecurity awareness, firm characteristics, textual controls, and industry and year fixed effects. *ROA* is the ratio of operating income before depreciation to total book assets. Costs per employee, *COGS/employee*, is the cost of goods sold (COGS) scaled by the number of employees. *Loss* is a dummy variable equal to one if a firm's net income is negative. The regressions are OLS regressions, except for *Loss*, where we estimate a probit regression and report marginal effects computed as a change in the probability of reporting a loss for a unit change in a variable, holding all other variables at their mean. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Dep var =	*ROA*		*Loss*		*COGS/ employee*	
	(1)	(2)	(3)	(4)	(5)	(6)
Cyber awareness	0.033***	0.011***	-0.115***	-0.047***	-26.688***	-29.896***
	(8.76)	(4.69)	(-10.28)	(-4.97)	(-3.45)	(-4.05)
	[9.17%]	[3.06%]			[-2.02%]	[-2.26%]
Bog index		0.003		0.001		0.001
		(0.79)		(1.01)		(1.01)
Uncertainty		-1.456		0.079***		0.079***
		(-0.25)		(3.16)		(3.16)
Tone		0.519		-0.004		-0.004
		(0.13)		(-0.29)		(-0.29)
Ln(Word count)		0.087**		-0.007		-0.007
		(1.97)		(-0.37)		(-0.37)
Ln(Total assets)		0.026***		-0.094***		18.563***
		(20.71)		(-28.92)		(5.04)
Market-to-book		0.024***		-0.078***		-13.925***
		(11.06)		(-14.83)		(-4.03)
Cash		-0.112***		0.171***		214.405***
		(-9.44)		(-5.27)		(8.38)
Leverage		-0.112***		0.573***		65.849**
		(-11.57)		-22.17		(2.15)
R&D		-1.046***		2.061***		261.543***
		(-30.61)		(-19.76)		(4.63)
Capital invest		0.174***		(-0.252***)		-402.284***
		(5.38)		(-2.63)		(-2.75)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,770	31,770	31,770	31,770	31,770	31,770
Adj. *R*-sq	0.175	0.515			0.269	0.270
Pseudo *R*-sq			0.077	0.254		

Appendix A. Variable definitions

Name	Definition (data source)
Text-based variables	
Cyber awareness	The number of cyber-related keywords divided by the total number of words in the respective section (Item 1, 1A, or 7) of 10-K, multiplied by 100. See section 3.1 for additional details on the construction of this measure.
Bog index	The index reported by the software package *StyleWriter*. This index provides a comprehensive measure of a document's plain English complexity, including passive voice, redundant verbs, use of jargon, and sentence complexity, among others. (Bonsall et al., 2017)
Uncertainty	Percentage of uncertain words in 10-K filing using the word list constructed by Loughran and McDonald (2011).
Tone	Percentage of excess positive words, computed as number of positive words minus negative words, in 10-K filing using the word lists from Loughran and McDonald (2011).
Word count	Total number of words in 10-K filling.
Firm Characteristics	
Total assets	Total book assets, CPI-adjusted. (Compustat)
Market-to-book	Market value of equity minus the book value of equity plus total assets all divided by total assets. (Compustat)
Leverage	The ratio of the book value of long-term debt plus debt in current liabilities to total book assets. (Compustat)
ROA	The ratio of operating income before depreciation to total book assets. (Compustat)
Cash	The ratio of cash and short-term investments to total book assets. (Compustat)
Sales growth	The average sales growth over last four years. (Compustat)
Stock returns	One-year stock return based on daily stock returns. (CRSP)
Returns vol	Variance of one year of daily stock returns. (CRSP)
R&D	R&D expenditures divided by total sales. Replaced to 0 if "not material" or missing. (Compustat)
Asset maturity	Asset maturity is the book value-weighted maturity of long-term assets and current assets, where the maturity of long-term assets is computed as gross property, plant, and equipment divided by depreciation expense, and the maturity of current assets is computed as current assets divided by the cost

	of goods sold (see Barclay and Smith, 1995; Billett et al. 2007). (Compustat)
Capital invest	The ratio of net property, plant, and equipment to total book assets. (Compustat)
Cash flow volatility	Standard deviation of annual cash flows from operations over the past five fiscal years, divided by the total assets. (Compustat)
Z- score	Modified Altman's (1968) Z-score=(1.2 working capital + 1.4 retained earnings + 3.3 EBIT + 0.999 sales) / total assets (Compustat)
Rated dummy	Dummy variable equal to one if the firm has a Standard & Poor's long-term debt rating. (Compustat)
Credit rating	Standard & Poor's long-term debt rating, coded from 1 (rating D) to 22 (rating AAA). (Compustat)
COGS/employee	The cost of goods sold (COGS) scaled by the number of employees. (Compustat)
Loss	Dummy variable equal to one if a firm's net income is negative. (Compustat)
Instrumental variables for cybersecurity awareness	
Geo cyber awareness	The yearly average of cybersecurity awareness measure of firms in different industries that are headquartered within a 250-km radius of firm *i* in year *t*.
Bank loan variables	
Loan spread	The All-In-Spread-Drawn (AISD) from the DealScan database. The total (fees and interest) annual spread in basis points over LIBOR (or LIBOR equivalent) for each dollar drawn down from a loan facility. (DealScan)
Loan maturity	Loan maturity measured in months. (DealScan)
Secured	Dummy variable equal to one if the loan facility is secured by collateral and zero otherwise. (DealScan)
Covenant count	Count of the number of covenants in the loan facility. (DealScan)
Covenant strictness	This is a measure of the probability of at least one covenant violation based on Monte Carlo simulation of financial variables and the strictness of covenants at loan origination (Murfin, 2012). We follow Kubick et al. (2020a) for a list of the financial variables used in the simulation. (Compustat and DealScan)
Performance pricing	Dummy variable equal to one if the loan facility has a performance pricing feature and zero otherwise. (DealScan)
No. of banks	The number of lenders funding the loan facility (i.e., the size of the loan syndicate). (DealScan)
Amount	The loan amount measured in dollars, CPI-adjusted. (DealScan)

Term loan	Dummy variable equal to one if the loan facility is a term loan and zero otherwise. (DealScan)
Revolver loan	Dummy variable equal to one if the loan facility is a revolver or 364-day facility and zero otherwise. (DealScan)
Bridge loan	Dummy variable equal to one if the loan facility is a bridge loan and zero otherwise. (DealScan)
General purpose loan	Dummy variable equal to one if the loan purpose is for general corporate purposes, project finance, or other purpose and zero otherwise. (DealScan)
Takeover/recap loan	Dummy variable equal to one if the loan purpose is for a takeover or recapitalization and zero otherwise. (DealScan)
Working capital loan	Dummy variable equal to one if the loan purpose is to finance working capital and zero otherwise. (DealScan)
Bond variables	
Bond spread	Difference between the yield to maturity of a corporate bond and the yield to maturity of its duration equivalent Treasury bond, measured in basis points. (FISD)
Maturity	The bond's maturity measured in months. (FISD)
Amount	The bond amount in US$. (FISD)
Subordinated dummy	Dummy variable equal to one if bond is subordinated, zero otherwise. (FISD)
Puttable dummy	Dummy variable equal to one if bond is puttable, zero otherwise. (FISD)
Callable dummy	Dummy variable equal to one if bond is callable, zero otherwise. (FISD)
Macroeconomic variables	
Default spread	The difference between BBB corporate bond yield and AAA corporate bond yield. (Federal Reserve Board of Governors)
Term spread	The difference between the 10-year U.S. constant maturity Treasury yield and the 3-month constant maturity U.S. Treasury yield (see Mauer et al., 2018). (Federal Reserve Board of Governors)
Post-crisis dummy	A dummy variable equal to one if the loan activation date is after calendar year 2008 and zero otherwise. (NBER)

Appendix B. Cybersecurity awareness measure

B1. List of cyber-related keywords

The table reports the keywords used for constructing our cybersecurity awareness measures at the firm-year level. We first search 10-Ks to identify if a firm includes a discussion about cybersecurity in its annual statement based on the keyword list from Gordon et al. (2010) and the National Initiative for Cybersecurity Careers and Studies (NICCS). We then search 10-K statements of more than 300 firms, representative across all Compustat industries for occurrences of these comprehensive set of keywords and then manually read the surrounding sentences and context to understand how firms use of these keywords and validate that they effectively refer to cyberawareness. Based on our manual reading, we construct the following three different keyword lists to capture firms' cyberawareness disclosure.

List 1	
cloud	technology
computer	telecommunication
customer data	third party
cyber	valuable information
cyberattack	virus
cyberguard	
cybersecurity	
firewall	
identity	
information security	
it asset	
malware	
network	
privacy related	
sensitive information	
sensitive data	
software	
spyware	

List 2		
attack	hazards	resilience
breach	improper access	resiliency measures
breakin	incident	sabotage
bypass	infiltration	spoof
cease	Infringe	steal
compromise	intentional release	stolen
corrupt	interrupt	surveillance
crime	intrusion	tampering
destroy	leak	theft
disrupt	malfunction	thieves
disruption	malicious	threat
encrypt	misconduct	unauthorize
exfiltration	missapprop	unprivileged
exploit	misuse	vulnerability
expose	penetrate	vulnerable
extortion	perpetrators	unlawful attempts
hack	phishing	
hacker	remedial actions	

List 3		
attacks sabotage	data leak	security breach
attempted attack	data loss	security incident
corrupting data	data theft	security measures
critical data	external hazards	security threat
cyber terrorism	hacking tool	security violation
cybersecurity risk	information theft	security vulnerability
data corruption	operational disruption	social engineering

B2. Examples of cybersecurity awareness disclosure

a) Science Applications International Corporation: fiscal year ended January 30, 2015.

As a U.S. government contractor and a provider of IT services operating in multiple regulated industries and geographies, we handle sensitive information, including personally identifiable information, protected health information, personnel information, classified information, financial information and other confidential information concerning our business and employees and those of our customers (collectively referred to below as sensitive information). We are continuously exposed to cyber and other security threats, including computer viruses, attacks by hackers or physical break-ins. Any electronic or physical break-in or other security breach or compromise may jeopardize security of sensitive or other information stored or transmitted through our IT systems and networks. This could lead to disruptions in mission critical systems, unauthorized release of confidential or otherwise protected information and corruption of data. Although we have implemented policies, procedures and controls to protect against, detect and mitigate these threats, attempts by others to gain unauthorized access to our IT systems are becoming more sophisticated. These attempts include covertly introducing malware to our computers and networks and impersonating authorized users, among others, and may be perpetrated by well-funded organized crime or state sponsored efforts. We seek to detect and investigate all security incidents and to prevent their occurrence or recurrence. We continue to improve our threat protection, detection and mitigation policies, procedures and controls. In addition, we work with other companies in the industry and government participants to promote increased awareness and enhanced protections against cybersecurity threats.

b) Outerwall Inc*:* fiscal year ended December 31, 2013.

As our business expands to provide new products and services, such as Redbox Instant by Verizon, ecoATM kiosks, and Coinstar's gift card exchange business, we are increasing the amount of consumer data that we collect, transfer and retain as part of our business. These activities are subject to laws and regulations, as well as industry standards, in the United States and other jurisdictions in which our products and services are available. These requirements, which often differ materially and sometimes conflict among the many jurisdictions in which we operate, are designed to protect the privacy of consumers' personal information and to prevent that information from being inappropriately used or disclosed. We maintain and review technical and operational safeguards designed to protect this information and generally require third party vendors and others with whom we work to do so as well. However, despite those safeguards, it is possible that hackers, employees acting contrary to our policies, third-party agents or others could improperly access relevant systems or improperly obtain or disclose data about our consumers, or that we may be determined not to be in compliance with applicable legal requirements and industry standards for data security, such as the Payment Card Industry guidelines. A breach or purported breach of relevant security policies that compromises consumer data or determination of non-compliance with applicable legal requirements or industry standards for data security could expose us to regulatory enforcement actions, card association or other monetary fines or sanctions, or contractual liabilities, limit our ability to provide our products and services, subject us to legal action and related costs and damage our business reputation, financial position, and results of operations.

c) MSC Industrial Direct Co., Inc: fiscal year ended September 1, 2012.

We believe that our information technology ("IT") systems are an integral part of our business and growth strategies. We depend upon our IT systems to help process orders, to manage inventory and accounts receivable collections, to purchase, sell and ship products efficiently and on a timely basis, to maintain cost-effective operations, to operate our website and to help provide superior service to our customers. Our IT systems may be vulnerable to damage or disruption caused by circumstances beyond our control, such as catastrophic events, power outages, natural disasters, computer system or network failures, computer viruses, physical or electronic break-ins, and cyberattacks. The failure of our IT systems to perform as we anticipate could disrupt our business and could result in transaction errors, loss of data, processing inefficiencies, downtime, litigation, substantial remediation costs (including potential liability for stolen assets or information and the costs of repairing system damage), and the loss of sales and customers. Any one or more of these consequences could have a material adverse effect on our business, financial condition and results of operations.

Appendix C. Computation of Merton and naïve $\boldsymbol{EDF}$ measures Merton $\boldsymbol{EDF}$

The Merton expected default frequency (EDF) measure is based on the Merton (1974) bond pricing model. The model assumes that (1) the total value of the firm, V, follows geometric Brownian motion with constant expected return, μ, and volatility, σ_V, and (2) the firm has outstanding one issue of pure discount bonds maturing T years from today. There are three steps to compute EDF. The first step is to solve numerically the following equations for V and σ_V:

$$E = VN(d_1) - e^{-rT}FN(d_2) \tag{C1}$$

and

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V \tag{C2}$$

where E is the market value of equity, F is the face value of debt, r is the assumed constant risk-free rate, $N(\cdot)$ is the cumulative standard normal distribution function with

$$d_1 = \frac{ln\,(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_v\sqrt{T}} \tag{C3}$$

and $d_2 = d_1 - \sigma_v\sqrt{T}$.

Given values for V and σ_V, we next compute the distance to default as

$$DD = \frac{ln\,(V/F) + (\mu + 0.5\sigma_V^2)T}{\sigma_v\sqrt{T}} \tag{C4}$$

where μ is expect return on the firm's assets. The Merton expected default frequency is then computed as

$$Merton\ EDF = N(-DD) \tag{C5}$$

The inputs to the Merton EDF model include μ, the expected return on the firm's assets; σ_E, the volatility of stock returns; F, the face value of debt; r, the risk-free rate; and the forecasting horizon (maturity of the firm's debt) T. Following the literature (Vassalou and Xing, 2004; Sundaram and Yermack, 2007; Bharath and Shumway, 2008), we estimate μ as the ratio of EBITDA to book value of total assets, σ_E as the annualized standard deviation of equity returns over the prior year, F as debt in current liabilities plus one-half the amount of long-term debt, r as the one-year treasury rate, and $T = 1$ year. The market value of the firm's equity, E, is the product of the end of year share price and the number of shares outstanding.

Naïve $\boldsymbol{EDF}$

The naïve expect default frequency (EDF) measure is based on the "simplified" Merton model probability of default suggested by Bharath and Shumway (2008). Assuming the market value of the firm's debt is equal to the total face value of debt (i.e., $D = F$) and the volatility of debt is $\sigma_D = 0.05 + 0.25 \times \sigma_E$, the naïve model approximates firm value volatility as

$$\sigma_V = \frac{E}{E+F}\sigma_E + \frac{E}{E+F}\sigma_D \tag{C6}$$

The distance to default is then computed as

$$naive\ DD = \frac{\ln((E+F)/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_v\sqrt{T}} \tag{C7}$$

and the naïve expected default frequency is computed as

$$\text{naïve } EDF = N(-\text{naïve } DD) \tag{C8}$$

Chapter 3: Judge Ideology and Corporate Policies

1. Introduction

New filings of securities class action lawsuits grew by approximately 80% between 2015 and 2017, with the number of new annual filings remaining steady between 420 and 430 filings from 2017 to 2019 (McIntosh and Starykh 2021).[48] These lawsuits are costly to firms. Costs include financial losses due to legal fees and settlements (i.e. direct costs), as well as losses in market capitalization, market share and reputation, among others (i.e., indirect costs). Among the group of firms sued in 2020, the median stock price decline was 15% around the filing date and the median settlement amount was $10.1 million from 77 settlements reached in the year.[49] Litigation risk and its impact on corporate policies has been the subject of numerous studies in the literature.[50] These studies generally use actual lawsuit data as a measure of litigation risk (e.g., Lowry and Shu 2002; Deng et al. 2014; Arena and Julio 2015; Arena 2018) or industry and firm characteristics to estimate the likelihood of litigation for a given firm (e.g., Francis et al. 1994; Johnson et al. 2000; Field et al. 2005; Rogers and Stocken 2005). Unfortunately, because these measures are likely to capture characteristics that are unrelated to ex ante litigation risk, they are not able to establish a causal relation between litigation risk and corporate policies (e.g., Huang et al. 2019; Kubick et al. 2021). In this paper, I overcome this limitation by using federal judge

[48] In the year 2020, the total number of securities class action lawsuits filed against U.S. firms was 334. The decrease in lawsuit filings is likely due to the unprecedented disruptions to the U.S. court system from the COVID-19 pandemic as well as a disruption in corporate activity also due to the pandemic (Kasner et al. 2021; McIntosh and Starykh 2021).
[49] See “Securities Class Action Filings, 2020 Year in Review”, Cornerstone Research (2021) and “Securities Class Action Settlements, 2020 Year in Review”, Cornerstone Research (2021).
[50] Lawsuits have been shown to be associated with lower stock prices (e.g., Bhagat et al. 1998; Klock 2015) higher cash holdings (Arena and Julio 2015; Malm et al. 2017a), higher leverage and share repurchase (Crane 2011); lower capital expenditure (Arena and Julio 2015) and higher R&D and capital expenditure (Malm et al. 2017b). Studies have also examined how litigation risk affects debt contracting (Deng et al. 2014; Chu 2017); initial public offerings (Lowry and Shu 2002), financial reporting (e.g., Johnson et al. 2000) among other firm policies and outcomes.

ideology at firm's headquarter circuit as a measure of ex ante litigation risk and examine whether (and how) ex ante litigation risk influences corporate policies.

