Fall 2021

Three Essays on Agency Costs in Corporate Finance

Eyad Alhudhaif

THREE ESSAYS ON AGENCY COSTS IN CORPORATE FINANCE

By

Eyad Alhudhaif

Bachelor of Science
King Saud University, 2010

Master of Business Administration
Indiana State University, 2013

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Finance

Darla Moore School of Business

University of South Carolina

2021

Accepted by:

Eric Powers, Major Professor

Allen Berger, Committee Member

Hugh Kim, Committee Member

Omrane Guedhami, Committee Member

Tracey L. Weldon, Intern Vice Provost and Dean of the Graduate School

DEDICATION

This dissertation is dedicated to the sake of **Allah**, my Creator and my Master, and to my great teacher and messenger, **Mohammed** (Peace be upon him), who taught us the purpose of life.

A special feeling of gratitude to my loving parents. My father, **Sulaiman**, you are the main reason for all my accomplishments in life, because you have taught me to work hard for the things that I aspire to achieve. To my dear mother, **Hanan** you have always loved me unconditionally, and your good examples have shaped my journey in life.

To my beloved brothers and sisters; **Shahd**, **Razan**, **Lana**, **Husam**, **Retan**, **Rayan**, and **Anas**, the symbol of love and giving.

This dissertation is dedicated to my future wife **Alhanouf**, you kept me going through the hard times of this journey.

ACKNOWLEDGMENTS

It is a genuine pleasure to show my appreciation and thanks to my mentor and guide **Dr. Eric Powers**. His knowledge and patience has helped me with great extend to accomplish this task.

I also would like to thank **Dr. Allen Berger** and **Dr. Hugh Kim** for their suggestions and support in completing this dissertation.

I thank my dear friends and colleagues **Gerard Pinto, Yafei Zhang, Mosab Hammoudeh, Milos Pavlovic** and **Jake Terry** for their emotional support throughout my journey.

ABSTRACT

This dissertation attempts to explain several firm corporate choices under the classical framework of contractual agency problems in corporate finance. Essay 1 examine firms' debt maturity structure following exogenous changes in growth opportunities due to the COVID-19 shock. I Find companies experiencing an increase in growth options choose longer-term debt, a result that supports the arguments presented by Diamond and He, 2014 and Childs et al., 2005. Essay 2 examine the effect of firm's risk exposure concentration on debt maturity choices. We find short-term debt is preferred over covenants in mitigating debt-related agency problems of risk-shifting. These results indicate that maintaining future investment flexibility is important for firms with high risk exposure concentration, despite the higher liquidity risk associated with the use of short-term debt. Essay 3 examine corporate payouts following changes in the level of US economic policy uncertainty. I show firm choices of payout following increases in the level of economic policy uncertainty go against the theoretical predictions of the Free Cash Flow Hypothesis. The title for the three essays are as follows:

1. The Asymmetry Between Growth Opportunities and Debt Maturity Structure

2. Firm Risk Exposure Concentration and Debt Structure Choice

3. Corporate Payout and Economic Policy Uncertainty in the U.S.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

THE ASYMMETRY BETWEEN GROWTH OPPORTUNITIES AND DEBT MATURITY STRUCTURE[1]

JEL Code : G30; G32

Keywords : Maturity Structure, Growth Opportunities, Public Health Pandemic, Financial Disclosure, Firm-level Risk Exposures, COVID-19

[1]Author: Eyad Alhudhaif. To be submitted to the Journal of Corporate Finance

CHAPTER 1

The Asymmetry Between Growth Opportunities and Debt Maturity Structure

Abstract

Using the recent public health pandemic (COVID-19) as a laboratory experiment, I find evidence of an asymmetrical relation between a firm's debt maturity structure choice and its growth opportunities. Firms with high pre-pandemic exposure to growth-inducing factors obtained from 10-K filings have increased debt maturity and are more likely to exercise a call on their callable bonds, while firms with high pre-pandemic exposure to growth-reducing factors are null in taking any actions to adjust their debt maturity structure. Further, the increase in debt maturity following exogenous changes in growth opportunities suggests a unique *type* of change in firms' growth options following the recent pandemic, supporting the arguments proposed by Diamond and He, 2014 and Childs et al., 2005.

1.1 Introduction

The recent body of literature on capital structure studies have gone beyond the scope of leverage choices and shifted towards the determinants of other debt characteristics, such as maturity structure choices. Tradeoffs among the different debt structure choices has been the focus of several new studies in the literature; see

Choi et al., 2018, 2020; Diamond and He, 2014. While the seminal work of Myers, 1977 and Jensen and Meckling, 1976 theorize the use of short-term debt as one of several tools in mitigating agency costs of debt overhang, empirical studies find inconsistencies to the prediction. For example, Barclay and Smith, 1995, Billett et al., 2007, and Custódio et al., 2013 find a positive link between proxies for growth opportunities and short-term debt, Datta et al., 2005 find a negative relation between a firm's Market-to-Book and short-term debt, Stohs and Mauer, 1996 and Johnson, 2003 find mixed results. Overall, the empirical findings suggest the relation between growth options in a firm's investment opportunity set and its optimal debt maturity choice is arguably more complex than initially thought.

At first, debt maturity choice is usually accompanied by several other decisions, to which some may serve as partial or complete substitute in mitigating underinvestment incentives. Billett et al., 2007 find debt covenant protection to be used as a substitute for short-term debt in resolving debt overhang, while Johnson, 2003 finds firm leverage attenuates the negative relation between growth opportunities and debt maturity. Second, when choosing an optimal debt maturity, the firm makes tradeoffs between the benefits and costs for each option. For example, short-term debt may mitigate the underinvestment problem, but also increases refinancing/liquidity risk (Diamond, 1991; Harford et al., 2014), signals a borrower's quality (A. N. Berger et al., 2005; Flannery, 1986), and improves financial flexibility for leverage adjustments (Chen et al., 2021; Childs et al., 2005). Third, many empirical studies examining this relation (i.e., growth opportunities and debt maturity) rely on noisy proxies for firms' future investment opportunity set, such as the Market-to-Book ratio or R&D expenses. Despite the simplicity of constructing these measures, they tend to correlate with other unobservable firm characteristic;

e.g., information asymmetry, management quality, or product market competition[1] (Bartlett and Partnoy, 2020; Peters and Taylor, 2017). Finally, the work of Diamond and He, 2014 and Childs et al., 2005 suggest within the debt-agency costs framework, debt maturity optimality depends not only on growth opportunities but the *characteristics* of these options as well.