Prior studies in the literature find conflicting results of the effect of litigation risk, measured by actual lawsuits, on firms' corporate decision-making. On one hand some studies document that litigation risk is associated with higher cash holdings (Arena and Julio 2015; Malm et al. 2017a), lower leverage (Malm et al. 2017c), lower dividend payout (Malm et al. 2020), higher share repurchases (Crane 2011) and higher capital expenditure (Malm et al. 2017b). Albeit the limitations of using actual lawsuits for the analysis, taken together these results are consistent with the view that litigation risk has a *prevention effect* on corporate risk taking, with litigation risk incentivizing managers to adopt policies that can provide the firm with flexibility and curb the firm's risk profile. Such behavior could be explained by litigation serving as a disciplining device, aligning managers with shareholders' interests (Romano 1991; Fich and Shivdasani 2007; Appel 2019) or it could be consistent with self-interested managers' risk-aversion and desire to protect their job and reputation. On the other hand, there are studies which show that litigation risk is associated with higher leverage (Crane 2011) and higher expenditure in research and development (Malm et al. 2017b). The latter results could be consistent with the view that litigation risk has a *strategic action effect* on managers' corporate policies, encouraging them to take measures that favor claims of current capital providers at the expense of potential plaintiffs' claims on firms' resources (Scott 1977; Crane 2011). My study contributes to the literature examining the implications of litigation risk at the corporate level, by using a measure of ex ante litigation risk exogenous to the firm (i.e., judge ideology), to better understand if managers are aware of judge ideology and what effect does it have on corporate policies.

Importantly although as discussed above, the incidence and economic costs of class action lawsuits and the evidence documented by existing studies strongly hint to the idea that litigation risk should influence firms, it is possible that litigation risk does not significantly influence corporate policies because measuring such risk is not straightforward for corporations. Furthermore, driven by optimism bias management may view the occurrence of lawsuits as a rare event, unlikely to occur to their firm and decide to focus time and resources to manage other risks.[51] Additionally, if the benefits from holding on to what managers view as optimal corporate policies overshadow the expected litigation costs associated with judge ideology, managers may find adequate to neglect judge ideology in corporate decisions. Furthermore, states allow firms to purchase director and officer (D&O) liability insurance. Such type of insurance may significantly reduce the motivation for management to adjust corporate policies given the level of ex ante litigation risk they face in their federal circuit court (e.g., Romano 1991; Crane 2011; Appel 2019). Nevertheless, there is also evidence suggesting that there are non-pecuniary (e.g., reputational) costs associated with litigation that directors and executives must ultimately bear. Ultimately, whether and how the threat of shareholder litigation influences firms' corporate policies is an empirical question.

In this paper, I examine whether ex ante litigation risk influences corporate policies using a large sample of U.S. public firms during the period from 1993 to 2019. My analysis distinguishes from previous work because I use a measure of litigation risk that is strictly exogenous to the firm. Following Huang et al. (2019) and Kubick et al. (2021) I measure ex ante litigation using federal judge ideology, defined as the probability that Democratic presidents' appointees dominate a three-judge panel randomly selected from the firm's headquarters circuit court. This measure builds on

[51] Over the period from 2001 to 2019 5.5% of all the S&P 500 companies were a defendant in a federal lawsuit filing. See "Securities Class Action Filings, 2020 Year in Review", Cornerstone Research (2021).

research in the political and legal science studies, which shows that judge ideology is a crucial factor in determining lawsuit outcomes (Johnston 1976; Tate 1981; Staudt et al. 2006). Furthermore, research in the political science literature examining securities class action lawsuits shows that liberal judges are more likely to vote in favor of investors (litigants) and against firms (defendants).[52] Therefore, the probability that Democratic presidents' appointees dominate a circuit court panel suggests higher ex ante litigation risk to firms.

The use of judge ideology as measure of ex ante litigation risk overcomes the limitations associated with existing measures of litigation risk (i.e., actual lawsuits, firm and industry characteristics), allowing me to identify a causal effect of ex ante litigation risk on financial policies. First, judge ideology is a measure of ex ante litigation risk that is based on the makeup of the group of judges on the circuit court with jurisdiction over the state where a firm is located (Huang et al. 2019). Relative to actual lawsuits, industry membership and firm attributes, judge ideology at the circuit level is less endogenous to omitted correlated variables that are likely to influence firms' policies and outcomes (Kim and Skinner 2012). Second, a circuit's judge composition changes when there is a vacancy and the president in office appoints a new judge. A vacancy can originate because a judge retires, resigns, or passes away. Thus, there is a rich interaction of exogenous cross-sectional and time series variation in judge ideology, which allows for strong identification (Huang et al. 2019; Kubick et al. 2021). Overall, the measure I use in this study is based on a group of critical actors, judges, who play a central role in expected and realized lawsuit outcomes filed against corporations (Cross and Tiller 1997), but the measure does not capture litigation risks originating from firms' corporate policies (Huang et al. 2019; Kubick et al. 2021).

[52] See Huang et al. (2019) for a complete discussion of the political and legal sciences studies on how ideology influences civil liberties and economic lawsuit outcomes.

I first construct *Liberal court*, the variable that measures judge ideology, estimated as the probability that democratic presidents' appointees dominate a panel of three judges randomly selected from a circuit court. Over the sample period from 1993 to 2019, I find that this probability is on average 38%, suggesting that firms face significant litigation risk. Noteworthy, the probability of liberal judges dominating a federal circuit panel has two distinct effects. On one hand, it increases the likelihood that the panel of judges resolves against a firm if it finds itself facing a class action lawsuit. Additionally, it increases the likelihood of corporations being sued because plaintiffs and plaintiffs' attorneys will recognize that they have a higher probability of winning should they decide to file a lawsuit.

Next, I examine whether judge ideology influences business risk in my sample. In panel regressions controlling for firm, industry, and state characteristics, as well as circuit, industry and year fixed effects, I find that judge ideology (i.e., *Liberal court*) decreases business risk. In terms of economic significance, a one-standard-deviation increase in *Liberal court* decreases stock return volatility (asset volatility) y by 2.5% (3%). This result, although not particularly strong, is suggests that firms do factor into their corporate policies and risk management the threat of litigation originating from the probability of having a majority of antibusiness judges preside over a potential lawsuit. The evidence suggests that on average, although the incidence of lawsuits is relatively low and firms can insulate executives from bearing monetary litigation costs, corporations are not indifferent to this risk.

I next examine the relation between judge ideology and various corporate policies. In multivariate analysis, I find a robust positive relation between judge ideology and cash holdings and no effect on leverage. A one-standard-deviation increase in *Liberal court* increases cash holdings by 5.11%. Regarding payout policy, I document a decline in dividends and an increase in share repurchases. A one-standard-deviation increase in *Liberal court* decreases (increases) dividend payout (share repurchases) by 8.9% (12.46%) for the average firm in the sample. Lastly, the data suggests a decline in capital expenditure which occurs with a lag, and no change in research expenditures. A one-standard-deviation increase in *Liberal court* decreases capital expenditure by 3.30%.

To understand whether the documented effects of judge ideology on corporate policies are consistent with shareholder wealth maximization or if they are indicative of managers acting in their own self-interest, I next investigate how judge ideology influences the marginal value of cash to shareholders (Faulkender and Wang 2006). On one hand, to the extent that litigation risk serves as a governance mechanism that can discipline managers, I expect judge ideology to have a positive effect on the marginal value of cash (e.g., Romano 1991; Fich and Shivdasani 2007; Dittmar and Mahrt-Smith 2007; Appel 2019). Alternatively, another stream of literature documents that a significant proportion of class action litigations are frivolous, inflict nontrivial direct and indirect costs on firms, and ultimately destroy firm value (e.g., Alexander 1990; Romano 1991; Appel 2019). Results show that litigation risk has a positive impact on the value of cash, with a one-standard-deviation increase in *Liberal court* increasing the marginal value of cash by roughly 8.4%.

Taken together, the results in this paper are not consistent with the *strategic action effect* prediction, rather they seem to lend support to the *prevention effect* hypothesis. Dittmar and Mahrt-Smith (2007) find a positive relation between good corporate governance and the value of cash. Thus, to the degree that ex ante litigation risk operating as an effective external governance mechanism(e.g., Romano 1991; Fich and Shivdasani 2007; Appel 2019) my findings are in line with those reported by Dittmar and Mahrt-Smith (2007). Faulkender and Wang (2006) predict and document that the marginal value of cash declines as firms choose greater cash distribution via dividends rather than repurchases. The payout policy and marginal value of cash results combined, are consistent with their findings. Furthermore, the slight decline in capital expenditure does not support the notion that managers accumulate cash for self-serving empire building and are consistent with higher cash reserves. The finding are consistent with previous literature that examines the effects of litigation risk on firm outcomes (e.g., Donelson and Yust 2014; Appel 2019), and suggest that the changes in corporate policies are beneficial to shareholders.

Lastly, I conduct cross-sectional tests to explore heterogeneity in the main results. First, I examine differential effects of judge ideology based on measures of corporate governance using four alternative measures of corporate governance. The results are weak and noisy, and for the most part show there is virtually no evidence that internal governance measures accentuate or play down the effect of litigation risk on corporate policies. Second, I investigate the moderating effect of financial constraints. Higher litigation risk may increase cash-flow uncertainty making firms vulnerable to liquidity shortages in bad states of the world and hence, potential underinvesting (Phan et al. 2017). This problem is likely to be exacerbated for financially constrained firms. Furthermore, given that litigation risk leads to costly external finance (Kubick et al. 2021), equity holders should be more willing to allow firms to hold more cash on hand to operate efficiently in more volatile states of the world (Phan et al. 2017). Thus, I hypothesize that litigation risk may have a stronger effect on firms that have higher financial constraints. For such firms the heightened uncertainty of finding themselves facing a lawsuit may be sufficient to prompt them to preventively adopt a more flexible payout policy and increase internal funds. Consistent with this argument, results suggest that the positive effect of judge ideology on cash holdings and marginal value of cash is stronger in the sub-group of financially constrained firms.

My paper contributes to the literature on shareholder litigation risk and its effect on firms' corporate policies. The majority of this literature examines actual lawsuits or industry and firm characteristics to measure litigation risk (e.g., Johnson et al. 2000; Lowry and Shu 2002; Field et al. 2005; Rogers and Stocken 2005; Cheng et al. 2010; Deng et al. 2014; Arena and Julio 2015). Such measures are directly related to firm behavior or characteristics, making the analysis based on them prone to endogeneity concerns. This paper, however, joins a growing literature that exploits judge ideology at the circuit court level as a measure of litigation risk, to offer a causal identification of the effect of ex ante litigation risk on corporate policies (Huang et al. 2019; Chow et al. 2020; Kubick et al. 2021). I add to this stream of literature by showing that ex ante litigation risk affects corporate policies. My results show that judge ideology has a *prevention effect* on firms, influencing them to hold more cash, lower dividend payout and favor share repurchase schemes and as such business risk is lessened.

Furthermore, this study contributes to inform the stream of literature that examines the relation between litigation risk and firms' outcomes (e.g., Donelson and Yust 2014; Appel 2019). I contribute to this body of literature by documenting a positive effect of judge ideology on profitability and the value of cash to shareholders. Overall, the empirical evidence I document in this paper shows that political appointments are relevant for firms' corporate policies and outcomes.

The remainder of the paper is organized as follows. Section 2 provides a background on class action lawsuits, federal circuit court judge ideology and develops testable hypotheses. Section 3 discusses sample construction and definitions of the major variables used in the empirical analysis. Section 4 presents the main empirical results. Section 5 discusses additional tests concerning cross-sectional heterogeneity. Section 6 concludes. Appendix A reports variable definitions, and Appendix B and C report supplementary information and additional tests.

2. Background and predictions

In this section, I first discuss the background and institutional details of securities class action lawsuits and judge ideology in the U.S. Federal Court System. I then present testable predictions for the impact of judge ideology on firm business risk.

2.1. Securities class action lawsuits and U.S. judicial system

Securities class action lawsuits are the most common legal recourse by which multiple shareholders seek to recover damages based on claims of fraudulent statements made in relation to a particular security. Financial recoveries from class actions go directly to the group of shareholders filing the lawsuit.[53] However, in practice plaintiffs only receive a fraction of the money paid by defendants when the lawsuit ends in a settlement or judgement. Instead, the plaintiffs' bar receives roughly 40% of any settlement or judgement, besides monies to reimburse the costs they have incurred (Yingling 2017).

Securities class action lawsuits usually are based on violation of the Securities Exchange Act of 1934. These lawsuits are costly to corporations and their managers, with executives facing the possibility of significant economic, reputational, and criminal consequences (Romano 1991; Huang et al. 2019; Kubick et al. 2021). Given the resources and costs associated to defending securities fraud class action suits, defendants often prefer to settle suits quickly. In addition, if executives and directors are protected by D&O insurance which is paid by the corporation, it incentivizes both firms and plaintiffs' attorneys to agree on a quick settlement, because in most

[53] This is in sharp contrast to derivative lawsuits, which are filed by shareholders on behalf of the corporation. Any monies paid in a derivate lawsuit go to the corporation itself. See Romano (1991) and Appel (2019) for more details on the differences between derivative and class action lawsuits.

cases D&O insurance covers the costs for both the defendants and plaintiffs' lawyers. As such, neither party internalizes litigation costs (Romano 1991; Appel 2019). Thus, frivolous "strike" lawsuits that deepen the pockets of plaintiffs' lawyers via settlements are not uncommon (e.g., Alexander 1990; Romano 1991; Yingling 2017). To curb the incentives for such "strike" lawsuits, U.S. Congress enacted the Private Securities Litigation Reform Act (PSLRA) in 1995. The PSLRA includes provisions to protect firms against perceived abuses in securities class action lawsuits ordering standards that must be met by plaintiffs to file a lawsuit (Huang et al. 2019). Nevertheless, data suggests that the PSLRA has not significantly deterred frivolous lawsuits (Perino 2003; Yingling 2017).[54]

Securities fraud class action suits are filed at the federal district court level in one of the 94 federal district courts. Mostly, lawsuits are filed in the circuit court where the defendant is headquartered. Consistently, Cox et al. (2009) and Huang et al. (2019) document that 85% and 87% of securities class action lawsuits in their respective samples, are filed in the corporation's headquarter circuit. The defendants in class action lawsuits include the corporation, current and former members of the board of directors as well as current and former executive officers.

Only a small number of securities class action suits are tried before a judge or jury. Instead, the cases are mostly dismissed or settled. If a securities class action is dismissed with prejudice by a district court, the plaintiff can appeal the case to a circuit court. There are 12, geographically determined circuit courts in the U.S., with the number of judgeships in each court defined based on the population size of the circuit.[55] When a case is appealed to a circuit court, it is assigned to

[54] See Perino (2003) for a discussion on the primary goals of the PSLRA (discourage filing on meritless suits, reduce litigation risk for high technology issuers, and reduce the "race to the courthouse" in response to stock price declines) and an assessment of the results in practice in achieving these objectives.

[55] As of June 2021, the number of judgeships in each circuit ranges from 6 (First Circuit) to 29 (Ninth Circuit). See Table 9 in Appendix C for details on the states covered by each circuit as well as the corresponding number of judgeships.

a panel of three randomly selected judges. This panel decides the case based on a majority opinion, by either reversing or upholding the district court ruling. As a final resource, after the circuit court decides a case, the losing party may request the Supreme Court to review it. However, the Supreme Court is not obliged to hear a case. Moreover, historically the Supreme Court only makes discretionary and rare reviews.[56] Thus, effectively, circuit courts are the final judges for securities class actions (Huang et al. 2019; Kubick et al. 2021).

2.2. Judge ideology

Research in the legal and political science studies shows that judge ideology is a crucial factor in determining lawsuit outcomes (Johnston 1976; Tate 1981; Staudt et al. 2006). It is well documented that in securities class action lawsuits liberal judges are more likely to vote in favor of investors (litigants) and against firms (defendants). In contrast, conservative judges are more likely to vote in favor of corporations (e.g., Grundfest and Pritchard 2002; Sullivan and Thompson 2004; Fedderke and Ventoruzzo 2016).[57] This crucial role of judge ideology in judicial decisions and the fact that lawsuits against corporations are generally filed in the federal circuit where the firm is headquartered serves as motivation for Huang et al. (2019) to propose judge ideology at the firm-circuit level as a measure of firms' ex ante litigation risk. Judge ideology is calculated as the probability that Democratic presidents' appointees dominate a panel of three judges randomly selected from a circuit court. I follow Kubick et al. (2021) and denote the judge ideology measure as *Liberal court* for variable definition purposes. Importantly, this measure is objective and exogenous to the firm. Furthermore, it is characterized by significant variation in the cross-section

[56] Bowie and Songer (2009) document that the Supreme Court takes less than 1% of over 10,000 review requests received each year.

[57] See Huang et al. (2019) for a comprehensive review of the literature addressing the influence of judge ideology on judicial decisions.

and the time series, which are key properties to establish a causal relation in my analysis (Huang et al. 2019; Kubick et al. 2021).

2.3. Hypotheses

Securities class action lawsuits impose significant direct and indirect costs on corporations and are considered an important mechanism through which shareholders can influence corporations, attenuate agency conflicts, as well as deter ex ante detrimental behavior from self-serving managers (e.g., Bhagat et al. 1987; Romano 1991; Porta et al. 1998; Appel 2019). Ultimately, it is the legal recourse for shareholders to find remedies ex post when they believe executives' deceitful actions have violated their rights.