This paper examines firms' debt maturity structure choices following exogenous changes to growth caused by the recent public health pandemic (COVID-19). The outbreak has triggered major shifts in consumer demand and preferences, and consequently, created a heterogeneous effect on firms' growth opportunities. As such, companies who had the infrastructure and capability to adapt easier to the new economic environment, relative to those that lack ex ante, are likely to enjoy significant growth. To determine at priori the characteristics leading to the observed changes in growth opportunities after the pandemic shock, I rely on information obtained from 10-K filings. Specifically, the U.S. Securities and Exchange Commission (SEC) requires all public firms to disclose any relevant risks affecting their current and future earnings. Thus, inspired by the work of Davis et al., 2021, I estimate firm-level risk exposures[2] derived from the written text in "Item 1" to determine what *growth-changing* risk factors are important following the outbreak. By examining debt structure choices within a narrow window around the COVID-19 shock, other unobservable characteristics that usually correlates with firm's growth options are likely to remain constant, such as information asymmetry[3]. Further, since the

[1]For example, Barclay and Smith, 1995 interpret the negative coefficient on the Market-to-Book ratio as the effect of both firm's growth opportunities *and* the firm's level of information asymmetry.

[2]There are 44 risk factors. The type, and term dictionaries, of these factors are presented in greater detail in section 1.3.1.

[3]It is arguably unlikely for firms to experience changes in their private information due to the COVID-19 outbreak, the measures of risk exposures are obtained from publicly available documents. Thus, outside investors are able to asses the changes in growth prospects of the firm following the outbreak while levels of uncertainties regarding private information are likely to remain the same. Moreover, I control for unobservable firm characteristics with firm fixed effects in virtually all of the regressions in my analyses.

period after the COVID-19 outbreak has created favorable as well as unfavorable conditions depending on the firm's portfolio of risk exposures, such an empirical design enables the examination of debt maturity structures following *positive* and *negative* shocks to growth opportunities. Finally, I examine debt maturity choices for firms who have a maturing bond during the post-pandemic period. Such firms are forced to make a capital structure choice.

I document several facts on firms' debt structure choices following changes in growth opportunities. First, firms with high exposures to topics related to (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce) have experienced a significant positive change in growth opportunities (Growth-inducing factors), while firms with high exposures to (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries) experienced a significant negative change to growth (Growth-reducing factors). Second, despite the theoretical predictions by Myers, 1977 and Jensen and Meckling, 1976, firms with high pre-pandemic exposure to the total eight growth-inducing factors have *increased* their debt maturity, and are more likely to exercise a call option on their outstanding callable bonds. Moreover, I find mild evidence of covenant increases, and no evidence of changes in debt maturity concentrations. The increase in debt maturity is driven mainly by firms with low levels of cash, suggesting firms that tend to be frequent visitors to capital markets (Opler et al., 1999) and are likely to have severe underinvestment problems (Harford et al., 2014) prefer longer maturity debt after positive changes in growth opportunities. Further, the relation between growth opportunities and debt maturity seems to feature an asymmetric component. I find no relation between total exposure to growth-reducing factors and any of the maturity structure choices, even when using alternative empirical specifications. These results are robust while using a subset of these risk-changing factors, and controlling for the joint choice of leverage and debt maturity.

Taken together, the findings suggest growth opportunities and debt maturity has an asymmetric feature similar to the observed ratchet effect in leverage choices (Admati et al., 2018). Further, the documented positive link between growth opportunities and debt maturity shed some light on how the optimality of maturity can be influenced by the characteristics of these growth options[4]. According to Diamond and He, 2014, long-term debt is valuable in reducing underinvestment problems only if the firm's growth A) is accompanied with low uncertainties about the investment opportunity set (i.e., future opportunities are known), and B) returns from assets-in-place are not informative about these future opportunities. The observed increase in maturity can be partially explained within Diamond and He, 2014's framework. The COVID-19 shock may have caused changes in firms' *known* growth options due to permanent shifts in consumer and labor preferences. For example, Barrero et al., 2021 and Bick et al., 2021, using employee survey data, document evidence of a lasting increase in workers' preference to work from home, and such a preference may actually increase productivity in the post-pandemic economy. Bloom et al., 2021 find evidence that the share of new U.S. patent applications advancing the work-from-home productivity is significantly higher after the COVID-19 outbreak, and thus, may reinforce a shift to working remotely even after the pandemic ends.

The remainder of this article is organized as follows. Section 1.2 presents the literature review and the hypothesis development. Section 1.3 describes the data

[4]See Diamond and He, 2014 and Childs et al., 2005.

collection and measures of risk exposures. Section 1.4 tests the relation between estimates of risk exposures and growth opportunities. Section 1.5 examine debt maturity choices and growth-changing risk factors, and section 1.6 concludes.