The extant literature finds mixed results on the relation between litigation risk and corporate policies. Some studies finds evidence consistent with the rationale that litigation risk increases business risk, although the direct effect of litigation risk on business risk is not tested. Using actual lawsuit data as their measure of litigation risk Crane (2011) finds that litigation risk is positively related to leverage and share repurchase. In a similar setting Malm et al. (2017b) finds a positive link between lawsuits and R&D expenditure. Yet, consistent with the view that litigation risk decreases business risk, Arena and Julio (2015) and Malm et al. (2017a) show a positive association between litigation risk and cash holdings, and Malm et al. (2020) presents evidence of a negative relation between litigation risk and dividend payout. However, as discussed in previous sections, because these studies use actual lawsuits or firm and industry characteristics as a measure of litigation risk, the results suffer from the problem of omitted correlated variables that are likely to influence the likelihood of class action lawsuits and firm operation and management's policies (Kim and Skinner 2012; Kubick et al. 2021). In my analysis I use judge ideology at the circuit court level to overcome those limitations. Building on the extant literature, I present hypotheses on the relation between ex ante litigation risk and firm's business risk.

Prevention hypothesis. Litigation risk and business risk are negatively related. Conservative corporate policies are increasing in litigation risk.

Securities class action lawsuits impose significant direct and indirect costs on corporations. To avoid incurring such costs managers in high liberal judge ideology circuits may be incentivized to pursue less risky policies with the purpose of building flexibility and financial slack if a lawsuit is materialized, as well as to reduce the likelihood of triggering lawsuits due to aggressive corporate policies that may lead to high volatility in the stock price and firms' cash flows. Consistent with this argument studies have documented a positive correlation between litigation risk and firms' cash holdings and conjecture that firms do so to build a "war chest" to defend against litigation (Crane 2011; Arena and Julio 2015; Malm et al. 2017a).

Note that pursuing less risky policies may be consistent with at least two rationales. First, if in the absence of this ex ante litigation risk corporate policies set in place by managers imply excessive risk taking without a commensurate increase in expected reward for equityholders, then conservative and risk-reduction policies would be consistent with litigation risk serving as an external governance device that disciplines managers (Romano 1991; Ferris et al. 2007; Pukthuanthong et al. 2017). However, it is also possible that conservative policies are driven by litigation risk exacerbating risk averse managers' career concerns (e.g., job security, reputation) discouraging them from pursuing risky but value-enhancing investments (Lin et al. 2016). In the latter case, it is likely that prevention-type policies would not correspond to maximizing shareholders' wealth.

Strategic action hypothesis. Litigation risk and business risk are positively related. Risky corporate policies are increasing in litigation risk.

Managers facing ex ante litigation risk, can find advantageous to pursue policies that favor the claims of current capital suppliers at the expense of potential plaintiffs' rights on firms' future cash flows (e.g., Scott 1977; Crane 2011). By pursuing policies that commit managers to pay higher proportions of firms' cash flows to capital providers (i.e., debtholders or equityholders), managers can expect to achieve two goals. First, they can expect to reduce the expected payoff for potential plaintiffs. Second, in doing so, they may also dissuade plaintiffs and plaintiffs' bar from taking legal action against the firm since the expected value of a potential payoff would be reduced. Consistent with this rationale, Crane (2011) shows that heighten threat of lawsuits at the industry level is correlated with higher leverage and share repurchases. Crane (2011) findings are consistent with Scott (1977) and Spier and Sykes (1998) who suggest that firms may use both secured and unsecured debt to reduce the value of litigation claims in bankruptcy, since the former two take priority.

Regardless of which hypothesis, the *prevention effect,* or the *strategic action effect,* is supported by the empirical tests, it is important to try to better understand if changes in corporate policies are consistent with pursuing shareholders' benefits or if they are driven by self-interested managers looking after themselves. To shed light on this question, I examine the effect of judge ideology on the marginal value of cash to shareholders (Faulkender and Wang 2006).

Nevertheless, it is possible that litigation risk has no effect on corporate policies. Evidence suggests that a significant number of class action lawsuits are meritless ((e.g., Alexander 1990; Romano 1991). Moreover, the effects of litigation risk may be limited because executives and directors are often insulated from bearing personal liability due to the purchase of director and officers (D&O) insurance policies by corporations (Romano 1991; Crane 2011; Appel 2019).[58] Additionally, if the benefits of maintaining management's optimal corporate policies outweigh the expected litigation costs associated with judge ideology or if it is hard for managers to estimate future judge ideology, firms may find optimal to nearly disregard judge ideology in corporate decisions. The preceding arguments suggest that judge ideology could have no significant effect on corporate policies and business risk. In summary, whether and how liberal judge ideology affects corporate policies is an empirical question.

3. Data and variables

3.1. Sample construction

My sample is constructed from the intersection of Compustat and CRSP databases for fiscal years 1993 to 2019. Annual firm-level accounting data and stock prices data come from Compustat and CRSP, respectively. Following conventions in the literature, I exclude financial firms (SIC codes 6000-6999) and regulated utilities (SIC codes 4900-4999) and require firm-years to have positive book assets and positive net sales. I start the sample in 1993 due to limited data availability for some state economic variables and historic headquarter data for earlier periods. The main sample consists of 83,475 firm-year observations from 9,628 unique firms. Sample sizes in multivariate analysis vary due to data availability for some of the variables used.

3.2. Variables

3.2.1. Judge ideology

I follow the methodology used by Huang et al. (2019) to construct the judge ideology measure *Liberal Court* as a proxy for ex ante litigation risk. I obtain data on each judge's

[58] Due to data limitations, I do not attempt to estimate a firm-year measure of insurance. However, D&O insurance coverage will bias the results against finding a change in corporate policies in either direction to a change in judge ideology.

appointing president from the Federal Judicial Center.[59] *Liberal Court* is estimated as the probability that democratic presidents' appointees dominate a panel of three judges randomly selected from a circuit court, using the following specification:

$$Liberal\ court = [C(x,3) + C(x,2) \times C(y-x,1)]/C(y,3) \tag{1}$$

where C(*n*, *r*) is a binomial coefficient indicating the number of possible combinations of *r* objects from a set of *n* distinct objects, *x* is the number of Democratic appointees in the circuit, and *y* is the total number of judges in the circuit. Ex ante litigation risk at the firm-year level is measured by matching each firm-year observation to a circuit-month. The matching is based on the location of the firms' headquarters at the beginning of the year.[60] I use historical headquarters data to guarantee proper match of the firm's headquarters circuit at the beginning of the year.[61] Higher values of *Liberal court* indicate that the circuit is more liberal.

In my empirical tests I analyze the impact of judge ideology on firm business risk, a set of corporate policies including financial, investment, and payout decisions, as well as the marginal value of cash. I define the main variable in the following sections.

3.2.2. Firm risk

Following the literature (e.g., Coles et al. 2018; Mauer et al. 2021) I measure firm risk using stock return volatility and asset volatility. *Stock return volatility* is computed as the annualized standard deviation of daily stock returns over the fiscal year. *Asset volatility* is

[59] The Federal Judicial Center (FJC) reports biographical data of circuit court judges including the party of the appointing president, the appointing president, appointment confirmation date, and details about the court to which the judge is appointed. https://www.fjc.gov/history/judges/biographical-directory-article-iii-federal-judges-export.
[60] As discussed in previous sections, civil procedure normally requires securities class action lawsuits to be filed in the circuit where the firm is headquartered, thus the matching is based on the firms' headquarters at the beginning of the year (Huang et al. 2019).
[61] I extract historical headquarters information from Professor Bill McDonald's augmented 10-X header data. I thank Professor McDonald for providing this data. https://sraf.nd.edu/data/.

constructed following Schwert and Strebulaev (2014) as the standard deviation of returns on a portfolio of the firm's equity and debt over the fiscal year.[62]

3.2.3. *Corporate policies*

For measures of financial policies, I estimate financial leverage as the ratio of long-term debt plus debt in current liabilities to the book value of total assets (*Book leverage*). For robustness, I also compute market leverage (*Market leverage*) as the ratio of long-term debt plus debt in current liabilities to the market value of assets, which is estimated as the book value of assets minus the book value of equity plus the market value of equity. I measure corporate liquidity, *Cash*, as the ratio of cash and marketable securities to net assets, where net assets is the book value of assets minus cash and marketable securities (Opler et al. 1999; Liu et al. 2014).

Following the literature on firms' payout policies (e.g., Grullon and Michaely 2002; Hsieh and Wang 2008; Chino 2016, Ye et al. 2019), I estimate the dividend payout ratio, computed as the ratio of dividends to the book value of assets (*Dividends*). *Dividend yield* defined as the dividends divided by fiscal year-end price, and *Share repurchase* constructed as the expenditure on the purchase of common and preferred stocks minus the change in redemption value of preferred stocks, all to the book value of assets. I also estimate *Total payout* as ratio of dividends plus the expenditure on the purchase of common and preferred stocks minus change in the redemption value of preferred stocks, all to the book value of assets.

I measure corporate investment with the variable *CAPEX* defined as the ratio of capital expenditures to the book value of assets and the variable *R&D* defined as the ratio of research and development expense to the book value of assets (the variable is set equal to zero when research and development expense is missing).

[62] I provide details on variables construction in Appendix A.

3.3. Control variables

I follow the corresponding literature to select control variables pertaining to firm, industry, and state level characteristics in my model specifications. State characteristics are common across all models and follow Kubick et al. (2021). Specifically, the models control for state GDP growth, state unemployment rate, and dummy variables for republican governor and republican majority state legislature. All variables are defined in Appendix A.

3.4. Descriptive statistics

Panel A of Table 1 presents descriptive statistics of main variables for the sample. All continuous variables are winsorized at the 1 and 99 percentiles of their distributions. Appendix A provides definitions of all variables. The average (median) judge ideology (i.e., *Liberal court*) is 0.38(0.37), consistent with the values reported by Huang et al. (2019) and Kubick et al. (2021). This signifies that in the event of a class action lawsuit filed against a firm, the likelihood of having at least two democratic appointees on a three-judge circuit court panel is on average 38%. Considering that it is well documented in the political and legal studies literature that liberal judges are more likely to vote in favor of investors (litigants) and against corporations(defendant) (e.g., Grundfest, and Prichard 2002; Sullivan and Thompson 2004; Fedderke and Ventourruzzo 2016), this suggests that firms face significant ex ante litigation risk. As in Huang et al. (2019), to illustrate the significant variation of judge ideology over the sample period, both in the cross-section and the time series, Figure 1 plots *Liberal court* for the two most liberal circuits (Second and Ninth Circuits) and the two most conservative circuits (Seventh and Eighth Circuits). As the figure shows, judge ideology varies significantly across circuits and within circuits over time.[63]

[63] Table 10 in Appendix C reports the mean and median values Liberal court per circuit over the sample period.

Table 11 in Appendix C reports the distribution of firms' headquarters per circuit over the sample period. From the 9,628 firms included in the final sample, 37% are headquartered in the two most liberal circuits. The Ninth Circuit, which comprises nine states, including California, Oregon, Nevada and Washington, is home to 26% of the firms. The Second Circuit, which covers three states, Vermont, Connecticut, and New York, hosts 11% of the firms in the sample. The Fifth Circuit ranks third and is home to a little over 10% of the firms.

Panel B of Table 1 reports Pearson correlations between judge ideology and firm characteristics. *Liberal court* is positively associated with firm risk, cash, share repurchases and research and development. Additionally, judge ideology is negatively associated to dividend payout and capital expenditure. These correlations suggest that firms that face higher ex ante litigation risk hold more cash reserves, favor share buyback schemes over dividends and display lower business risk. However, note that it is necessary to control for firm, industry, and state characteristics, as well as industry, circuit, and year fixed effects before drawing any conclusions.

4. Results

In this section, I first report regressions of firm risk on judge ideology. I subsequently report results for regressions that explore the effect of judge ideology on financial, cash, payout, and investment policies. In general, I estimate regressions of the following form:

$$y_{it} = \alpha_t + \alpha_j + \alpha_c + \beta_1 Liberal\ court_{it-1} + \gamma_1 Firmcontrols_{it-1} + \gamma_2 State\ controls_{it} + \varepsilon_{it} \quad (2)$$

where i indexes firm, t indexes time, j indexes industry, and c indexes circuit. Industry fixed effects are based on Fama-French 49 industry categories. $Liberal\ court$ is the principal variable of interest. It quantifies the likelihood of facing a liberal panel of judges in the firm's home circuit should the firm be a defendant in a class action lawsuit. State characteristics follow

Kubick et al. (2021) and include state GDP growth, state unemployment rate, and dummy variables equal to one for republican governor and republican majority state legislature. I include circuit, Fama-French 49 industry categories, and year fixed effects in all regressions. Standard errors are clustered by firm. Dependent variables are measured at time *t* and explanatory variables are measured at time $t + 1$. In addition to coefficient estimates and their *t*-statistics (in parentheses), I report economic significance (in square brackets) for the coefficient estimates on judge ideology. Economic significance is computed as the effect of a one-standard-deviation increase in *Liberal court* on the dependent variable relative to its mean.

4.1. Judge ideology and firm risk

I first examine the effects of judge ideology on firm risk. If the threat of litigation induces managers to reduce risky corporate policies to have flexibility and financial slack if a lawsuit is materialized as well as to reduce the likelihood of triggering lawsuits with highly volatile stock prices, then I anticipate that $\beta_1 < 0$. Conversely, if higher ex ante litigation risk induces a strategic response by management to reduce the expected payoff for potential plaintiffs and probably deter litigation, I expect that $\beta_1 > 0$ because as discussed in the hypotheses section (section 2.3) such strategies would imply taking more debt and pursuing , both of which would increase firms' risk.

Following Coles et al. (2018) firm controls include size (natural logarithm of total assets), stock return, sales growth, growth opportunities (Market-to-book), and book leverage. At the industry level the model controls for industry stock return volatility (defined within a firm's Fama-French 49 industry).

Table 2 reports the results. Columns (1) and (4) report estimates from a regression that includes only *Liberal court,* and circuit, industry and year fixed effects. Results show that stock return and asset volatility are significantly decreasing in *Liberal court*. In terms of economic significance, for the average firm in the sample a one-standard-deviation increase in judge ideology reduces stock return volatility (asset volatility) by 2.1% (2.7%). Focusing on the full model results reported in columns (3) and (6), results show a slightly increase in the magnitude of the coefficient estimate on *Liberal court.* A one-standard-deviation increase in litigation risk reduces stock return volatility (asset volatility) by 2.5% (2.9%). Although inconsistent with the *Strategic action hypothesis*, the negative relation between judge ideology and business risk is consistent with the *Prevention hypothesis.*[64] [65]

4.2. Judge ideology and corporate policies

The results documented in section 4.1. show that all else equal, consistent with the *Prevention hypothesis*, higher judge ideology reduces firm business risk. To identify the mechanisms driving this result, I next turn to examine how *Liberal court* influences corporate policies. Overall, if the benefits of adhering to policies chosen for reasons unrelated to *Liberal court* outweigh the expected direct and indirect litigation costs due to judge ideology, managers would uphold their corporate strategies despite the ex ante litigation risk faced by the firm. However, given the reduction in business risk documented in the previous section, I expect to find some corporate policies respond to judge ideology. My analysis begins with financial and liquidity policies. Subsequently I examine firm's payout and investment decisions.

4.2.1. Judge ideology, leverage, and cash policies

In this section, I investigate the effect of litigation risk on firms' leverage and cash holdings policies. Variable definitions are discussed in section 3.2.3. The choice of firm controls for

[64] I check the robustness of my firm risk results by augmenting the Coles et al. (2018) model to control for the different channel variables I examine (i.e., leverage cash, payout, and investment policies). Table 12 in Appendix C reports a selection of these models. In all cases, the results are virtually the same as those reported in Table 2.

[65] Appendix B discusses an empirical analysis where I exploit the Supreme Court's decision on June 21, 2077 *Tellabs Inc. v. Makor Issues & Rights*, as a source of exogenous variation in judge ideology. The results are reported in Table 14 Appendix C.

leverage and cash holdings regressions follows the capital structure literature (e.g., Billett et al. 2007; Mauer et al. 2021) and cash holdings literature (e.g., Opler et al. 1999; Liu and Mauer. 2011; Liu et al. 2014) respectively. Leverage regressions control for firm size, growth opportunities, profitability, tangible assets, asset's beta, and tax shield alternatives (*NOLCF* and *ITC*). The cash holdings model controls for firm size, growth opportunities, profitability, asset's beta, *R&D*, capital expenditure, firm's cash flows and net working capital, whether the firm pays dividends, acquisition activities, leverage, net debt, and net equity issuance.

Table 3 reports the results. The leverage regressions in columns (1) and (2) show that judge ideology does not influence firms' leverage choice. The coefficients on *Liberal court* are not significantly different from zero for neither book nor market leverage. This result suggests that with regards to financial policy the benefits of adhering to the levels of debt chosen for reasons unrelated to judge ideology exceed the expected ex ante litigation costs associated to it.[66]. Results for the cash regression, reported in column (3), show that *Liberal court* has a significant positive effect on cash balances. Specifically, a one-standard-deviation increase in *Liberal court* increases cash holdings by 5.11% for the average firm in the sample.[67] The cash holdings result is consistent with the findings in Arena and Julio (2015) and Malm et al. (2017a), both of which use actual lawsuits data for their analysis. The results, however, differ from Crane (2011) who finds no effect of litigation risk on cash. All else equal, higher cash reserves offer firms more flexibility and can lower firm risk. It may be optimal for firms to increase cash balances in response to judge ideology for at least two reasons. First, it is a policy over which managers have considerable discretion to delay or cut back investments in areas such as research and development and capital expenditure.

[66] It is also possible that cross-sectional tests uncover subsets of firms among which judge ideology does impact leverage decisions.
[67] In unreported results, I document that my cash regression results are robust to alternatively, defining cash holdings as the ratio of cash plus marketable securities to total assets.

A reduction in the former would not only contribute to higher cash reserves but would also reduce the risk profile of the firm (e.g., Liu et al. 2014; Arena and Julio 2015; Elyasiani and Zhang 2015). Whereas a reduction in capital expenditure would mean more cash reserves, it could erode the firm's hard assets and potentially contribute to increase risk (Nguyen et al. 2018). Managers also have considerable flexibility over the firm's payout policies. They may choose to retain more internally generated funds and scale back payout to equityholders. Second, increasing cash reserves allows firms to hedge future funding needs (Kim et al. 1998) and provides a cushion for managers to deal with unforeseen headwinds that may arise from lawsuits (Opler et al. 1999). Furthermore, if over time managers' assessment of judge ideology in their headquarter circuit improves, they have the leeway to adjust firm's investment and payout policies accordingly. Thus, in the next sections I examine the influence of judge ideology on payout and investment policies.

4.2.2. Judge ideology and payout policy

In this section I estimate the model specified in equation (2) for payout decisions. Following the literature, I first construct the ratio of dividends to the book value of assets (*Dividends*), and the ratio of dividends divided by fiscal year-end price (*Dividend yield*). Both of these measures capture distributions of cash to shareholders through dividends. Next, I also construct the variable *Share repurchases*, defined as the ratio of expenditure on the purchase of common and preferred stocks minus any change in redemption value of preferred stocks, to the book value of assets. This measure captures firms' payout in the form of stock repurchase schemes. Finally, I construct the variable *Total payout*, as the ratio of dividends plus the expenditure on the purchase of common and preferred stocks minus change in the redemption value of preferred stocks, all to the book value of assets. Total payout is a measure of the overall distribution of capital from the firm to equityholders.

I control for firm characteristics identified in the literature as important predictors of dividend payment decision (e.g., Grullon and Michaely 2002; Fama and French 2002; Chino 2016). I control for size, market-to-book ratio, leverage, profitability. Likewise, I include the ratio of retained earnings to book assets to control for the life cycle stage of the firm (DeAngelo et al. 2006). Firm characteristics also include asset growth and a loss dummy. Lastly, I control for firm's asset beta as a proxy for risk (Lintner 1956).

Several studies have shown that starting in 1990s open market stocks repurchase programs have become more popular to distribute capital to equity holders (Jagannathan et al. 2000; Fama and French 2001). Share buybacks have the advantage of providing firms higher flexibility relative to dividends because they do not give raise to an implicit firm commit to future payouts, whereas dividends are "sticky" with the market having negative reactions to dividend cuts (Jagannathan et al. 2000). Furthermore, repurchases are more tax-advantageous from shareholders' perspective, since they are taxed as capital gains rather than as ordinary income (e.g., Fama and French 2001; Dittmar and Dittmar 2002; Faulkender and Wang 2006; Hsieh and Wang 2008). These characteristics suggest that if firms were to increase payout as a response to litigation risk, it is more likely they would do so through repurchases rather than through dividends. Crane's (2011) findings support this conjecture, as he documents a positive correlation between lawsuits at the industry level and share repurchases by firms in that industry.

The discussion above suggests that the coefficient estimate on *Liberal court* for the *Share repurchases* regression could be positive (e.g., $\beta_1 > 0$), which would be consistent with firms facing higher litigation risk favoring a more flexible means to distribute cash back to shareholders and/or shifting value from future litigants to current shareholders. The flexibility that comes with shares buyback would allow corporations to scale back payout and reallocate those funds to deal with potential litigation related costs or fund investing opportunities reducing dependency from external capital markets, facing little or no negative reaction from shareholders. Such payout policy would be cost efficient since litigation risk has been shown to increase firms' cost of debt (e.g., Kubick et al. 2021). In addition, shareholders would see with favorable eyes higher share repurchases given its tax-advantage over dividends distribution. Paired with this rationale would be a negative coefficient estimate on *Liberal court* (e.g., $\beta_1 < 0$) for dividends regressions, suggesting that a reduction in payout to equityholders contributes to higher cash reserves.

Lastly, the expected sign on the coefficient estimate on *Liberal court* for the *Total Payout* regression will depend on the net effect of what we observe for dividends and share repurchases. Higher payout would effectively transfer value from future litigants to current shareholders (e.g., Scott 1977; Crane 2011).

Table 4 reports the results. For each of the four payout variables I estimate a regression with the dependent variable measured at time t and another one with the dependent variable measured at time $t + 1$. Because changes in payout policy may be implemented gradually, this approach is more suitable to capture the impact (if any) of *Liberal court* on payout policy. The dividend payout regressions in Panel A show a strong inverse relation between judge ideology and *Dividends* (Columns (1) and (2)) and *Dividend yield* (Columns (3) and (4)), a result consistent with those reported in Malm et al. 2020. Economically, a one-standard-deviation increase in litigation risk decreases *Dividends* (*Dividend yield)* by 8.9% (10.1 %) relative to their corresponding mean sample values. The impact on the dividend payout measures is virtually the same at both time t and time $t + 1$.

Panel B reports results for share repurchases and total payout. Perhaps surprisingly, yet consistent with the evidence in Crane (2011), *Liberal court* has a positive effect on *Share* *repurchases*. Notice that in contrasts with dividend payout, results indicate that changes in stock repurchase programs induced by *Liberal court* occur gradually. It is at time $t + 1$ that the effect has a higher statistical and economic significance. A one-standard-deviation increase in litigation risk increases *Share repurchases* by 12.46% at time t and by 17.80% at time $t + 1$. Finally, the results for *Total payout* are only marginally significant when evaluated at time $t + 1$ when a one-standard-deviation increase in litigation risk increases *Total payout* by 9.49%. Although not statistically different from zero, the coefficient estimate on *Liberal court* at time t conveys important information. It suggests that firms do not reduce total payout to shareholders, with the reductions (increases) in dividends (share repurchases) apparently offsetting each other at time t and payout marginally increasing at time $t + 1$. Taken together the payout policy results suggests that firms exposed to litigation risk favor a flexible payout policy which they procure by increasing the use of share repurchase programs and curtailing dividend payout. This evidence is consistent with share repurchases and dividends being substitutes (Grullon and Michaely, 2002).[68]

4.2.3. Judge ideology and investment policy

In this section I examine whether judge ideology affects firms' investment policy. For each investment policy, I estimate a regression with the dependent variable measured at time t and another one with the dependent variable measured at time $t + 1$. Because changes in payout policy may be implemented gradually, this approach is more suitable to capture the influence (in any) of *Liberal court* on firms' investing policy. Specifically, I examine the effect of judge ideology on the ratio of capital expenditure to book assets (*CAPEX*), the ratio of research and development

[68] As an additional test, I construct the variable *Payout preference,* as the difference between the distributions in share repurchases minus the distribution in dividends, all to the book value of assets. Results are tabulated in Table 13 Appendix C and indicate the preference of share repurchase programs over dividends is increasing in judge ideology for the average firm in the sample. In unreported results I estimate probit regressions to evaluate the effect of *Liberal court* on the probability on paying a dividend in the full sample and in the dividend-payer subgroup. In both cases I find a negative and significantly negative impact of judge ideology.

spending to book assets (*R&D*). Controls follow Coles et al. (2018) and are the same discussed in section 4.1. If firms in circuits with greater liberal judge ideology adjust their investment policy to hoard cash and lower business risk, I expect that the coefficient estimate on *Liberal court* will be negative ($\beta_1 < 0$) in the research and development expenditure models. A prediction for the capital expenditure regression is less clear. The case where $\beta_1 > 0$ would signal an increase in hard assets which is consistent with lower business risk. Alternatively, the case where $\beta_1 < 0$ could contribute to higher cash reserves which would also suggest lower business risk.

Table 5 reports the results. The evidence is mixed, with the coefficient on *Liberal court* is not significantly different from zero across all but one of the estimations. Judge ideology reduces capital expenditure at time $t + 1$, with a one-standard-deviation increase in litigation risk reducing *CAPEX* by 3.30%. Such results is consistent with that reported in Arena and Julio (2015) who using actual lawsuits data conclude that firms cut back capital expenditure to build cash reserves. The results are at odd with Malm et al. (2017b), who report litigation risk is associated with higher capital expenditure and higher research and development expenditure. As with the leverage results in section 4.2.1 the cases where there is no impact of judge ideology on investment would be consistent with the idea that the potential costs from future litigations are not sufficiently large to cause managers to alter their strategies in terms of innovation and investment in hard assets or that it takes time for managers to reasonably assign a value to them.

4.3. Judge ideology and the value of cash

Now I turn to examine the effect of judge ideology on the value of cash to equity holders. The purpose of this test is to get a better understanding of whether the policy changes associated with liberal judge ideology are in benefit of shareholder's wealth maximization or if they aim to benefit self-interested managers. Elyasiani and Zhang (2015) find that entrenched managers hold more cash because it helps lower firm risk, increase job security, and gives them leeway in pursuing personal interests. If managers hoarding cash for self-interests drive the increase in cash holdings documented in section 4.2.1, I expect judge ideology to have a negative effect on the marginal value of cash.

On the other hand, if higher cash reserves are beneficial for shareholders' interests, I expect to find a positive effect of ex ante litigation risk on the value of cash. The flexibility that comes with greater internal funds can allow firms to reduce the need to raise funds from the capital markets, which would likely be well received by shareholders since litigation risk has been shown to increase firms' cost of debt (e.g., Kubick et al. 2021). This evidence would suggest that stockholders view as positive the effect of judge ideology on managers' corporate policies and compound the value of cash when the firm's headquarter circuit is composed of more liberal judges. Equityholders for instance, may find valuable for the firm to hold more cash for precautionary reasons expecting the firm to respond in a prompt and efficient manner to unexpected negative events (Opler et al. 1999) such as legal fees or settlements derived from lawsuits (Arena and Julio 2015). The increased use of share repurchases relative to dividends as part of firms' payout policy may also contribute to higher cash valuations. Faulkender and Wang (2006) show that the marginal value of cash declines as firms choose greater cash distribution via dividends rather than repurchases.

I use the methodology developed by Faulkender and Wang (2006) to estimate the influence of judge ideology on the value of an additional dollar of cash to equityholders. This methodology estimates the value of cash to stockholders in regressions in which excess stock returns are regressed on the change in cash and other corporate policy variables. I estimate the Faulkender and Wang regression augmented to include judge ideology as follows:

$$R_{it} - RB_{it} = \alpha + \beta_1 \frac{\Delta C_{it}}{M_{it-1}} + \beta_2 \frac{\Delta E_{it}}{M_{it-1}} + \beta_3 \frac{\Delta NA_{it}}{M_{it-1}} + \beta_4 \frac{\Delta RD_{it}}{M_{it-1}} + \beta_5 \frac{\Delta I_{it}}{M_{it-1}} + \beta_6 \frac{\Delta D_{it}}{M_{it-1}}$$
$$+ \beta_7 \frac{C_{it-1}}{M_{it-1}} + \beta_8 L_{it} + \beta_9 \frac{NF_{it}}{M_{it-1}} + \beta_{10} \frac{C_{it-1}}{M_{it-1}} \times \frac{\Delta C_{it}}{M_{it-1}} + \beta_{11} L_{it} \times \frac{\Delta C_{it}}{M_{it-1}}$$
$$+ \beta_{12}\, Liberal\ court_{it} + \beta_{13} \times Liberal\ court_{it} \times \frac{\Delta C_{it}}{M_{it-1}} + \varepsilon_{it} \qquad (3)$$

where the dependent variable is the difference between firm *i*'s stock return over year $t-1$ to year t (r_{it}) estimated using monthly returns from CRSP and the Fama and French (1993) size and book-to-market matched portfolio return from year $t-1$ to year t (R^B_{it}).[69] For the right-hand-side variables ΔX_t denotes the one-year change in variable *X* for firm *i* over year $t-1$ to year t, where the scaling variable, $M_{it\text{-}1}$, is firm *i*'s market value of equity at time $t-1$. The vector of controls include cash and marketable securities (C_{it}), earnings before extraordinary items (E_{it}), net assets (NA_{it}), research and development expense (RD_{it}) (set equal to zero if missing), interest expense (I_{it}), common dividends (D_{it}), long-term debt plus debt in current liabilities divided by the market value of assets at time *t* (L_{it}), and net new finance (NF_{it}).[70] Table 1 reports descriptive statistics for these variables. I follow Faulkender and Wang (2006), and winsorize the variables at the 1st and 99th percentiles.

The coefficient on *Liberal court* (β_{12}) measures the direct influence of *Liberal court* on excess equity returns, and the coefficient on the interaction of *Liberal court* with the change in cash (β_{13}) measures the effect of judge ideology on the value of and additional dollar of cash. I

[69] Specifically, for each year, I group every firm in the sample into one of 25 size and book-to-market portfolios based on the intersection between size and book-to-market independent sorts. Thus, stock *i*'s benchmark return in year *t* is the return to which stock *i* belongs at the beginning of fiscal year *t*. I retrieve returns on these 25 portfolios from Kenneth R. French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. I thank Professor French for making these data available.

[70] Net new finance, NF_{it}, is calculated as sales of common and preferred stock net of stock repurchases, plus issuance of long-term debt net of long-term debt reduction.

am interested in examining how the marginal value of cash changes with ex ante litigation risk; therefore, I focus on the sign and magnitude of β_{13}.

If the increase in cash reserves documented in Table 3 benefit shareholders, I expect the effect of judge ideology on the marginal value of cash to be positive ($\beta_{13} > 0$). Alternatively, if the higher cash holdings are held driven by self-interested managers (e.g., to protect their job and reputation from potential lawsuits), I predict that the effect of judge ideology on the marginal value of cash will be negative ($\beta_{13} < 0$).

Table 6 reports a baseline Faulkender and Wang (2006) regression specification without judge ideology in models (1) and (2). Model (1) includes industry and year fixed effects, whereas model (2) also incorporates state controls circuit fixed effects. Model (3) presents the augmented specification, where *Liberal court* and its interaction with the change in cash are included. From the baseline specification in Models (1) and (2), the value of an additional dollar of cash for a firm with zero cash balances and zero leverage is \$1.554. Focusing on model (2), the value of an additional dollar of cash for the average firm with cash holdings of 18.7% of the market capitalization of equity at the beginning of the fiscal year and a market leverage ratio of 22.3% is 1.554 − 0.702 × .187 – 1. 468 × .223 = \$1.09 .

When the baseline regression specification is augmented to include *Liberal court* as a measure of ex ante litigation risk, the coefficient of the annual change in cash holdings remains positive and significant. The estimated coefficient on ex ante litigation risk is negative and insignificant (measures the direct effect of *Liberal court* on excess equity returns). In contrast, the coefficient of the interaction between *Liberal court* and the change in cash is significantly positive (measures the effect of *Liberal court* on the value of an additional dollar of cash held by the firm). This indicates that ex ante litigation risk increases the marginal value of cash. From column (3) I find that for the average firm in the sample, the value of an additional dollar of cash is 1.355– 0.7027× 0.187 – 1. 449 × 0.223 + 0.514×0.378 = \$1.09. The effect of judge ideology is economically significant, for the average firm in the sample a one-standard-deviation increase in *Liberal court* increases the marginal value of cash by roughly 8.4% to \$1.18. The evidence on the effect of judge ideology on the marginal value of cash suggests that the change in cash policy induced by liberal judge ideology is aligned with shareholders' interests.[71]

5. Variation in the cross-section

In this section, I examine cross-sectional heterogeneity in the findings. My analysis focuses on firms' corporate governance and financial constraints.

5.1. Corporate governance

I first investigate whether corporate governance moderates the relation between judge ideology and the corporate policies that I have identified as been more strongly influenced by it. On one hand, it is possible that ex ante litigation risk is most effective when there are good governance measures in place that allow firms to be sensitive to liberal judge ideology. This would suggest a complementary relation between judge ideology and corporate governance (Appel 2019). Alternatively, weak governance firms (e.g., with powerful managers) could react the most to *Liberal court* since this is an external governance mechanism over which management exerts no control. I use four different governance measures in my analysis. *E-index* is the Bebchuk et al. (2009) entrenchment index based on the sum of indicator variables for six antitakeover provisions. *Powerful CEO* is a dummy variable equal to one if the CEO is the only insider on the board of directors and serves as the chairman of the board of directors and president of the company, and

[71] In unreported regressions, I estimate the Faulkender and Wang (2006) value of cash regressions in Table 6 using alternative winsorization schemes. The results are robust to these variations and remain qualitatively the same.

zero otherwise. *Board size* is the number of directors in the board, and *Board independence* is the percentage of outside directors in the board.[72] For the three continuous variables, I group firms into strong and weak governance based on sample yearly median. Where lower E-index, smaller boards, and more independent boards proxying for strong governance. For *Powerful CEO* , the strong governance group is that without a powerful CEO.

Table 7 reports the results. Subsamples of weaker (stronger) corporate governance are reported in the left (right) columns. There are less than a handful of cases in which a statistically significant difference is reported. Splits based on board size for business risk (Panel A and B) suggest the effect of *Liberal court* on firm risk is stronger for firms with small boards. The rest of the results are insignificant. for business risk (Panels A and B), cash and its marginal value to shareholders (Panels C and D), and for payout policies regressions (Panels E and F).[73] [74] In general, the results reported in Table 7 do not help to inform whether litigation risk and corporate governance have a complementary relation (Appel 2019) or that is serves a substitute for poor internal governance.