1.2 Literature and Hypothesis Development

When a firm decides to issue debt to fund its operational and investment needs, among the key elements accompanying this choice is the maturity of the new debt. The neoclassical models of Myers, 1977, Jensen and Meckling, 1976, and Barnea et al., 1980 highlight the contractual problems of external financing, and more specifically, the various debt-related agency costs. Debt overhang (also referred to as the underinvestment problem) raise the possibility of bondholders, or creditors, to benefit from future enhancements in firm value. This may lead shareholders to forego future positive NPV projects, and therefore, make suboptimal investment choices. Both Myers, 1977 and Barnea et al., 1980 suggest the use of short maturity debt to mitigate these suboptimal incentives. Shorter debt maturity allows shareholders to adjust their capital structure sooner when growth opportunities arrive. Other classical theories, such as Smith and Warner, 1979, find investment disincentive costs can be mitigated through the use of covenants. While empirical studies find support to this view (Billett et al., 2007; Kolasinski, 2009), studies on debt maturity find inconsistencies to this prediction. Barclay and Smith, 1995; Billett et al., 2007; Custódio et al., 2013 find a positive link between growth opportunities and short-term debt, while Datta et al., 2005; Johnson, 2003; Stohs and Mauer, 1996 find mixed results.

Although short-term debt is argued to decrease investment disincentives, it comes with other potential considerations. One important factor is the liquidity/refinancing risk (Diamond, 1991; Harford et al., 2014). That is, short-term debt increases repayment risk, which can lead to inefficient liquidation of the firm. Dynamic models proposed by Titman and Tsyplakov, 2007 and Diamond and He, 2014 analyze debt maturity choices within the context of investment incentives and the probability of default in greater detail. Another use or determinant of debt maturity is the signaling hypothesis, proposed by Flannery, 1986. In his framework, when outsiders are less informed about the quality of the borrower, and debt issue is costly, a separating equilibrium exists where good quality borrowers choose short-term debt and informationally opaque borrowers self-select into the long-term debt market. Empirical studies are mixed in supporting this view. Barclay and Smith, 1995 finds no evidence of signaling with short-term debt. However, they find evidence of a pooling equilibrium where firms with *potential* information asymmetries issue more short-term debt[5]. A. N. Berger et al., 2005 examine the signaling hypothesis using data on bank loans to small businesses. They find substantial increase in average maturity for low-risk borrowers when their informational asymmetries are lessened, supporting the predictions of Flannery, 1986 and Diamond, 1991. Recent work by Chen et al., 2021 propose the value of short-term debt for timely leverage adjustments.

Given the complexity and the tradeoffs of these concerns, it is not clear whether the documented negative relation between firm growth opportunities and debt maturity is indeed related to the debt overhang problem. For instance, debt maturity is usually accompanied with debt amount (leverage) and covenant intensity, either one can affect firm's debt maturity choice in mitigating debt overhang. Further, it is not clear if short-term debt is optimal for reducing underinvestment problems. Both Diamond and He, 2014 and Childs et al., 2005 present dynamic models in

[5]The authors use the Market-to-Book ratio as the proxy for information asymmetry, in which I emphasize throughout this article that the measure proxies for several other firm characteristics. Thus, it is not clear whether informationally opaque firms indeed choose short-term debt.

which long-term debt can mitigate the agency cost of debt, depending on the characteristic of the firm's growth options. The empirical strategy of this research is to examine debt structure choices within a narrow window following an exogenous shock to the firm's investment opportunity set due to the COVID-19 shock. Thus, I test the following hypotheses:

Hypothesis 1 : A Firm's exposure to a subset of risk factors lead to positive (negative) changes in its growth opportunities

Once the subset of factors are identified, I test the following:

Hypothesis 2 : Positive (Negative) changes in growth opportunities lead to changes in debt maturity structure

1.3 Sample and Data Description

The final sample comes from the intersection of EDGAR 10-K filings and Compustat, then supplemented by additional debt variables from Mergent FISD. Because data on debt structure is only available at fiscal year level, analyses on growth opportunities are conducted using quarterly data while analyses on maturity choices are conducted using annual data. Section 1.3.1 describes the data on firm-level risk exposures and section 1.3.2 describes the rest of the financial variables. Additional details on all the variables used in this paper is available in the appendix A.II.

1.3.1 Firm-level Risk Exposures

Firm-level risk exposures are derived by parsing all public 10-K filings available in the EDGAR database reported between 1/1/2018 and 3/1/2020[6]. More specifi-

[6]The choice for the end date is mainly for two reasons. First, the COVID-19 virus was declared as a national health pandemic around this date. Therefore, any text obtained after may have keywords or risk topics that are influenced by the crisis itself, and thus, raising endogeneity concerns to the measure I use. The objective of this research is to measure a company's pre-pandemic risk exposures. Second, 10-K filings covering the recent fiscal year may take up to three months to be available in EDGAR's website.

cally, all readable text under "Item 1" is processed by a Python program[7] to ensure the extracted raw terms are following the standard procedure in the text-analysis literature; i.e., the text is cleaned from abbreviations, headings, plurals, stop words, and numbers, leaving only relevant lower-cased terms (Baker et al., 2016; Davis et al., 2021; Loughran and Mcdonald, 2011, 2014).

In order to estimate risk exposures from the language firms use to describe their risks, one needs to define a set of risk factors (or topics), then use an appropriate methodology to quantify the text content. A common method used in the literature is *the bag-of-words* dictionary approach (Baker et al., 2016; Loughran and Mcdonald, 2011; Tetlock, 2007), where a set of terms are grouped to represent a topic or a factor created by experts in the field of interest. Despite its simplicity, expert curated dictionary methods rely heavily on human input, which in some cases can be subjective and limited. Further, the focus of this paper is finding a set of *distinct* topics that are relevant to the COVID-19 pandemic. That is, a set of factors that is able to explain a firm's exposure to risks related to public health and human contact. A more accurate methodology in statistical text analysis involves the use of topic modeling, to which the latent (or unobserved) topic is estimated through the relationship and appearance of terms within the text corpus. In the Statistical Text Analysis Literature, a topic is defined as a probability distribution over words (terms) in a vocabulary and documents in a corpus share the same set of K[8] topics, each document has a different exposure to each topic (Blei et al., 2010). Traditional topic models, such as Latent Dirichlet Allocation (LDA), model

[7]Item 1 in the annual 10-K filing typically includes three sections; Business, Risk Factors, and Unresolved Staff Comments. Although corporation are required by the Securities and Exchange Commission to disclose all risk factors that are relevant to their future earnings under item 1.A (Davis et al., 2021), many companies discuss their operational and/or non-operational risks under the business section as well. The Python code and the risk exposure variables are available by the author upon request.