5.2. Financial constraints

Next, I examine heterogeneity in the main findings conditioning on financial constraints. Higher litigation risk may increase cash flow uncertainty making firms susceptible to liquidity shortages in bad states of the world and therefore, potential underinvesting (Phan et al. 2017). This problem is expected to be exacerbated for financially constrained firms. Furthermore, given that litigation risk leads to costly external finance (Kubick et al. 2021), equity holders should be more

[72] The governance literature documents that smaller boards are more effective (e.g., Yermack 1996).
[73] Splits based on the *E-index* and *Powerful* CEO for the marginal value of cash regressions reported in Panel D are also significant but lead to opposing conclusions. As such, the results are unreliable.
[74] In unreported robustness tests, I also use busy board and classified board (Hoechle et al. 2012) to estimate subsamples regressions as those reported in Table 7. I find no significant differences between weak and strong governance subsamples in this analysis.

willing to allow firms to hold more cash on hand for managers to respond appropriately to unforeseen headwinds that may arise from lawsuits (Opler et al. 1999). Thus, I hypothesize that litigation risk may have a stronger effect particularly on cash and payout policies among high financial constrained firms. I use four proxies for financial constraints. The *WW-index* is the Whited and Wu (2006) index. *Size* is proxied by firms' total assets. *Growth opportunities* are measured by firm's market-to-book ratio. *Dividend payer* is a dummy equal to one when the firm pays dividends and zero otherwise. Finally, I also conduct a sub-sample analysis by splitting the sample into firms that are part of the high litigation risk industries or those that not. This split is based on the *FPS* indicator variable (Francis et al. 1994), which is equal to one for biotech firms, computer firms, electronics firms, and retail firms, and zero otherwise. More than a proxy for financial constraint, the *FPS* variable proxies for potential uncertainty/likelihood of being sued based on industry membership.

Table 8 reports the results. Financially constrained firm subsamples are reported in the left columns, and none-constrained firm subsamples are reported in the right columns. Results for cash (Panel C), the marginal value of cash (Panel D), and stock repurchase programs (Panel E) are for the most part consistent with the effect of litigation risk being accentuated (or only present) among firms with high financial constraints. Consistent with expectations, results show that *Liberal court* has a significantly more positive effect on cash holdings and the marginal value of cash when the financial constraints are high. Results are similar for share repurchase regressions. Overall, the results show that the effect of judge ideology is accentuated when the firm is financially constrained.

6. Conclusions

Securities class action lawsuits are costly to firms. Not surprisingly, several studies in the literature have examined how litigation risk affects firms' corporate policies and outcomes. Due to data availability most of these studies use actual lawsuit data, or firm and industry characteristics to proxy for litigation risk. This empirical strategy is prone to endogeneity problems and causal interpretation is compromised. In this study I contribute to understand the effect of ex ante litigation risk on corporate policies by using a novel measure of ex ante litigation risk exogenous to the firm. I measure ex ante litigation, risk using judge ideology, determined by the ideology of federal circuit judges and the partisanship of the appointing president.

I find that *Liberal court*, as measured by the probability of having a majority of judges on a circuit court panel appointed by Democratic presidents, increases cash holdings, the marginal value of cash to equity holders and the use of share repurchases schemes. In contrast, liberal judge ideology is associated with lower dividend payout and firm business risk. Cross-sectional tests show that the effect of judge ideology on corporate policies is stronger in subsamples of high financially constrained firms. The evidence seems to support that, even though some of the lawsuits brought before the legal system may be meritless and divert firms' resources, there are also benefits that derive from ex ante litigation These results are consistent with the idea that ex ante litigation risk serves as an external governance mechanism to influence self-interested managers behavior, and that specially for financially constrained firms it is valuable to enhance financially flexibility via internal funds and a more elastic payout policy when ex ante litigation risk is high. These findings illustrate the importance of political appointments in the choice of corporate policies and show that managers are aware of judge ideology's effect on litigation risk and factor into corporate decisions.

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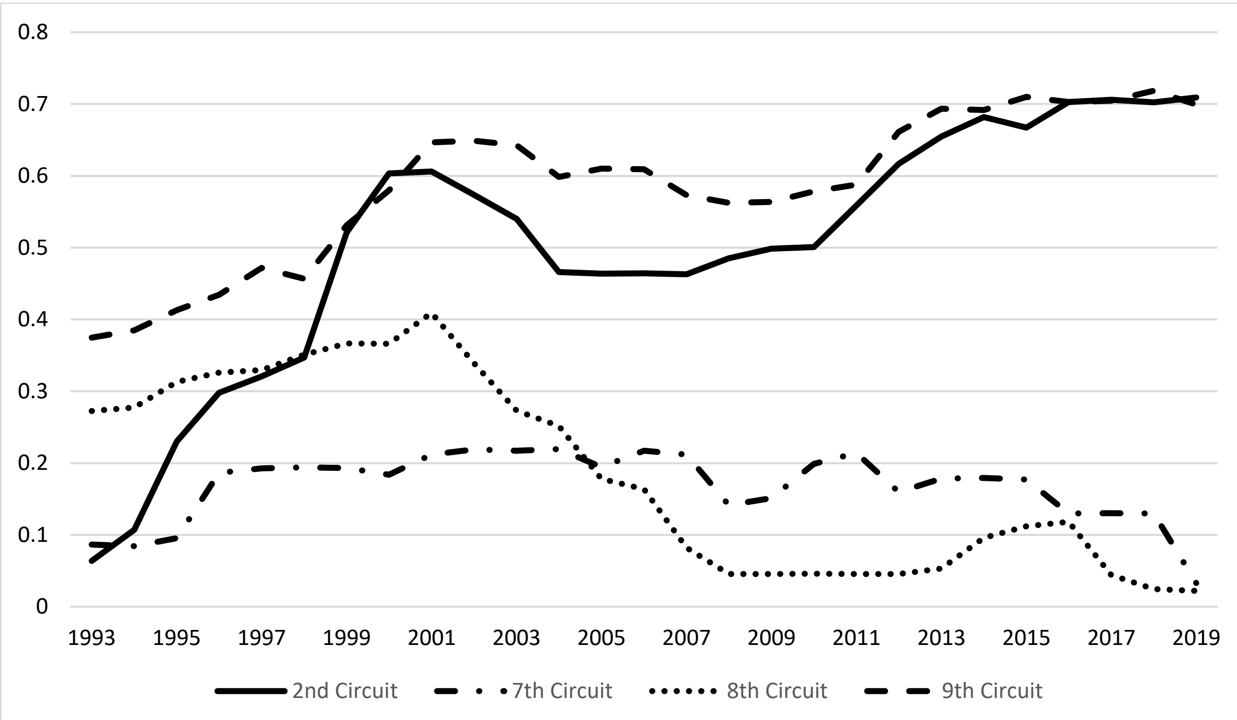
Figures

Figure 3.1. Annual time trend of judge ideology for the most liberal and most conservative circuits
The figure plots yearly mean values of judge ideology (i.e., *Liberal court*) of the two circuits with the highest ex ante litigation risk (2nd and 9th Circuits) and the two circuits with the lowest ex ante litigation risk (7th and 8th Circuits) during the sample period from 1993 to 2019.



Tables

Table 3.1. Descriptive statistics and correlations

The sample runs from 1993 to 2019 and corresponds to 83,475 firm-year observations and 9,628 unique firms. Panel A reports descriptive statistics of main variables and Panel B reports Pearson correlation coefficients between *Liberal court* and key variables. All variables are defined in Appendix A. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. Descriptive statistics

	Mean	Std. dev.	1st quartile	Median	3rd quartile	Obs.
Key independent variable: Judge ideology						
Liberal court	0.379	0.178	0.247	0.371	0.500	83,475
Dependent variables						
Stock return volatility	0.633	0.411	0.352	0.518	0.779	83,475
Asset volatility	0.495	0.322	0.278	0.393	0.609	83,475
Cash	0.505	0.951	0.029	0.113	0.382	83,475
Book leverage	0.233	0.228	0.023	0.190	0.361	83,475
Market leverage	0.167	0.178	0.011	0.113	0.261	83,475
Dividends	0.008	0.019	0.000	0.000	0.006	83,475
Dividend yield	0.007	0.017	0.000	0.000	0.007	83,475
Share repurchases	0.019	0.047	0.000	0.000	0.016	83,475
Total Payout	0.030	0.238	0.000	0.003	0.034	83,475
Payout preference	-0.007	0.073	-0.004	0.000	0.003	83,475
Capex	0.054	0.061	0.017	0.035	0.067	82,957
R&D	0.061	0.129	0.000	0.002	0.067	83,475
Firm characteristics						
Assets ($M)	2,666	7,451	78	335	1,515	83,475
Stock return	0.123	0.671	-0.280	0.025	0.351	83,475
Sales growth	0.310	1.017	-0.002	0.081	0.236	83,475
Asset tangibility	0.261	0.230	0.081	0.186	0.375	83,475
Market-to-book	2.139	1.880	1.135	1.543	2.366	83,475
Asset beta	0.950	0.692	0.515	0.832	1.268	83,475
Dividend payer	0.298					83,475
ROA	0.043	0.269	0.026	0.106	0.165	83,475
Cash flow/Assets	-0.028	0.863	-0.004	0.064	0.107	83,475
NOLCF	0.448					83,475
ITC	0.138					83,475
Loss	0.372					83,475
NWC/Assets	0.159	0.170	0.000	0.110	0.262	83,475
FPS	0.362					83,475
Net debt issuance	32.340	232.293	-3.746	0.000	6.000	83,322
Net equity issuance	-30.524	186.516	-0.87	0.090	3.333	83,475
Retained earnings	-0.075	0.404	-0.003	0.000	0.001	83,475
Asset growth	0.114	0.719	-0.076	0.025	0.153	83,475
Industry stock return vol.	4.092	1.484	2.972	3.827	5.062	83,475

Table 3.1—*Continued*

	Mean	Std. dev.	1st quartile	Median	3rd quartile	Obs.
State variables						
State GDP growth (%)	2.914	2.493	1.500	2.800	4.400	83,475
State unemployment rate (%)	5.765	1.841	4.500	5.400	6.600	83,475
Republican governor	0.597					83,475
Republican legislature	0.299					83,475
Cash value regression variables						
$r_{it} - R_{it}^B$	0.000	0.660	-0.398	-0.092	0.241	71,508
ΔC_t	0.008	0.154	-0.030	0.001	0.037	71,508
C_{t-1}	0.187	0.266	0.035	0.098	0.226	71,508
ΔE_t	0.039	0.377	-0.031	0.006	0.044	71,508
ΔNA_t	0.009	0.525	-0.047	0.022	0.120	71,508
ΔRD_t	-0.002	0.028	0.000	0.000	0.002	71,508
ΔI_t	0.001	0.030	-0.001	0.000	0.003	71,508
ΔD_t	0.000	0.008	0.000	0.000	0.000	71,508
L_t	0.223	0.241	0.013	0.145	0.351	71,508
NF_t	0.042	0.246	-0.033	0.000	0.059	71,508
Liberal court	0.378	0.179	0.245	0.371	0.534	71,508
Corporate governance variables						
E-index	2.339	1.354	1.000	2.000	3.000	25,126
Powerful CEO	0.182					25,126
Board independence	0.712	0.174	0.615	0.750	0.857	25,126
Board size	9.050	2.299	7.000	9.000	10.000	25,126

Panel B. Pearson correlations

	1	2	3	4	5	6
1. Stock return volatility	0.036***	1				
2. Asset volatility	0.067***	0.821***	1			
3. Cash	0.124***	0.118***	0.255***	1		
4. Book leverage	-0.034***	0.067***	-0.306***	-0.203***	1	
5. Market leverage	-0.058***	0.120***	-0.321***	-0.244***	0.858***	1
6. Dividends	-0.065***	-0.279***	-0.241***	-0.062***	-0.013***	-0.099***
7. Dividend yield	-0.083***	-0.239***	-0.251***	-0.093***	0.075***	0.074***
8. Share repurchase	0.025***	-0.157***	-0.106***	-0.015***	-0.050***	-0.135***
9. Total payout	0.004	-0.056***	-0.036***	-0.010***	-0.002	-0.037***
10. Payout preference	0.025***	-0.209***	-0.152***	-0.032***	-0.084***	-0.067***
11. Capex	-0.093***	-0.046***	-0.068***	-0.162***	0.103***	0.093***
12. R&D	0.148***	0.244***	0.385***	0.447***	-0.148***	-0.254***
13. $r_{it} - R_{it}^B$	0.198***	-0.057***	0.055***	0.034***	-0.073***	-0.167***

Table 3.1—*Continued*

Panel B. Pearson correlations

	7	8	9	10	11
6. Dividends	1				
7. Dividend yield	0.723***	1			
8. Share repurchase	0.136***	0.027***	1		
9. Total payout	0.115***	0.065***	0.368***	1	
10. Payout preference	-0.202***	-0.176***	0.492***	0.178***	1
11. Capex	-0.004	-0.002	-0.015***	-0.008**	-0.010***
12. R&D	-0.133***	-0.160***	-0.022***	0.004	-0.083***
13. $r_{it} - R_{it}^{B}$	0.010***	-0.047***	0.001	0.002	0.032***

Table 3.2. Effect of judge ideology on firm risk

The table reports OLS regressions of firm risk on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. The dependent variable is *Stock return volatility* in columns (1) – (3) and *Asset volatility* in columns (4) – (6). *Stock return volatility* is the annualized standard deviation of daily stock returns over the fiscal year. *Asset volatility* is constructed following Schwert and Strebulaev (2014) as the standard deviation of returns on a portfolio of the firm's equity and debt over the fiscal year. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. The economic significance of the coefficient estimates on judge ideology are reported in square brackets. They measure the effect of a one-standard-deviation increase in *Liberal court* on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent var. =	*Stock return volatility*			*Asset volatility*		
	(1)	(2)	(3)	(4)	(5)	(6)
Liberal court	-0.073***	-0.085***	-0.090***	-0.075***	-0.074***	-0.082***
	(-3.23)	(-4.74)	(-4.89)	(-4.33)	(-5.58)	(-5.95)
	[-2.05%]	[-2.39%]	[-2.53%]	[-2.70%]	[-2.66%]	[-2.95%]
Ln(Assets)		-0.101***	-0.101***		-0.075***	-0.076***
		(-72.17)	(-72.23)		(-69.12)	(-69.20)
Stock return		-0.047***	-0.047***		0.024***	0.024***
		(-19.90)	(-19.92)		(14.14)	(14.15)
Sales growth		0.027***	0.027***		0.020***	0.020***
		(13.82)	(13.81)		(12.54)	(12.52)
Market-to-book		-0.014***	-0.015***		0.008***	0.008***
		(-14.07)	(-14.13)		(9.52)	(9.41)
Book leverage		0.313***	0.313***		-0.150***	-0.149***
		(29.36)	(29.36)		(-23.25)	(-23.29)
Industry stock return volatility		0.043***	0.043***		0.028***	0.028***
		(27.48)	(27.47)		(24.23)	(24.22)
State GDP			0.004***			0.004***
			(4.57)			(7.36)
State unemployment			0.011***			0.008***
			(5.16)			(4.74)
Republican governor			-0.009***			-0.005*
			(-2.61)			(-1.94)
Republican legislature			0.003			0.000
			(0.58)			(0.08)
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.201	0.459	0.459	0.250	0.508	0.508
Observations	83,475	83,475	83,475	83,475	83,475	83,475

Table 3.3. Effect of judge ideology on financial leverage and cash holdings

The table reports OLS regressions of leverage and cash on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. The dependent variable is identified at the top of each column. *Book leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the book value of total assets. *Market leverage* is defined as the ratio of long-term debt plus debt in current liabilities to the market value of assets (i.e., the book value of assets minus the book value of equity plus the market value of equity). *Cash* is defined as the ratio of cash and marketable securities to net assets. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. The economic significance of the coefficient estimates on judge ideology are reported in square brackets. They measure the effect of a one-standard-deviation increase in *Liberal court* on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variable =	*Book leverage*	*Market leverage*	*Cash*
	(1)	(2)	(3)
Liberal court	-0.003	-0.002	0.145***
	(-0.23)	(-0.18)	(2.97)
	NA	NA	[5.11%]
Ln(Assets)	0.023***	0.013***	-0.025***
	(22.21)	(15.65)	(-6.44)
Market to book	-0.003***	-0.019***	0.030***
	(-3.67)	(-34.53)	(5.94)
ROA	-0.131***	-0.072***	0.915***
	(-18.24)	(-18.52)	(18.70)
Asset beta	-0.048***	-0.035***	0.072***
	(-32.43)	(-34.67)	(8.93)
Asset tangibility	0.207***	0.169***	
	(17.26)	(16.96)	
NOLCF	0.034***	0.023***	
	(10.51)	(9.82)	
ITC	-0.036***	-0.029***	
	(-9.47)	(-11.05)	
R&D/sales			0.082***
			(8.78)
Capex/net assets			0.635***
			(7.16)
Cash flow/net assets			-0.694***
			(-30.26)
NWC/net assets			1.152***
			(15.39)
Dividend payer			-0.025**
			(-2.00)
Acquisition Activity			-0.503***
			(-12.32)
Book leverage			-0.008
			(-0.16)

Table 3.3 —*Continued*

Dependent variable =	*Book leverage*	*Market leverage*	*Cash*
	(1)	(2)	(3)
Net debt issuance			-0.000
			(-0.80)
Net equity issuance			0.008**
			(2.55)
State GDP	0.001	-0.000	0.004*
	(1.17)	(-0.21)	(1.70)
State unemployment	-0.000	-0.000	0.005
	(-0.15)	(-0.27)	(0.76)
Republican governor	-0.000	-0.001	0.017
	(-0.03)	(-0.74)	(1.59)
Republican legislature	-0.000	0.002	-0.071***
	(-0.04)	(0.52)	(-5.53)
Circuit FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj *R*-sq	0.229	0.297	0.485
Observations	83,475	83,475	82,793

Table 3.4. Effect of judge ideology on payout

The table reports OLS regressions of payout measures on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. Panel A reports results for *Dividends* and *Dividend yield*. *Dividends* is defined as the ratio of dividends to the book value of assets. *Dividend yield* is defined as dividends divided by fiscal year-end price. Panel B reports results for *Share repurchases* and *Total Payout*. *Share repurchases* is defined as the expenditure on the purchase of common and preferred stocks minus change in the redemption value of preferred stocks, all to the book value of assets. *Total Payout* is defined as the ratio of dividends plus the expenditure on the purchase of common and preferred stocks minus change in the redemption value of preferred stocks, all to the book value of assets. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. The economic significance of the coefficient estimates on judge ideology are reported in square brackets. They measure the effect of a one-standard-deviation increase in *Liberal court* on the dependent variable relative to its mean. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A.

Dependent variable =	*Dividends* $_{t}$	*Dividends* $_{t+1}$	*Dividend yield* $_{t}$	*Dividend yield* $_{t+1}$
	(1)	(2)	(3)	(4)
Liberal court	-0.004***	-0.004***	-0.004***	-0.004***
	(-2.77)	(-2.82)	(-3.04)	(-3.13)
	[-8.90%]	[-8.90%]	[-10.17%]	[-10.17%]
Ln(Assets)	0.001***	0.001***	0.001***	0.001***
	(8.81)	(8.08)	(15.18)	(13.55)
Book leverage	-0.007***	-0.007***	-0.003***	-0.003***
	(-8.10)	(-7.93)	(-4.21)	(-4.10)
Market to book	0.002***	0.002***	0.000	0.000
	(12.57)	(12.49)	(0.84)	(1.29)
ROA	0.007***	0.010***	0.001	0.002***
	(9.37)	(10.41)	(1.31)	(3.00)
Retained earnings	-0.001***	-0.005***	0.000	-0.001***
	(-4.98)	(-11.27)	(1.64)	(-4.83)
Asset beta	-0.002***	-0.003***	-0.002***	-0.002***
	(-16.50)	(-15.42)	(-20.71)	(-19.03)
Asset growth	-0.002***	-0.002***	-0.001***	-0.001***
	(-6.00)	(-5.53)	(-5.25)	(-5.03)
Loss	-0.005***	-0.005***	-0.003***	-0.002***
	(-22.12)	(-20.48)	(-12.27)	(-10.94)
State GDP	-0.000	-0.000	-0.000	-0.000
	(-0.27)	(-0.50)	(-0.48)	(-0.56)
State unemployment	-0.000*	-0.000*	-0.000***	-0.000***
	(-1.86)	(-1.71)	(-2.93)	(-2.73)
Republican governor	0.001**	0.001**	0.000	0.000
	(2.25)	(2.03)	(1.51)	(1.15)
Republican legislature	-0.000	-0.000	0.000	0.000
	(-0.49)	(-0.45)	(0.07)	(0.12)
Circuit FE	Yes	Yes	Yes	Yes

Table 3.4 —*Continued*

Dependent variable =	*Dividends* $_{t}$	*Dividends* $_{t+1}$	*Dividend yield* $_{t}$	*Dividend yield* $_{t+1}$
	(1)	(2)	(3)	(4)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.173	0.181	0.142	0.140
Observations	83,475	72,706	83,475	72,706

Panel B.

Dependent variable =	*Share rep* $_{t}$	*Share rep* $_{t+1}$	*Total payout* $_{t}$	*Total payout* $_{t+1}$
	(1)	(2)	(3)	(4)
Liberal court	0.014*	0.020**	0.011	0.016*
	(1.91)	(2.34)	(1.44)	(1.84)
	[12.46%]	[17.80%]	NA	[9.49%]
Ln(Assets)	0.005***	0.005***	0.006***	0.006***
	(6.86)	(6.76)	(8.25)	(8.06)
Book leverage	-0.019***	-0.019***	-0.027***	-0.026***
	(-3.20)	(-3.01)	(-4.34)	(-4.08)
Market to book	0.007***	0.008***	0.009***	0.010***
	(9.33)	(9.44)	(11.33)	(11.36)
ROA	0.022	0.022	0.032	0.032
	(0.87)	(0.84)	(1.28)	(1.24)
Retained earnings	-0.050***	-0.053***	-0.054***	-0.058***
	(-3.08)	(-3.13)	(-3.37)	(-3.39)
Asset beta	-0.005**	-0.004*	-0.007***	-0.007***
	(-2.10)	(-1.86)	(-3.21)	(-3.04)
Asset growth	-0.016***	-0.016***	-0.018***	-0.018***
	(-6.06)	(-6.11)	(-6.54)	(-6.56)
Loss	-0.017***	-0.016***	-0.022***	-0.021***
	(-3.75)	(-3.59)	(-4.81)	(-4.64)
State GDP	-0.000	0.000	-0.000	0.000
	(-0.35)	(0.23)	(-0.39)	(0.19)
State unemployment	-0.000	-0.001	-0.001	-0.001
	(-0.73)	(-0.82)	(-1.17)	(-1.22)
Republican governor	0.001	0.000	0.001	0.001
	(0.24)	(0.12)	(0.50)	(0.35)
Republican legislature	0.002	0.002	0.002	0.002
	(1.01)	(1.13)	(0.90)	(1.03)
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.010	0.010	0.015	0.015
Observations	83,475	72,706	83,475	72,706

Table 3.5. Effect of judge ideology on corporate investment policy

The table reports OLS regressions of investments measures on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. *CAPEX* is defined as the ratio of annual capital expenditures to the book value of assets. *R&D* is defined as the ratio of annual research and development expenditure to the book value of assets. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable=	$CAPEX_{t}$	$CAPEX_{t+1}$	$R\&D_{t}$	$R\&D_{t+1}$
	(1)	(2)	(2)	(4)
Liberal court	-0.003	-0.010**	-0.004	-0.002
	(-0.79)	(-2.43)	(-0.65)	(-0.32)
	NA	[-3.30%]	NA	NA
Ln(Assets)	0.001***	0.003***	-0.010***	-0.010***
	(3.50)	(9.49)	(-19.32)	(-19.32)
Stock return	-0.000	-0.001**	-0.009***	-0.009***
	(-0.53)	(-2.58)	(-13.16)	(-13.16)
Sales growth	0.001***	0.002***	0.008***	0.008***
	(3.56)	(4.35)	(6.61)	(6.61)
Market-	0.003***	0.001***	0.009***	0.009***
to-book	(13.38)	(6.61)	(13.16)	(13.16)
Book	-0.007***	0.008***	-0.005	-0.005
Leverage	(-3.82)	(3.85)	(-1.23)	(-1.23)
Industry stock	-0.000***	-0.001***	0.002***	0.002***
return vol.	(-2.68)	(-3.34)	(5.14)	(5.15)
State GDP	0.000	-0.000	0.000	0.000
	(1.00)	(-0.02)	(1.26)	(1.25)
State	-0.001**	-0.002***	0.002**	0.002**
Unemployment	(-2.43)	(-4.06)	(2.22)	(2.23)
Republican	-0.001	-0.001*	0.001	0.001
Governor	(-1.61)	(-1.84)	(0.49)	(0.55)
Republican	0.001	0.001	-0.008***	-0.008***
Legislature	(1.28)	(0.83)	(-4.54)	(-4.48)
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.308	0.105	0.422	0.422
Observations	72,296	72,296	72,701	72,701

Table 3.6. Effect of judge ideology on the value of cash

The table reports OLS regressions of excess stock returns, $r_{it} - R_{it}^B$, defined as the stock return of firm *i* during fiscal year *t*, r_{it}, minus stock *i*'s benchmark return in year *t*, R_{it}^B, where the benchmark return is the return of the Fama and French size and book-to-market portfolio to which stock *i* belongs at the beginning of fiscal year *t*. All variables except *Liberal court* and *Leverage* are scaled by the lagged market value of equity M_{t-1}. Model (1) is the benchmark Faulkender and Wang (2006) specification. Model (3) is the augmented specification where *Liberal court* and its interaction with the change in cash is included as an explanatory variable. In the regressions, C_t is cash plus marketable securities, E_t is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits, NA_t is total assets minus cash holdings, RD_t is research and development expense (which is set equal to zero if missing), I_t is interest expense, D_t is common dividends, L_t is the ratio of long-term debt plus debt in current liabilities to the market value of assets at time *t,* and NF_t is total equity issuances minus repurchases plus debt issuance minus debt redemption. ΔX_t is notation for the one-year change, X_t - X_{t-1}, where t $(t-1)$ denotes end of fiscal year t $(t-1)$. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variable =	Excess stock returns ($r_{it} - R_{it}^B$)		
	(1)	(2)	(3)
ΔC_t	1.554***	1.553***	1.351***
	(33.49)	(33.47)	(19.06)
$C_{t-1} \times \Delta C_t$	-0.704***	-0.702***	-0.708***
	(-11.44)	(-11.40)	(-11.49)
$L_t \times \Delta C_t$	-1.467***	-1.467***	-1.446***
	(-15.50)	(-15.50)	(-15.30)
Liberal court $\times \Delta C_t$			0.511***
			(3.65)
Liberal court			-0.010
			(-0.44)
ΔE_t	0.166***	0.165***	0.165***
	(16.29)	(16.25)	(16.26)
ΔNA_t	0.191***	0.191***	0.191***
	(25.92)	(25.89)	(25.95)
ΔRD_t	0.914***	0.913***	0.902***
	(7.47)	(7.45)	(7.37)
ΔI_t	-0.376***	-0.372***	-0.372***
	(-3.03)	(-3.00)	(-3.00)
ΔD_t	2.247***	2.252***	2.259***
	(8.29)	(8.30)	(8.33)
C_{t-1}	0.187***	0.191***	0.191***
	(12.37)	(12.53)	(12.52)
L_t	-0.501***	-0.504***	-0.504***
	(-45.50)	(-45.39)	(-45.43)
NF_t	-0.074***	-0.072***	-0.073***
	(-4.65)	(-4.55)	(-4.60)

Table 3.6— *Continued*

Dependent variable =	Excess stock returns ($r_{it} - R_{it}^{B}$)		
	(1)	(2)	(3)
State GDP		-0.002	-0.002
		(-1.60)	(-1.61)
State Unemployment		0.007***	0.007***
		(2.69)	(2.70)
Republican Governor		-0.006	-0.006
		(-1.35)	(-1.38)
Republican Legislature		0.014***	0.014**
		(2.59)	(2.38)
Circuit FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj *R*-sq	0.243	0.243	0.243
Observations	71,508	71,508	71,508

Table 3.7. Judge ideology and firm risk grouping sample by corporate governance measures

The table reports results for firm risk, cash, marginal value of cash, and main payout policies OLS regressions for sub-samples grouped by measures of corporate governance. The dependent variables are *Stock return volatility* and *Asset volatility* in Panels A and B. Panel C and D report results for *Cash* and *Excess returns* (i.e., marginal value of cash estimations). Lastly Panel E and F report results for *Dividends* and *Share repurchases*. Subsamples of weaker corporate governance are reported in the left columns, and subsamples of stronger corporate governance are reported in the right columns *E-index* is the Bebchuk et al. (2009) entrenchment index based on the sum of indicator variables for six antitakeover provisions. *Powerful CEO* is a dummy variable equal to one if the CEO is the only insider on the board of directors and serves as the chairman of the board of directors and president of the company, and zero otherwise. *Board size* is the number of directors in the board and *Board independence* is the percentage of outside directors in the board. Higher (lower) values of *E-index* and *Board Size* (*Board* independence) are indicatives of weak governance. A value of one for *Powerful CEO* is indicative of weak governance. All variables are defined in Appendix A. For brevity, I only report coefficient estimates on litigation risk. For each grouping, the table reports *p*-values from tests of the null hypothesis that the coefficient estimates on litigation risk are equal. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Dependent variable = *Stock return volatility*

	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	-0.097***	-0.115***	-0.204***	-0.141***
	(-3.43)	(-4.35)	(-3.89)	(-5.83)
p-value	[0.6265]		[0.2515]	
Adj *R*-sq	0.385	0.431	0.462	0.445
Observations	11,329	13,825	3,883	17,478

Panel A. Dependent variable = *Stock return volatility*

	Board size		*Board independence*	
	(5)	(6)	(7)	(8)
	Big	Small	Low	High
Liberal court	-0.080***	-0.217***	-0.143***	-0.154***
	(-2.83)	(-6.61)	(-4.42)	(-5.58)
p-value	[0.0009]		[0.7905]	
Adj *R*-sq	0.424	0.448	0.450	0.448
Observations	11,116	10,244	10,611	10,749

Panel B. Dependent variable = *Asset volatility*

	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	-0.077***	-0.081***	-0.159***	-0.114***
	(-3.58)	(-4.61)	(-4.61)	(-6.73)
p-value	[0.8640]		[0.2082]	
Controls	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.473	0.515	0.563	0.523
Observations	11,329	13,825	3,883	17,478

Table 3.7 —*Continued*

Panel B. Dependent variable = *Asset volatility*				
	Board size		*Board independence*	
	(5)	(6)	(5)	(6)
	Big	Small	Low	High
Liberal court	-0.058***	-0.172***	-0.101***	-0.137***
	(-3.37)	(-7.02)	(-4.76)	(-6.71)
p-value	[0.0001]		[0.1734]	
Adj *R*-sq	0.487	0.526	0.522	0.537
Observations	11,116	10,244	10,611	10,749
Panel C. Dependent variable = *Cash*				
	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	0.046	0.000	-0.132	0.015
	(0.72)	(0.00)	(-0.67)	(0.27)
p-value	NA		NA	
Adj *R*-sq	0.580	0.379	0.316	0.359
Observations	11,239	13,695	3,860	17,323
Panel C. Dependent variable = *Cash*				
	Board size		*Board independence*	
	(5)	(6)	(7)	(8)
	Big	Small	Low	High
Liberal court	-0.064	0.069	0.031	-0.035
	(-1.64)	(0.59)	(0.38)	(-0.47)
p-value	NA		NA	
Adj *R*-sq	0.355	0.333	0.282	0.401
Observations	11,024	10,158	10,511	10,671
Panel D. Dependent variable = *Excess stock returns* ($r_{it} - R^B_{it}$)				
	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	-2.231**	0.370	-0.964	0.737**
	(-2.42)	(0.82)	(-1.44)	(2.22)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.283	0.280	0.279	0.277
Observations	8,973	9,630	3,306	14,972

Table 3.7 —*Continued*

Panel D. Dependent variable = *Excess stock returns* ($r_{it} - R^{B}_{it}$)				
	Board size		*Board independence*	
	(5)	(6)	(7)	(8)
	Big	Small	Low	High
Liberal court	0.093	0.574	0.388	0.421
	(0.22)	(1.40)	(0.90)	(1.01)
p-value	NA		NA	
Adj *R*-sq	0.289	0.279	0.284	0.274
Observations	9,894	8,385	9,024	9,255
Panel E. Dependent variable = *Dividends*				
	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	-0.003	-0.001	0.007	-0.005
	(-1.04)	(-0.16)	(1.18)	(-1.58)
p-value	NA		NA	
Adj *R*-sq	0.279	0.327	0.369	0.302
Observations	11,323	13,803	3,879	17,456
Panel E. Dependent variable = *Dividends*				
	Board size		*Board independence*	
	(5)	(6)	(7)	(8)
	Big	Small	Low	High
Liberal court	-0.005	-0.002	-0.008*	0.001
	(-1.38)	(-0.62)	(-1.93)	(0.45)
p-value	NA		NA	
Adj *R*-sq	0.390	0.230	0.268	0.374
Observations	11,107	10,227	10,596	10,738
Panel F. Dependent variable = *Share repurchases*				
	E-index		*Powerful CEO*	
	(1)	(2)	(3)	(4)
	High E-index	Low E-index	Powerful	Non- powerful
Liberal court	0.003	-0.002	-0.008	0.005
	(0.36)	(-0.21)	(-0.53)	(0.76)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj *R*-sq	0.257	0.254	0.277	0.264
Observations	9,995	12,149	3,591	15,909

Table 3.7 —*Continued*

Panel F. Dependent variable = *Share repurchases*				
	Board size		*Board independence*	
	(5)	(6)	(7)	(8)
	Big	Small	Low	High
Liberal court	0.002	0.001	0.002	0.006
	(0.26)	(0.12)	(0.18)	(0.64)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-sq	0.289	0.279	0.284	0.274
Observations	9,894	8,385	9,024	9,255

Table 3.8. Judge ideology and firm risk grouping sample by financial constraints measures

The table reports results for firm risk, cash, marginal value of cash, and main payout policies OLS regressions for sub-samples grouped by financial constraints measures. The dependent variables are *Stock return volatility* and *Asset volatility* in Panels A and B. Panel C and D report results for *Cash* and *Excess returns*. Lastly Panel E and F report results for *Dividends* and *Share repurchases*. Financially constrained firm subsamples are reported in the left columns, and none-constrained firm subsamples are reported in the right columns. *WW-index* is the Whited and Wu (2006) index. *Size* is proxied by firms' total assets. *Growth opportunities* are measured by firm's market-to-book ratio. *Dividend payer* is a dummy equal to one when the firm pays dividends and zero otherwise. *Industry litigation risk* is proxied by the FPS indicator variable (Francis et al. 1994), which is equal to one for biotech firms, computer firms, electronics firms, and retail firms, and zero otherwise. A firm is classified as financially constrained if the proxy used is above the sample yearly median. All variables are defined in Appendix A. For brevity, I only report coefficient estimates on litigation risk. For each grouping, the table reports *p*-values from tests of the null hypothesis that the coefficient estimates on litigation risk are equal. *T*-statistics (in parentheses) are computed using robust standard errors with clustering of observations at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively.