[8]The number of topics are usually set at priori.

words in the document to infer the set of associated terms that maximize the likelihood of the document collection. New alternative estimation methods involve the use of Supervised Topic Models, where the *predictability* of the topic to observed outcomes is the objective. For example, Blei et al., 2010 introduces Supervised Latent Dirichlet Allocation (sLDA), which is based on the traditional LDA estimation technique but adds an observed response variable for each document in the topic modeling approach. Examples of observable variables can be the number of times an on-line article was downloaded or the share price response following the document release. The sLDA approach has the advantage of finding latent topics that will best predict the response variables for future unlabeled documents as well.

There are several new estimation techniques introduced in the Supervised Topic Modeling literature. Davis et al., 2021 apply a hybrid approach to identify 45 risk factors (topics) that explain firm-level abnormal returns post COVID-19 shock. Their approach is to first use the high dimensional Multinomial Inverse Regression (MNIR) modeling approach introduced by Taddy, 2013[9], then systematically expanding each dictionary set with terms from the corpus based on similarity in both content and observed abnormal daily returns. Thus, the risk factors the authors find contain a finite set of terms for a finite set of categories that are sufficient to distinguish firms' varying response in market valuations to the recent COVID-19 pandemic.

In this paper, I rely on the risk categories created by Davis et al., 2021. Categories (or factors) include Commercial Property, Display Technology, Traditional Retail, E-commerce, and Franchising. All 44 risk factors[10], and their terms, are obtained

[9]MNIR has an efficiency advantage over sLDA through dimension reduction in the estimation methodology, see Taddy, 2013 for detailed description on his methodology.

[10]The authors construct 45 categories. However, following their approach, I drop the manufacturing category due to its high correlation with the other categories, leaving 44 in total.

from the authors' article and re-listed in the appendix A.I. To estimate firm i's exposure to risk factor j, I use the following approach:

$$\text{Risk Exposure (R.E.)}_{i,j} = \frac{\sum_{yj=1}^{Yj} term_{yj}}{\sum_{j=1}^{J=44} \sum_{yj=1}^{Yj} term_{yj}} \tag{1.1}$$

In essence, equation 1.1 estimates the risk exposure as the total number of terms extracted from the document falling under risk factor j, divided by the total number of terms captured for all 44 risk factors. Alternatively, $R.E._{i,j}$ can be measured as the total number of terms for factor j over the *total* number of terms in the document, or using sentences instead of terms. The approach in equation 1.1 insures the proxy is not influenced by either the size or the readability of the document itself (Loughran and Mcdonald, 2014). Nonetheless, using any of the alternative approaches does not alter the findings of this paper.

Looking at the descriptive statistics for the sample examining growth opportunities in table 1.1, certain factors have averages that are close to zero (e.g., Clearing Houses, Card Payments, and Deposits). These factors are likely misrepresenting the true population mean of all public firms in the economy due to the exclusion of regulated industries[11]. Further, a subset of risk exposures have high averages along with high deviations, such as Drug Trials and Software Services. One potential explanation might be related to the unique distribution of firms' organizational structure that tend to be exposed to such factors. For example, companies exposed to such risks tend to be either small and operating in a niche market with low vertical integration in the supply chain, or big and diversified conglomerates with high vertical integration in the supply chain. Figures 1.1 and 1.2 show the correlation

[11]Firms operating in the financial and utilities sectors are dropped from the sample. Such firms may have significant constraints on their capital structure choices.

matrix among the different risk factors[12]. Pairs such as (Software and Hardware Products, Software Services), (Oil and Gas, Energy Infrastructure), (Airlines and Aircraft, Travel), and (Communications, Traditional Media) have relatively high correlations, the highest being 0.65. One concern is whether these factors simply reflect various industries/sectors within the economy. While Davis et al., 2021 address this concern in greater detail, I control for industry effects in all of the reported regressions by using either industry fixed effects or setting the error terms to be clustered at the industry level (Fama-French 49 industry classification). Additionally, the following two examples obtained from the sample may shed some light on whether firm-level risk exposure estimates are heterogeneous across industries: A) Companies having high exposure to travel (above 10%) while operating in different industries; Marriott Vacations Worldwide Corp. (SIC 6531) and American Airlines Group (SIC 4512). B) Companies operating in the same industry (SIC 5812) but have different exposure levels to e-commerce; Cheese Cake Factory Inc. (2.81%) and Texas Roadhouse, Inc. (0.04%). Certainly, the variation in exposure is not constant across pairs of industry groups.

1.3.2 Firm Characteristics

U.S. Firm-Quarterly data is obtained from Compustat. Following the literature, I control for firm characteristics that explain observed changes in growth opportunities, such as ROA, Capital Expenditures, R&D/Sales, R&D Dummy, and an indicator taking the value of 1 if a firm's head quarters is in the state of Delaware. To proxy for growth opportunities (Tobin's q), I use the standard market-to-book asset ratio as the main variable due to its wide use in the literature. Further, empirical evidence show that it has the highest correlation with actual investment

[12]The factors are reported in two separate matrices for readability purposes. The factors are grouped based on similarity in business practices. The full correlation matrix is available by the author upon request.

opportunities, it contains the information in alternative proxies, and it is the least affected by other factors (Adam and Goyal, 2008). However, market-to-book asset ratio is admittedly a noisy proxy for Tobin's q. Specifically, in an increasingly intangible economy, the classical measure does not account for a firm's level of intangible assets, especially ones that are created internally, such as brand names, patents, and databases. Peters and Taylor, 2017 develop an alternative proxy for Tobin's q to account for such intangible assets "Total q". I use their measure as an alternative proxy for growth opportunities to alleviate concerns on whether risk exposure measures are explaining other correlated characteristic of the firm. Empirical studies that use alternative proxies for firm growth options typically use the ratio of research and development expenses (Barclay and Smith, 1995; Billett et al., 2007; Johnson, 2003). While R&D is likely a form of investment rather than a proxy for firm growth options, I use R&D in an un-tabulated robustness check. The results of this paper remain qualitatively the same. Following Peters and Taylor, 2017, I measure Total q as:

$$\text{Total } q_{i,t} = \frac{V_{i,t}}{K_{i,t}^{phy} + K_{i,t}^{int}} \tag{1.2}$$

where firm i's Total q at time t is the total market value of the firm divided by the sum of its replacement cost of capital; physical capital K^{phy} (Property, Plant, and Equipment) and intangible capital K^{int}. Intangible capital includes externally obtained capital (Goodwill from the balance sheet) and internally generated capital of knowledge and organization. Since the latter type of capital does not appear on the firm's balance sheet, Peters and Taylor, 2017 estimate knowledge and organizational capital using the perpetual inventory method:

$$G_{i,t} = (1 - \theta_C)G_{i,t-1} + \text{New Intangible Capital}_{C,i,t} \tag{1.3}$$

$G_{i,t}$ is the current level of knowledge (organizational) capital at time t, θ_C is the depreciation rate; either θ_{know} for knowledge or θ_{org} for organizational. New Intangible Capital is measured by the firm's R&D expense at time t for knowledge and 30% of SG&A expense for organization. Additional details on Total q is available in the appendix A.II. While the rates in equation 1.3 are held fixed across industries, I allow the depreciation rate, as well as the fraction of SG&A expense, to vary by industry using estimates found by Ewens et al., 2021[13].

The final sample for examining firm growth opportunities include U.S. firm quarterly data from 1/1/2018 to 12/31/2020 that are not in regulated industries (SIC codes 6000-6999, 4900-4999), have total book assets above $10 million, and the share price is at least $1. Table 1.1 reports the summary statistics. Quarterly reports covering the months of March to May of 2020 are dropped from the final sample. The complete lock down at the initial period had created uncertainties toward the length and severity of the pandemic, and the economy was at an early stage of adapting to the so called "New Normal". Since testing for growth prospects is the objective here, using data after May 2020 alleviate concerns related to whether measures of growth prospects is affected by this initial economic uncertainties rather than firm fundamentals.

1.4 Firm Risk Exposures and Growth Opportunities

The recent health pandemic crisis has created polarizing effects on firms' ongoing business environment, yet whether the change is permanent remains an open question. However, companies that were able to adapt easier to the new norms, at the organizational level or/and with its supply chain affiliates, relative to their

[13]Results of the paper remain unchanged when using either approach. I also would like to thank Ryan Peters for supplying the most recent data on Total q. Historical data for Total q is available at WRDS.

competitors certainly have enjoyed a positive demand shock to their products. However, such adaptability may require the firm to engage or expose itself to risks competitors were unwilling to do so ex ante. For example, Dollar General Corp., which has a pre-pandemic exposure of 9.7% in e-commerce, experienced an increase in sales of roughly 21.6% during the fiscal year 2020 relative to its competitor Dollar Tree Inc., which has an exposure of of 0% and an increase of only 8.04% during the same year[14]. The relative easiness to adopt due to the firm's ex ante risk exposure can also create future opportunities for the firm to expand its goods and lines of services ahead of competitors. Davis et al., 2021 examine the stock market response to firm-level risk exposures in pre-pandemic 10-K filings. While they find bad COVID-19 news has varying effect on company stock market returns, depending on their risk exposures, firm growth prospects remain an unanswered question. Thus, I first examine what risk exposures have caused an increase or a decrease in firm growth opportunities after the COVID-19 crisis, then I group these growth-changing factors to test debt maturity structure changes in section 1.5.

The neoclassical Tobin's q ratio measures the market value of the firm's assets relative to their replacement costs. Theoretically, holding all other aspects constant, an increase in q is likely the result of market participants expecting higher investment prospects in the firm's future. By examining Tobin's q, or a proxy of it, in a *narrow* window setting, it is safe to assume that other aspects affecting q, such as management quality, information asymmetry, or product market competition, are likely to remain constant. Thus, following the literature in corporate governance studies (Coles et al., 2008; Gompers et al., 2003; Yermack, 1996, and others), the

[14]Revenue numbers are obtained from Yahoo.com.

baseline regression takes the form:

$$\begin{aligned} Q_{i,t} &= \alpha_i + \beta_1 Shock + \beta_2 R.E._{i,t-1,y} \\ &+ \beta_3 Shock \times R.E._{i,t-1,y} + \lambda' X_{i,t} + \delta_{jt} + \varepsilon_{i,t} \end{aligned} \tag{1.4}$$

where $Q_{i,t}$ is a Tobin's q proxy for firm i at quarter-year t. α_i is a firm fixed effect, $Shock$ is an indicator for the COVID-19 pandemic period, i.e. the time period after 3/1/2020, $R.E._{i,t-1,y}$ is firm i's pre-pandemic risk exposure to factor y. The coefficient of interest in equation 1.4 is β_3, which captures the average effect of risk exposure y on the firm's growth opportunities after the COVID-19 shock. X is a host of controls used in the literature (Delaware Incorp., Log(Assets), ROA, Capital Expenditures, R&D / Sales, R&D Dummy, and Book Leverage), and δ_{jt} is an industry-time fixed effects, controlling for unexplained economic time trends across different industries. Industry classifications follow the Fama-French 49 industries. Figure 1.3 plots the coefficient estimates (β_3) for each risk factor[15] as well as the confidence interval when estimating equation 1.4 using Market-to-book as the proxy for Tobin's q. As can be seen, Alternative Energy, Semiconductors, Software Services, and Web Services show a positive and significant effect on the Market-to-book ratio, while REITs, Oil and Gas, and Healthcare Providers show a negative and significant effect.