Panel A. Dependent variable = *Stock return volatility*

	WW-index		*Size*		*Growth opportunities*	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	-0.029	-0.067***	-0.055*	-0.091***	-0.085***	-0.084***
	(-1.00)	(-3.65)	(-1.87)	(-5.16)	(-3.95)	(-3.09)
p-value	NA		[0.2849]		[0.9557]	
Adj *R*-sq	0.415	0.396	0.409	0.391	0.526	0.423
Observations	41,332	42,143	41,245	42,230	41,773	41,702

Panel A. Dependent variable = *Stock return volatility*

	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	-0.093***	-0.027*	-0.058*	-0.068***
	(-3.81)	(-1.70)	(-1.79)	(-2.96)
p-value	[0.0192]		[0.8001]	
Adj *R*-sq	0.402	0.382	0.485	0.428
Observations	58,375	25,100	30,211	53,264

Panel B. Dependent variable = *Asset volatility*

	WW-index		*Size*		*Growth opportunities*	
	(1)	(3)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	-0.035	-0.058***	-0.054**	-0.083***	-0.084***	-0.064***
$\times \Delta C_t$	(-1.55)	(-4.96)	(-2.37)	(-7.41)	(-4.73)	(-3.37)
p-value	NA		[0.2379]		[0.4055]	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.439	0.420	0.423	0.461	0.553	0.463
Observations	41,332	42,143	41,245	42,230	41,773	41,702

Table 3.8 —*Continued*

Panel B. Dependent variable = *Asset volatility*

	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	-0.084***	-0.022*	-0.071***	-0.050***
$\times \Delta C_t$	(-4.67)	(-1.73)	(-2.77)	(-3.08)
p-value	[0.0036]		[0.4842]	
Adj *R*-sq	0.463	0.447	0.519	0.460
Observations	58,375	25,100	30,211	53,264

Panel C. Dependent variable = *Cash*

	WW-index		*Size*		*Growth opportunities*	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	0.199**	0.019	0.309***	-0.055	0.220***	0.051
	(2.08)	(1.53)	(3.36)	(-1.59)	(2.70)	(1.05)
p-value	NA		NA		NA	
Adj *R*-sq	0.445	0.436	0.470	0.355	0.496	0.366
Observations	40,994	41,791	40,936	41,849	41,453	41,332

Panel C. Dependent variable = *Cash*

	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	0.222***	0.008	0.314**	0.005
	(3.16)	(0.17)	(2.51)	(0.14)
p-value	NA		NA	
Adj *R*-sq	0.476	0.192	0.497	0.216
Observations	57,852	24,933	29,973	52,812

Panel D. Dependent variable = *Excess stock returns* ($r_{it} - R^B_{it}$)

	WW-index		*Size*		*Growth opportunities*	
	(1)	(3)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	0.392**	0.367	0.514***	0.338	0.487*	0.333**
$\times \Delta C_t$	(2.41)	(1.36)	(2.93)	(1.50)	(1.87)	(2.00)
p-value	NA		NA		NA	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.263	0.241	0.258	0.244	0.247	0.263
Observations	34,749	36,759	34,492	37,016	35,092	36,416

Table 3.8 —*Continued*

Panel D. Dependent variable = *Excess stock returns* ($r_{it} - R^{B}_{it}$)

	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	0.527***	-0.103	0.557**	0.321*
×ΔC_t	(3.41)	(-0.32)	(2.50)	(1.78)
p-value	NA		[0.048]	
Adj *R*-sq	0.250	0.254	0.250	0.248
Observations	48,677	22,831	25,378	46,130

Panel E. Dependent variable = *Dividends*

	WW-index		*Size*		*Growth opportunities*	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	-0.003	-0.005***	-0.004**	-0.004*	-0.008***	-0.002
	(-1.33)	(-2.77)	(-2.09)	(-1.85)	(-3.21)	(-1.48)
p-value	NA		[0.052]		NA	
Adj *R*-sq	0.109	0.235	0.110	0.249	0.227	0.117
Observations	41,331	42,142	41,243	42,230	41,773	41,700

Panel E. Dependent variable = *Dividends*

	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	NA	NA	-0.003	-0.005***
	NA	NA	(-0.93)	(-2.92)
p-value	NA		NA	
Adj *R*-sq			0.128	0.199
Observations			30,210	53,263

Panel F. Dependent variable = *Share repurchases*

	WW-index		*Size*		*Growth opportunities*	
	(1)	(3)	(3)	(4)	(5)	(6)
	High	Low	Small	Large	High	Low
Liberal court	0.035**	0.003	0.032**	0.006	0.023	0.009*
×ΔC_t	(2.16)	(0.75)	(2.08)	(1.13)	(1.59)	(1.83)
p-value	NA		NA		NA	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.006	0.135	0.004	0.104	0.010	0.015
Observations	34,686	38,000	34,850	37,836	35,608	37,078

Table 3.8 —*Continued*

Panel F. Dependent variable = *Share repurchases*				
	Dividend Payer		*Industry litigation risk*	
	(7)	(8)	(9)	(10)
	Non-Payer	Payer	High	Low
Liberal court	0.025**	0.004	0.033	0.006
$\times \Delta C_t$	(2.20)	(0.61)	(1.64)	(1.05)
p-value	NA		NA	
Controls	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj R-sq	0.006	0.145	0.007	0.038
Observations	49,530	23,156	26,000	46,686

Appendix A. Variable definitions

Name	Definition (data source)
Judge ideology	
Liberal court	The construction of this measure follows Huang et al. (2019). It is the probability that a three-judge panel randomly selected from a circuit court has at least two judges appointed by Democratic presidents. Computed as: $[C(x, 3) + C(x, 2) \times C(y - x, 1)] / C(y, 3)$ where $C(n, r)$ is a binomial coefficient indicating the number of possible combinations of r objects from a set of n distinct objects, x is the number of Democratic appointees in the circuit, and y is the total number of judges in the circuit. The variable is measured at the end of each month. I match firm-year data to a circuit court-month based on the firms' headquarters at the beginning of the year. Historical headquarters information are from files shared by Professor Bill McDonald through his website.[75] Circuit court judges' appointing presidents are obtained from the Federal Judicial Center's website.[76]
Dependent variables	
Stock return volatility	The annualized standard deviation of daily stock returns over the fiscal year. (CRSP)
Asset volatility	The unleveraged annualized asset volatility is calculated following Schwert and Strebulaev (2014), as the square root of $\sigma_A^2 = (1 - W)^2\sigma_E^2 + W^2\sigma_D^2 + 2W(1 - W)\sigma_E\sigma_D\rho_{ED}$, where W is the ratio of the book value of debt to the sum of the book value of debt and market value of equity, σ_E is equity volatility, estimated as the standard deviation of excess returns over the trailing 12-month window, σ_D is debt volatility, estimated as $\sigma_D = -0.02 + 0.38W$, and ρ_{ED} is the correlation between equity and debt returns, estimated as $\rho_{ED} = -0.13 + 0.72W$. (Compustat/CRSP)
Firm variables	
Cash	The ratio of cash and marketable securities to net assets, where net assets is the book value of assets minus cash and marketable securities. (Compustat)
Book leverage	The ratio of long-term debt plus debt in current liabilities to the book value of total assets. (Compustat)
Market leverage	The ratio of long-term debt plus debt in current liabilities to the market value of assets, where the market value of assets is computed as the book value of assets minus the book value of equity plus the market value of equity. (Compustat)

[75] https://sraf.nd.edu/
[76] https://www.fjc.gov/history/judges

Dividends	Dividend payout ratio, computed as the ratio of dividends to the book value of assets. (Compustat)
Dividend yield	Dividends divided by fiscal year-end price. (Compustat)
Share repurchases	The expenditure on total share repurchase (i.e., the purchase of common and preferred stocks) minus change in the redemption value of preferred stocks, all to the book value of assets. (Compustat)
Total payout	The ratio of dividends plus the expenditure on the purchase of common and preferred stocks minus change in the redemption value of preferred stocks, all to the book value of assets. (Compustat)
Payout Preference	The difference between the distributions in share repurchases minus the distribution in dividends, all to the book value of assets. (Compustat)
Capex	The ratio of capital expenditures to the book value of assets. (Compustat)
R&D	The ratio of research and development expense to the book value of assets. The variable is set equal to zero when research and development expense is missing. (Compustat)
Ln(Assets)	The natural logarithm of book value of assets in millions of constant 2018 dollars. (Compustat)
Stock return	One-year cumulative stock return computed over the fiscal year. (CRSP)
Sales growth	The average annual sales growth over fiscal years $t-4$ through $t-1$. (Compustat)
Asset tangibility	The ratio of net property, plant, and equipment to total assets. (Compustat)
Market-to-book	The ratio of the market value of assets to the book value of assets, where the market value of assets is computed as the book value of assets minus the book value of equity plus the market value of equity. (Compustat)
ROA	The ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to total book assets. (Compustat)
Asset beta	Following Schwert and Strebulaev (2014), the asset beta in fiscal year t is computed as $Asset\ beta = (1-W) \times Equity\ beta + W \times Debt\ beta$, where W is the ratio of the book value of debt (debt in current liabilities plus long-term debt) to the sum of the book value of debt and market value of equity, debt beta is computed as $Debt\ beta = -0.09 + 0.63 \times W$, and $Equity\ beta$ is the sum of the estimated beta coefficients ($\beta_0 + \beta_1 + \cdots + \beta_5$) from the regression: $r_{i,d} - r_{f,d} = \sum_{j=0}^{5} \beta_{i,j}\left(r_{m,d-j} - r_{f,d-j}\right) + \varepsilon_{i,d}$, which is estimated using daily stock returns during fiscal year $t-1$. In the regression specification, i denotes firm, d denotes day, f denotes risk-free, and m denotes market. (Compustat/CRSP)
Dividend payer	Indicator variable equal to one if the firm pays out dividends to its shareholders and zero otherwise. (Compustat)
R&D/Sales	The ratio of research and development expense to sales. The variable is set equal to zero when research and development expense is missing. (Compustat)

Cash flow/Assets	The ratio of earnings after interest, dividends, and taxes but before depreciation to the book value of assets. (Compustat)
NOLCF	Dummy variable equal to one if the firm has net operating loss carryforwards, and zero otherwise. (Compustat)
ITC	Dummy variable equal to one if the firm has investment tax credits, and zero otherwise. (Compustat)
Loss	Dummy variable equal to one if the firm reports negative earnings, and zero otherwise. (Compustat)
NWC/Assets	The ratio of net working capital to the book value of assets. (Compustat)
FPS	Indicator variable equal to one for biotech firms (SIC codes 2833–2836 and 8731–8734), computer firms (3570–3577 and 7370–7374), electronics firms (3600–3674), and retail firms (5200–5961), and zero otherwise. This definition follows Francis, Philbrick and Schipper (1994).
Net debt issuance	Debt issuance minus debt retirement divided by assets. (Compustat)
Net equity issuance	Equity sales minus equity purchases divided by assets. (Compustat)
Retained earnings	The ratio of retained earnings to assets. (Compustat)
Asset growth	The percentage change in book value assets from year t-1 to year t. (Compustat)
Ind. Stk. Rtn. Vol.	The average volatility of firms within a firm's Fama-French 49 industry based on daily stock return over the prior fiscal year. (Compustat/CRSP)
Whited-Wu index	The Whited and Wu (2006) index, computed as WW index= – 0.091 * CF – 0.062 * Div+0.021 * TLTD – 0.044 * Ln(Assets) +0.102 * ISG – 0.035 * SG, where *CF* is the ratio of cash flow to the book value of assets; *Div* is a dummy variable that equals to one if the firm pays cash dividends in a given year, and zero otherwise; *TLTD* is the ratio of the long-term debt to the book value of assets; *Ln(Assets)* is the natural log of the book value of assets; ISG is the firm's three-digit SIC industry sales growth; and SG is the firm's sales growth.
$r_{it} - R_{it}^B$	Excess stock return is the stock return of firm *I* during fiscal year *t*, r_{it}, minus stock *i*'s benchmark return in year *t*, R_{it}^B, where the benchmark return is the return of the Fama and French size and book-to-market portfolio to which stock *i* belongs at the beginning of fiscal year *t*.
M_{t-1}	Is the market value of equity at time $t-1$ computed as price times shares outstanding.
ΔC_t	Is the one-year change in cash plus marketable securities scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to *t*.

$C_{t\text{-}1}$	Is cash plus marketable securities at the end of fiscal year $t-1$ to t, scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
ΔE_t	Is the one-year change in earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits; scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
ΔNA_t	Is the one-year change in total assets minus cash holdings scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
ΔRD_t	Is the one-year change in research and development expense (which is set equal to zero if research and development is missing in either of both years), scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
ΔI_t	Is the one-year change in interest expense, scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
ΔD_t	Is the one-year change in common dividends, scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
L_t	Is the ratio of long-term debt plus debt in current liabilities to the market value of assets at time t, where the market value of assets is computed as the book value of assets plus the difference between the market and book values of equity, scaled by the lagged market value of equity, M_{t-1}.
NF_t	Is the total equity issuance minus repurchases plus debt issuances minus debt redemption, scaled by the lagged market value of equity, M_{t-1}. The one -year change is estimated over $t-1$ to t.
State variables	
GDP growth rate	The percentage change in state GDP from year *t – 1* to year *t*. (Bureau of Economic Analysis)
Unemployment rate	The state unemployment rate in year *t* (Bureau of Economic Analysis)
Republican governor	A dummy variable equal to one if the governor of the firm headquarters state is Republican, and zero otherwise. (Inter-university Consortium for Political and Social Research, ICPSR)
Republican legislature	A dummy variable equal to one if the state legislature of the firm's head-quarters state is majority Republican, and zero otherwise. (National Conference of State Legislatures, NCSL)
Governance variables	
Powerful CEO	A dummy variable equal to one if the CEO is the only insider on the board of directors and serves as the chairman of the board of directors and president of the company, and zero otherwise. (ISS)
E-index	Bebchuk et al. (2009) entrenchment index based on the sum of indicator variables for six antitakeover provisions: limits to shareholder bylaw

	amendments, staggered boards, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. (ISS)
Board size	The number of directors in the board. (ISS)
Board independence	The percentage of outside directors in the board. (ISS)

Appendix B. Judge ideology and firm risk before and after Tellabs

In this appendix, I examine whether and how does the June 21, 2007, Supreme Court's decision in *Tellabs Inc. v. Makor Issues & Rights, Ltd.* affect my baseline findings. This ruling clarified the laws of securities fraud on pleading scienter and has been identified in the literature as an exogenous shock to securities class action litigation risk (Huang et al. 2019; Kubick et al. 2021).

Huang et al. (2019) argue that the *Tellabs* ruling virtually overturned the circuit courts' previous governing standings, and reason that this outcome effectively increased judges' discretion leading to a higher litigation risk for the firms. In contrast, Kubick et al. (2021) posit that by making it more difficult for litigants in a class action to win, the *Tellabs* ruling reduced litigation risk. Choi and Pritchard (2012) conclude that *Tellabs* led to higher uniformity in how lower courts apply pleading standards, but its overall effect is muted by the asymmetry of the right to appeal. Overall, it is an empirical question whether the *Tellabs* case has a significant in the inverse relation between liberal judge ideology and firm risk I document in Table 3.

In my setting, a potential downside of using the *Tellabs* ruling is that there is not an unambiguous counterfactual because the Supreme Court ruling applied equally to all circuit courts and as such all firms in our sample are exposed to the shock induced by the ruling. To overcome this hurdle, I follow a similar approach as that used by tax-related literature exploiting the *Federal Taxpayer Relief Act of 1997* as exogenous source of variation (e.g., Yost, 2018; Kubick et al. 2020; Lonare, 2020) where the shock in question affects all units of observation as in my setting. Specifically, I exploit variation in judge ideology before *Tellabs*' ruling to identify potential treatment and control groups. I recognize that this is not a true difference-in-differences analysis.

I estimate the following specifications, using a variety of fixed effects. I exclude the fiscal year 2007 to avoid ambiguous information in this transitory year.[77]

$$\begin{aligned} Risk_{it} = {} & \beta_1\, High\ pre\ liberal\ court_i + \beta_2 After\ Tellabs \times High\ pre\ liberal\ court_i \\ & + \gamma_1 Firm\ Controls_{it-1} + + \gamma_2 Industry\ controls_{it-1} + \gamma_3 State\ controls_{it} \\ & + Fixed\ Effects + \varepsilon_{it} \end{aligned}$$

where *After Tellabs* is an indicator variable equal to one for the post-Tellabs period (i.e., 2008 onwards), and equal to zero for the pre-Tellabs years. *High pre liberal court* is defined as an indicator variable equal to one if a firm has an above yearly median *Liberal court* value in year 2006. With this approach ,the group with above yearly median litigation risk in the year before the shock effectively becomes the treated group in my analysis.

Table 14 in Appendix C reports the results. Across all specifications I find that, the negative effect of judge ideology on business risk is stronger after the U.S. Supreme Court's ruling in the *Tellabs* case, a result consistent with Huang et al. 2019 interpretation of the ruling.

[77] In unreported results, I preserve the year 2007 in the sample, as part of the post period. The results are unchanged.

Appendix C. Additional Tests

Table 3.9. U.S. Circuit courts, judgeships, and corresponding states

The table reports the 12 circuits in the United States that have jurisdiction over securities class action lawsuits and the states that comprise each of them.[78]

Circuit	Judgeships	States
First Circuit	6	Maine, New Hampshire, Massachusetts, Rhode Island, and Puerto Rico
Second Circuit	13	Vermont, Connecticut, and New York
Third Circuit	14	New Jersey, Pennsylvania, Delaware, and the Virgin Islands
Fourth Circuit	15	Maryland, West Virginia, Virginia, North Carolina, and South Carolina
Firth Circuit	17	Mississippi, Louisiana, and Texas
Sixth Circuit	16	Ohio, Michigan, Kentucky, and Tennessee
Seventh Circuit	11	Indiana, Illinois, and Wisconsin
Eighth Circuit	11	Minnesota, Iowa, Missouri, Arkansas, Nebraska, North Dakota, and South Dakota
Ninth Circuit	29	California, Oregon, Washington, Arizona, Nevada, Idaho, Montana, Alaska, and Hawaii
Tenth Circuit	12	Colorado, Wyoming, Utah, New Mexico, Oklahoma, and Kansas
Eleventh Circuit	12	Georgia, Florida, and Alabama
District of Columbia Circuit	11	Washington, D.C.

Table 3.10. Statistics of judge ideology at the circuit level

The table reports the mean and median judge ideology (i.e., *Liberal court*) by circuit over the sample period, which covers from 1993 to 2019.