For the purpose of this study, finding a simplified and nonspecific industry categorization for the degree of positive vs. negative exposure to the pandemic opens the possibility to examine how firms generally respond when choosing a maturity structure after facing an *increase* compared to a *decrease* in growth opportunities.

[15] 5 factors are not reported in figure 1.3 due to A) The high confidence interval. and/or B)The factors do not display sufficient variation across firms probably because they are exclusively relevant to regulated industries. The dropped factors are: Clearing Houses, Foreign Exchange, Investment Funds, Workforce, and Deposits.

Since $\sum_{j=1}^{J=44} R.E._{\cdot j} = 1$ by construction for each firm at time t, I measure a firm's Total Risk Exposure to growth-inducing factors (T.R.E.$_{Pos.}$) as the sum of the following categories (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-commerce) while T.R.E.$_{Neg.}$ as the sum of the following growth-reducing factors (REITs, Oil and Gas, Healthcare Providers, Travel, Health Insurance, Shipping Containers, and Metal Products, Foreign Countries). Both figures 1.4 and 1.5 plot the time trend for the industry-adjusted Market-to-Book against companies with high levels of positive (negative) Total R.E. before and after the COVID-19 pandemic. Note that all the results of the paper remain qualitatively the same when using the top 4 to the top 10 factors[16] from figure 1.3.

Table 1.3 shows the estimated results for equation 1.4 when using the measure (T.R.E.$_{Pos.}$). Columns 3-6 report the coefficient estimates when using alternative proxies/model-specifications for Tobin's q. While the interaction term is consistently significant in statistical terms, the results are economically significant as well. For example, according to the interaction term in column 2, a firm having a total of 30% exposure to the eight growth-inducing factors had an average change in Market-to-Book of (-0.56+0.33+0.92×0.6= 0.046) post COVID-19 compared to (-0.14) for a firm in the same industry with a total exposure of only 10%, that is an increase in the Market-to-book ratio by roughly 0.19 or 9.13% from the sample mean. Table 1.4 on the other hand replicates the estimates when using the eight growth-reducing factors (T.R.E.$_{Neg.}$). The results are consistent here as well; from column 2, moving from 10% to 30% exposure in T.R.E.$_{Neg.}$ reduces the Market-to-Book ratio by 0.15 or -7.4% from the sample mean after the COVID-19 shock. Overall, results from both tables 1.3 and 1.4 show that the measures (T.R.E.$_{Pos.}$,T.R.E.$_{Neg.}$) include

[16]The maturity structure regressions are reexamined when using the top five factors instead of eight and are reported in the appendix.

factors that many firms in the economy are exposed to, and are suitable proxies for estimating a firm's level of exposure to growth-inducing and growth-reducing factors prior to the health pandemic shock.

1.5 Maturity Structures and Growth Prospects

As shown in the previous section, the recent health pandemic shock has affected firm growth opportunities. A natural question to follow is whether firms have adjusted their debt maturity structure to reflect such new changes to their growth prospects, and what is the direction of the adjustment. And more importantly, was the adjustment symmetrical?

To answer these questions, I start by merging Compustat annual data with firms' pre-pandemic risk exposure levels (using *CIK* codes) since corporate debt information from Compustat is only available at annual levels. I use the two growth-changing exposure measures (T.R.E.$_{Pos.}$ and T.R.E.$_{Neg.}$) to estimate the degree of positive and negative shocks to firms' growth prospects. Following the recent literature on corporate maturity structure, I compile variables that show to have significant importance in the maturity structure choice; ln(Assets), ln(Assets)^2, Leverage, σ(Profitability), Profitability, Cash, and Asset Maturity; (Barclay and Smith, 1995; Billett et al., 2007; Chen et al., 2021; Choi et al., 2018; Datta et al., 2021; Johnson, 2003; Stohs and Mauer, 1996). Firm-years are kept if the total book assets are above \$10M, the stock price is at or above \$1, the book value of equity is positive, the information related to outstanding debt is not missing, and the firm operates in an unregulated industry (SIC codes 6000-6999, 4900-4999). I proxy debt maturity structure choice by the amount of debt maturing in 3 years or less (dd1-dd3) divided by total debt outstanding (dlc+dltt). Alternative proxies are used as well, such as debt maturing in 5 years or less and the ratio of long-term debt (maturing after 5 years). Finally, I supplement the data with detailed information on corporate public debt from Mergent FISD[17]. More specifically, I follow Choi et al., 2018, 2020 in measuring debt granularity (GRAN), which estimates the concentration of debt maturity choices within the firm's public debt portfolio at time t. Further, $\ln(\overline{Maturity}_w)$ measures the log balance-weighted maturity (in years) for all outstanding bonds at time t. Billett et al., 2007 provide evidence suggesting bond covenants serve as a substitute for short-term debt in reducing shareholder-bondholder contracting problems. Thus, I follow the authors' approach in constructing a covenant index for the firm at time t. Finally, I use three indicators; a dummy variable taking a value of 1 if the firm exercised at least one call on its callable-outstanding bonds during time t, Maturing Bond_{2020} taking a value of 1 if the firm has an outstanding bond that matures during the COVID-19 pandemic shock, and a placebo dummy Maturing Bond_{2019} taking the value of 1 if the firm has an outstanding bond maturing in 2019[18]. Table 1.2 reports the descriptive statistics for the final sample used to examine debt maturity choices. Most of the variables follow distributions reported in other empirical studies; Billett et al., 2007; Choi et al., 2018; Harford et al., 2014. Additional details on the all variable definitions are available in appendix A.II.

The estimation model for testing firms' maturity structure choices takes the following form:

$$\begin{aligned} \text{Mat. Strct.}_{i,t} = \alpha_i &+ \beta_1 Shock + \beta_2 \text{T.R.E.}_{i,t-1} \\ &+ \beta_3 Shock \times \text{T.R.E.}_{i,t-1} + \lambda^{'} X_{i,t-1} \\ &+ \delta_j + \eta_t + \varepsilon_{i,t} \end{aligned} \tag{1.5}$$

[17]Compustat and FISD firms are matched using a similar methodology to Brown and Powers, 2020. Specifically, a match occurs when any of the issuer's 6-digit CUSIP key in a given year equals the firm-year Compustat historical CUSIP.

[18]Both indicators are measured after excluding bonds that were retired or defaulted at time $t-1$. There is an additional screen on the indicator Maturing Bond_{2020}; it only takes the value of 1 if the maturity date is after March 1st 2020, and zero otherwise

where Mat. Strct.$_{i,t}$ is a proxy for firm i's maturity structure; e.g., share of short-term debt, share of long-term debt, debt granularity, or log(maturity). $Shock$ is an indicator for the COVID-19 Shock[19], $T.R.E._{i,t-1}$ is firm i's total level of risk exposure to the eight positive (negative) factors during the pre-pandemic period. The coefficient of interest in equation 1.5 is β_3, measuring the effect of exposure to *growth-changing* risk factors on firms' maturity structure choice following the COVID-19 shock. X is a host of controls used in the literature, δ_j is an industry fixed effects (Fama-French 49), and η_t is a year fixed effect.

1.5.1 Baseline Regression

Table 1.5 presents the estimates for the baseline regression on the effect of positive changes in growth options (T.R.E.$_{Pos.}$) on debt maturity levels. The coefficient on the interaction term remains negative and statistically significant while using all alternative proxies of debt maturity structure; the proportion of debt maturing in 3 years or less, 5 years or less, or the proportion of debt maturing after 5 years. The effects are strong in economic terms as well. For example, according to column 2, a one standard deviation increase in the growth-inducing risk exposure level leads to a 2% reduction in the fraction of short-term debt[20], that is a 7% decrease from the sample mean. These results are in contrast to those reported by earlier findings concerning debt maturity choice and growth opportunities. One likely explanation is related to firms' endogenous and simultaneous choice of growth opportunities, leverage, and debt maturity (Billett et al., 2007). For example, Johnson, 2003 finds a negative relation between Market-to-Book and short-term debt only when using a two-stage fixed effect model, while Stohs and Mauer, 1996 finds mixed results

[19]Financial data reports dated after 6/1/2020 is considered post COVID-19 shock. I use this classification to insure at least 25% of the firm's fiscal year operation occurred after the health pandemic crisis.

[20]The shock indicator is suppressed because it is part of the year fixed effect dummies. The coefficient on the shock is -0.22.

when using alternative specifications. In addition, proxies for Tobin's q (mainly the Market-to-Book ratio) used by many studies tend to correlate with other firm characteristics, which in turn may have been driving the positive link between growth opportunities and short-term debt.

The negative relation observed between growth opportunities and short-term debt may shed some light on the *type* of change in firms' growth opportunities following the recent health pandemic shock. According to Diamond and He, 2014, growth firms with *known* future growth opportunities may have better investment incentives with longer term debt. The COVID-19 is the first health pandemic to take a global and lasting effect on all aspects of the economy. As such, perhaps market participants' expectations, following the COVID-19 shock, of future public health-related pandemics are higher. Consequently, firms having the infrastructure and capabilities to adopt more easily in delivering goods and services in a contact-less process (i.e., high levels of T.R.E.$_{Pos.}$) will always have a more stable demand during future states of health-pandemic shocks compared to companies that lack such adaptability, and thus, creating a higher *known* future opportunities relative to firms with low exposure to T.R.E.$_{Pos.}$.

Most of the control variables in table 1.5 have the expected signs across different regression specifications, albeit the statistical significance varies possibly due to the loss of power resulting from the small sample size. For example, asset maturity should have a negative relation with the fraction of short-term debt since firms should match the maturities of their assets and liabilities to reduce underinvestment problems (Johnson, 2003; Myers, 1977). Size and size squared have their predicted signs as they proxy for credit quality (Diamond, 1991). σ(Profitability) has a negative sign, consistent with the findings in Johnson, 2003.

Because cash holdings may assist the firm in fully investing in its growth opportunities while mitigating refinancing risk (Harford et al., 2014), and firms with greater access to capital markets tend to hold lower levels of cash (Opler et al., 1999), columns 5 and 6 in table 1.5 examine debt maturity choices on subsamples based on firms' prior cash levels relative to the industry median. Results indicate that the increase in maturity is mainly driven by firms with low levels of cash prior to the pandemic shock. The coefficient on the interaction term is -0.122 and significant at the 5% level, while the coefficient on the subsample of high cash holdings is virtually zero. Taken together, the increase in debt maturity choices following the positive shock in growth opportunities is driven by firms who probably are frequent visitors to the capital market

Table 1.6 replicates table 1.5 when using the firm's exposure to growth-reducing factors. The interaction term in column 1 shows a reduction in the fraction of short-term debt following the shock. However, after controlling for firm characteristics, the coefficient becomes insignificant. Moreover, there is no consistency in the sign of the coefficient when using alternative proxies for maturity structure choices (e.g., column 3). Finally, results remain insignificant when the model is estimated on subsamples of prior cash levels. The overall results in table 1.6 seem to suggest that firms do not change their maturity structure levels after experiencing a *negative* shock in growth opportunities, and the lack of response does not depend on prior cash levels.