Circuit	Mean	Median
First Circuit	0.232	0.183
Second Circuit	0.457	0.500
Third Circuit	0.246	0.247
Fourth Circuit	0.434	0.385
Firth Circuit	0.282	0.291
Sixth Circuit	0.308	0.308
Seventh Circuit	0.171	0.191
Eighth Circuit	0.224	0.272
Ninth Circuit	0.570	0.581
Tenth Circuit	0.354	0.360
Eleventh Circuit	0.441	0.453
District of Columbia Circuit	0.289	0.279

[78] Sources: U.S. Courts from https://www.uscourts.gov/sites/default/files/u.s._federal_courts_circuit_map_1.pdf and Ballotpedia from https://ballotpedia.org/United_States_federal_courts.

Table 3.11. Statistics of firms' headquarters by circuit

The table reports the distribution of firms headquartered per circuit over the sample period, which covers from 1993 to 2019. The last column ranks the circuits from most liberal (1st) to the most conservative (12th) based on their mean value of *Liberal court* over the sample period.

Circuit	No. of firms	Percentage	Liberal court ranking
First Circuit	650	6.8%	10th
Second Circuit	1,075	11.2%	2nd
Third Circuit	807	8.4%	9th
Fourth Circuit	600	6.2%	4th
Fifth Circuit	989	10.3%	8th
Sixth Circuit	559	5.8%	6th
Seventh Circuit	541	5.6%	12th
Eighth Circuit	518	5.4%	11th
Ninth Circuit	2,507	26.0%	1st
Tenth Circuit	597	6.2%	5th
Eleventh Circuit	755	7.8%	3rd
District of Columbia Circuit	30	0.3%	7th
Total	9,628	100.0%	

Table 3.12. Robustness test: Effect of judge ideology on firm risk

The table reports OLS regressions of firm risk on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. The dependent variable is *Stock return volatility* in Panel A and *Asset volatility* in Panel B. *Stock return volatility* is the annualized standard deviation of daily stock returns over the fiscal year. *Asset volatility* is constructed following Schwert and Strebulaev (2014) as the standard deviation of returns on a portfolio of the firm's equity and debt over the fiscal year. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. Dependent variable =				Stock return volatility			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liberal court	-0.090***	-0.089***	-0.096***	-0.089***	-0.090***	-0.098***	-0.099***
	(-4.89)	(-4.65)	(-5.18)	(-4.68)	(-4.81)	(-5.36)	(-5.42)
Ln(Assets)	-0.101***	-0.091***	-0.091***	-0.095***	-0.091***	-0.093***	-0.090***
	(-72.23)	(-64.88)	(-66.39)	(-69.08)	(-64.97)	(-65.65)	(-63.20)
Stock return	-0.047***	-0.041***	-0.047***	-0.047***	-0.049***	-0.040***	-0.041***
	(-19.92)	(-16.29)	(-19.45)	(-19.50)	(-20.33)	(-16.33)	(-17.07)
Sales growth	0.027***	0.029***	0.026***	0.029***	0.027***	0.023***	0.022***
	(13.81)	(12.94)	(13.24)	(14.20)	(13.06)	(11.14)	(10.32)
Market-to-book	-0.015***	-0.015***	-0.012***	-0.015***	-0.020***	-0.011***	-0.015***
	(-14.13)	(-14.28)	(-12.52)	(-15.11)	(-19.54)	(-10.15)	(-13.60)
Book leverage	0.313***					0.305***	0.300***
	(29.36)					(28.61)	(28.26)
Cash		-0.005***				0.002	-0.005***
		(-2.79)				(0.83)	(-3.04)
Dividends			-2.404***			-2.075***	-1.971***
			(-22.75)			(-19.90)	(-19.34)
Capex				-0.141***		-0.243***	-0.253***
				(-4.24)		(-7.24)	(-7.60)
R&D					0.399***		0.374***
					(18.53)		(16.35)
Industry stock	0.043***	0.059***	0.042***	0.045***	0.044***	0.055***	0.054***
return vol.	(27.47)	(31.58)	(26.47)	(27.51)	(27.21)	(30.87)	(30.51)
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.459	0.435	0.443	0.434	0.441	0.473	0.479
Observations	83,475	77,615	83,475	82,871	83,475	77,070	77,070

Table 3.12. — *Continued*

Panel B. Dependent variable =	*Asset volatility*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Liberal court	-0.082***	-0.087***	-0.088***	-0.084***	-0.086***	-0.088***	-0.089***
	(-5.95)	(-6.23)	(-6.32)	(-6.02)	(-6.26)	(-6.51)	(-6.65)
Ln(Assets)	-0.076***	-0.074***	-0.077***	-0.078***	-0.074***	-0.069***	-0.066***
	(-69.20)	(-65.46)	(-67.54)	(-69.84)	(-66.11)	(-62.68)	(-60.24)
Stock return	0.024***	0.029***	0.025***	0.024***	0.023***	0.029***	0.027***
	(14.15)	(16.89)	(14.62)	(14.28)	(13.48)	(16.67)	(15.75)
Sales growth	0.020***	0.016***	0.018***	0.019***	0.017***	0.016***	0.015***
	(12.52)	(9.21)	(11.15)	(11.96)	(10.35)	(9.57)	(8.56)
Market-to-book	0.008***	0.008***	0.010***	0.009***	0.004***	0.010***	0.006***
	(9.41)	(8.51)	(11.48)	(9.94)	(3.96)	(10.75)	(5.68)
Book leverage	-0.149***					-0.143***	-0.149***
	(-23.29)					(-22.34)	(-23.63)
Cash		0.014***				0.010***	0.002
		(8.52)				(5.80)	(1.38)
Dividends			-1.155***			-1.260***	-1.145***
			(-13.68)			(-14.88)	(-14.34)
Capex				-0.112***		-0.152***	-0.163***
				(-4.71)		(-6.40)	(-6.97)
R&D					0.432***		0.412***
					(23.08)		(21.37)
Industry stock	0.028***	0.038***	0.026***	0.027***	0.026***	0.037***	0.036***
return vol.	(24.22)	(28.41)	(22.23)	(23.05)	(22.80)	(28.47)	(28.11)
State controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Circuit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. *R*-sq	0.508	0.505	0.502	0.499	0.513	0.519	0.532
Observations	83,475	77,615	83,475	82,871	83,475	77,070	77,070
Adj. R-sq	0.508	0.505	0.502	0.499	0.513	0.519	0.532

Table 3.13. Effect of judge ideology on payout preference

The table reports OLS regressions of payout preference on liberal court, firm controls, state controls, and industry, year and circuit fixed effects. *Payout preference* is defined as the difference between the distributions in share repurchases minus the distribution in dividends, all to the book value of assets. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variable =	*Payout preference* $_t$	*Payout preference* $_{t+1}$
	(3)	(4)
Liberal court	0.013**	0.011*
	(2.15)	(1.76)
Ln(Assets)	0.006***	0.006***
	(14.49)	(13.90)
Book leverage	-0.034***	-0.032***
	(-8.33)	(-7.34)
Market to book	0.000	0.000
	(0.30)	(0.51)
ROA	0.061***	0.059***
	(13.05)	(10.71)
Retained earnings	0.007***	0.022***
	(3.75)	(4.24)
Asset	0.000	0.000
Beta	(0.46)	(0.37)
Asset growth	0.000	0.001
	(0.15)	(1.01)
Loss	-0.015***	-0.015***
	(-13.08)	(-12.21)
State GDP	-0.001***	-0.001***
	(-2.82)	(-3.04)
State unemployment	-0.001	-0.001*
	(-1.24)	(-1.68)
Republican governor	-0.000	-0.000
	(-0.44)	(-0.41)
Republican legislature	-0.002	-0.002
	(-1.23)	(-0.98)
Circuit FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adj *R*-sq	0.096	0.102
Observations	83,475	72,706

Table 3.14. Effect of judge ideology on firm risk before and after Tellabs

The table reports OLS regressions in which the dependent variables are *Stock return volatility* in Panel A, defined as the annualized standard deviation of daily stock returns over the fiscal year, and *Asset volatility* in Panel B, constructed following Schwert and Strebulaev (2014) as the standard deviation of returns on a portfolio of the firm's equity and debt over the fiscal year. The regressors are $High\ pre\ liberal\ court$ defined as a dummy variable equal to one if a firm has an above yearly median *Liberal court* value in year 2006, *After Tellabs* an indicator variable equal to one for the post-Tellabs period (i.e., 2008 onwards), and equal to zero for the pre-Tellabs years, firm, industry, and state level controls as those in the baseline specification. Columns (1), (4), and (7) report results with the same fixed effects as those in the baseline models (i.e., circuit, industry, and year fixed effects). Columns (2), (4), and (8) add firm fixed effects. Lastly, columns (3), (6), and (9) replace industry and year fixed effects for industry by year fixed effects. Industry fixed effects are based on Fama-French 49 industry classification. All variables are defined in Appendix A. All regressions are estimated over the full sample period from 1993 to 2019. *T*-statistics (in parentheses) are computed using robust standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A. Dependent variable =			*Stock return volatility*		
	(1)	(2)	(3)	(4)	(5)
$High\ pre\ liberal\ court$	0.044**	0.030*	0.027	0.045**	0.031*
	(2.42)	(1.72)	(1.48)	(2.48)	(1.76)
$After\ Tellabs \times$ $High\ pre\ liberal\ court$	-0.049***	-0.045***	-0.018**	-0.050***	-0.050***
	(-5.34)	(-5.40)	(-2.25)	(-5.35)	(-5.70)
State GDP				0.001	0.000
				(1.50)	(0.67)
State Unemployment				0.003	0.008***
				(1.00)	(3.55)
Republican Governor				-0.011**	-0.014***
				(-2.37)	(-3.92)
Republican Legislature				0.001	0.013**
				(0.14)	(2.45)
Circuit FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes
Industry × Year FE	No	No	Yes	No	No
Adj *R*-sq	0.216	0.561	0.595	0.217	0.562
Observations	49,851	49,818	49,803	49,851	49,818

Table 3.14 —*Continued*

Panel A. Dependent variable =	*Stock return volatility*			
	(6)	(7)	(8)	(9)
High pre liberal court	0.028	0.041***	0.029*	0.028
	(1.56)	(3.25)	(1.73)	(1.60)
After Tellabs × *High pre liberal court*	-0.021**	-0.047***	-0.051***	-0.020***
	(-2.51)	(-5.84)	(-6.29)	(-2.67)
Ln(Assets)		-0.078***	-0.069***	-0.072***
		(-50.38)	(-19.66)	(-21.08)
Stock return		-0.004	0.001	-0.003
		(-1.58)	(0.56)	(-1.00)
Sales growth		0.030***	0.010***	0.005
		(10.25)	(2.95)	(1.49)
Market-to-book		-0.008***	-0.010***	-0.014***
		(-6.35)	(-6.69)	(-10.82)
Book leverage		0.233***	0.245***	0.248***
		(18.07)	(15.79)	(16.81)
Industry stock return volatility		0.006***	0.003*	0.000
		(3.04)	(1.72)	(0.22)
State GDP	-0.000	0.002**	0.001	-0.000
	(-0.34)	(2.16)	(1.15)	(-0.00)
State Unemployment	0.005**	0.006***	0.005**	0.003
	(2.01)	(2.74)	(2.26)	(1.23)
Republican Governor	-0.008**	-0.011***	-0.016***	-0.010***
	(-2.40)	(-3.02)	(-4.44)	(-2.94)
Republican Legislature	0.007	0.004	0.018***	0.010*
	(1.22)	(0.80)	(3.38)	(1.91)
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	No
Year FE	No	Yes	Yes	No
Firm FE	Yes	No	Yes	Yes
Industry × Year FE	Yes	No	No	Yes
Adj *R*-sq	0.596	0.436	0.588	0.622
Observations	49,803	49,796	49,764	49,749

Table 3.14 —*Continued*

Panel B. Dependent variable =	*Asset volatility*				
	(1)	(2)	(3)	(4)	(5)
High pre liberal court	0.035**	0.026**	0.024*	0.035**	0.024*
	(2.28)	(1.99)	(1.83)	(2.29)	(1.88)
After Tellabs × *High pre liberal court*	-0.038***	-0.036***	-0.014**	-0.039***	-0.038***
	(-5.25)	(-5.66)	(-2.44)	(-5.13)	(-5.67)
State GDP				0.003***	0.002***
				(4.34)	(4.26)
State Unemployment				0.003	0.007***
				(1.36)	(3.73)
Republican Governor				-0.006*	-0.012***
				(-1.70)	(-4.16)
Republican Legislature				-0.000	0.018***
				(-0.06)	(4.18)
Circuit FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes
Industry × Year FE	No	No	Yes	No	No
Adj R-sq	0.267	0.617	0.656	0.267	0.618
Observations	49,851	49,818	49,803	49,851	49,818

Panel B. Dependent variable =	*Asset volatility*			
	(6)	(7)	(8)	(9)
High pre liberal court	0.024*	0.034***	0.020*	0.020
	(1.81)	(3.30)	(1.66)	(1.61)
$After\ Tellabs \times$ $High\ pre\ liberal\ court$	-0.015**	-0.035***	-0.038***	-0.014**
	(-2.38)	(-5.83)	(-6.30)	(-2.57)
Ln(Assets)		-0.062***	-0.061***	-0.064***
		(-48.80)	(-21.28)	(-23.10)
Stock return		0.037***	0.039***	0.035***
		(18.84)	(19.82)	(17.76)
Sales growth		0.023***	0.007***	0.002
		(10.26)	(2.65)	(0.79)
Market-to-book		0.009***	0.004***	-0.001
		(8.64)	(2.86)	(-0.89)
Book leverage		-0.120***	-0.081***	-0.071***
		(-14.61)	(-7.96)	(-7.44)
Industry stock return volatility		0.006***	0.004***	0.001
		(3.88)	(2.71)	(0.80)
State GDP	0.001*	0.003***	0.002***	0.001**
	(1.85)	(4.67)	(4.32)	(2.03)
State Unemployment	0.002	0.006***	0.003**	0.001
	(1.09)	(3.47)	(2.11)	(0.57)
Republican Governor	-0.007***	-0.007**	-0.012***	-0.007***
	(-2.65)	(-2.51)	(-4.45)	(-2.76)
Republican Legislature	0.010**	0.002	0.017***	0.009**
	(2.49)	(0.59)	(4.37)	(2.50)
Circuit FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	No
Year FE	No	Yes	Yes	No
Firm FE	Yes	No	Yes	Yes
Industry × Year FE	Yes	No	No	Yes
Adj R-sq	0.656	0.510	0.651	0.686
Observations	49,803	49,796	49,764	49,749

CONCLUSION

My research is motivated by the opportunity to provide new insights to open questions in the corporate finance literature, leveraging the availability of new datasets, and proposing the use of novel measures that combined with proper econometric methodologies allow going beyond correlations to plausible causal relations. Importantly the datasets used to construct the key variables of interests for each of my essays - *Brand equity*, *Cybersecurity awareness* and *Liberal court* – are publicly available. This guarantees that future studies can build upon my work to tackle other related research questions in contrast to proprietary data. Furthermore, this feature of the data sources used also translates into samples that are reasonably large and representative of the cross-section of public firms in the U.S.

In the first chapter, we develop measures of brand equity based on firms' portfolio of trademarks. We find that firms with higher brand equity have lower equity and asset volatility and higher cash flows. Although suggestive of greater debt capacity, we find that firms with high brand equity use less debt and shorter maturity debt. We exploit the passage of the Federal Trademark Dilution Act of 1996 as our identification framework to establish a causal relation in our findings. This work contributes to understand the impact of brands, firms' most valuable intangible asset per executive management assessment, on firms' choice of capital structure, one of the central topics in corporate finance. This has been an under examined topic due in great part to the lack of data, a hurdle we are able to overcome by using the United States Patent and Trademark Office (USPTO) recently released records on trademarks.

In the second chapter, we develop a measure of firms' cybersecurity awareness and find that firms' self-disclosed readiness to face potential cyberattacks is negatively correlated with firms' cost of debt, as measured by the loan spread in private debt (i.e., bank loan contracting) and public debt (i.e., bonds issuance). Results from an instrumental variable analysis support a causal interpretation of our findings. The positive effect of cyberawareness on debt contracting is consistent with creditors viewing investments in cyber security as an intangible asset that allows firms to protect and operate more effectively other assets, particularly intangible assets such as customers' lists and information, trademarks, patents, and trade secrets. Our work contributes to a nascent but growing stream of literature that examines the influence of cyber related risks, along with actions from firms and regulators prompted by such risks and opportunities, on firms' policies and outcomes.

In the third chapter, I find that firms' business risk is decreasing in ex-ante litigation risk, as measured by the probability that a three-judge panel at the federal circuit court is dominated by democratic presidents' appointees. I find higher cash holdings and lower dividend payout as the mechanisms through which the risk profile is reduced. These findings are consistent with a deterrence effect of litigation risk on corporate risk-taking.

Several avenues for future research emerge from my work. It would be interesting to examine how brand equity influences product market outcomes. Does brand equity translate into advantageous positions in the product market as suggested by the higher cash flows and profitability? In which groups of firms is such effect present and how are heavy brand equity firms' reactions to shocks in the product market (e.g., tariffs) different from firms with low or no brand equity? Similarly, it would be exciting to investigate how cybersecurity awareness influences average labor pay. Does the lower cyber risk attained by higher cyber readiness translate in lower compensation demanded from employees? If so, among which types of firms in the cross-section, are such effects more magnified? Concerning litigation risk, it would be interesting to explore whether and how does liberal judge ideology influences firms hedging policies as well as accounting conservatism? Lastly, my dissertation as a whole invites researchers and scholars in the field to explore how our discipline can leverage novel datasets broadly available as well as innovative measures, to inform various streams of literature. Where do questions remain unanswered due to the lack of suitable measures to tackle them? Where are there conflicting findings that could be enlightened by reexamining those research topics with new proxies that overcome some of the challenges posed by previous proposed measures?