1.5.2 The Simultaneous Choice of Leverage and Debt Maturity

Both tables 1.5 and 1.6 suggest an asymmetric relation between changes in growth opportunities and debt maturity choices. However, these results may be affected by the fact that firms choose the *level* and *maturity* of their debt simultaneously, and thus, endogeneity and reverse causality between leverage and the fraction of short-term debt in the regressions can create biasness and inconsistencies in the coefficient estimates. Following Johnson, 2003, Billett et al., 2007, and Datta et al., 2021, I estimate a two-stage simultaneous least square regression, where the first stage estimates the firm's leverage choice, and the second stage estimates the maturity structure choice. Specifically, the second stage takes the form:

$$\begin{aligned}\text{Mat. Strct.}_{i,t} = {} & \alpha_i + \beta_1 Shock + \beta_2 \text{T.R.E.}_{i,t-1} \\ & + \beta_3 Shock \times \text{T.R.E.}_{i,t-1} + \beta_4 \widehat{\text{Leverage}}_{i,t} \\ & + \beta_5 \text{Asset Maturity}_{i,t-1} + \beta_6 \ln(\text{Assets})^2_{i,t-1} \\ & + \delta_j + \eta_t + \varepsilon_{i,t}\end{aligned} \tag{1.6}$$

and the first stage takes the form:

$$\begin{aligned}\text{Leverage}_{i,t} = {} & \alpha_i + \beta_1 \ln(\text{Assets})_{i,t-1} + \beta_2 \text{Profitability}_{i,t-1} \\ & + \beta_3 \sigma(\text{Profitability})_{i,t-1} + \beta_4 \text{Fixed Assets} \\ & + \lambda' X_i + \delta_j + \eta_t + \varepsilon_{i,t}\end{aligned} \tag{1.7}$$

where $\widehat{\text{Leverage}}_{i,t}$ in the second stage is the predicted value from estimating equation 1.7, X_i are the variables in equation 1.6, δ_j is an industry fixed effects (Fama-French 49), and η_t is a year fixed effect. Table 1.7 reports the 2SLS for both measures of growth-inducing and growth-reducing risk exposures. Using both proxies of short-term debt (debt maturing in 3 year or less and debt maturing in 5 years or less), the asymmetric relation between growth opportunities and maturity structure remains consistent even after controlling for the simultaneous choice of leverage and debt maturity. Further, the negative coefficient on the interaction term when estimating leverage choice in columns 2 and 4 is consistent with firms reducing debt levels when growth opportunities arise (Myers, 1977). More importantly, columns 1 through 4 suggests that increases in growth options seem to reduce leverage while at the same time increase the maturity of debt. These results, taken together, support Diamond and He, 2014's theory on how debt overhang can be reduced with longer debt maturity depending on the *characteristics* of a firm's growth options. Childs et al., 2005 theoretical work on stockholder-bondholder agency costs concludes that firms with growth options that expands assets-in-place may choose lower initial debt levels if financial flexibility (i.e. short-term debt) is high. The COVID-19 health pandemic shock has likely expanded (decreased) firms' growth opportunities for *existing* rather than *future* goods and services, depending on their exposures to T.R.E.$_{Pos.}$ (T.R.E.$_{Neg.}$).

1.5.3 Capital Structure Choice and Debt Maturity

The observable fraction of short-term debt obtained from financial reports might be the product of either an active or a passive managerial choice. For example, it is possible that the observed reductions in short-term debt ratios merely reflect fewer loans maturing in years 4 and 6 among firms with high levels of growth-changing risk exposures, and consequently, a decrease in short-term debt will follow post COVID-19 shock. Alternatively, many firms do not necessarily have access to public debt, and the longer maturity observed could be driven by an increased supply of capital from banks and private lenders following government intervention in alleviating the economic crisis stemmed from the COVID-19 virus. Thus, in this section, I examine maturity choices using detailed information from Mergent FISD. More specifically, I examine maturity choices of firms who experienced an increase (decrease) in growth options and are forced to make a capital adjustment decision due to an existing bond that matures following the COVID-19 shock. Thus, the estimation model for the FISD sample takes the form:

$$
\begin{aligned}
\text{Mat. Strct.}_{i,t} = \beta_0 &+ \beta_1 Shock + \beta_2 \text{T.R.E.}_{i,t-1} \\
&+ \beta_3 \text{Maturing Bond at } t\text{+}1_{t-1} + \beta_4 Shock \times \text{T.R.E.}_{i,t-1} \\
&+ \beta_5 Shock \times \text{Maturing Bond at } t\text{+}1_{t-1} \\
&+ \beta_6 Shock \times \text{T.R.E.}_{i,t-1} \times \text{Maturing Bond at } t\text{+}1_{t-1} \\
&+ \beta_7 Cash_{t-1} + \delta_j + \varepsilon_{i,t}
\end{aligned}
\tag{1.8}
$$

Most of the variable definitions follow other equations (e.g., 1.5 and 1.6). I include prior cash levels since it is a relevant and important source of financing for firms experiencing changes in growth opportunities, and thus, can affect the choice of debt maturity as evident in the results of table 1.5. The coefficient of interest in equation 1.8 is β_6, which captures debt maturity changes for firms after the COVID-19 shock who are forced to make a capital structure choice given their changes in growth opportunities. This additional interaction term can help validate the results observed in the baseline regressions to whether debt maturity was actively increased by managers following the COVID-19 shock. I also test the model using a placebo, where I assume the COVID-19 shock occurred in 2019 instead of 2020. Additionally, because firms can reduce the debt overhang problems with callable bonds (Barnea et al., 1980), Becker et al., 2018 document that firms with callable debt are more likely to increase investments following increases in growth opportunities. Thus, I test whether firms with existing callable bonds are more (less) likely to exercise a call option after experiencing positive (negative) changes in growth opportunities[21]. The logistic estimation model takes the from:

$$\begin{aligned} Call_{i,t} = \alpha_i + \beta_1 Shock + \beta_2 \text{T.R.E.}_{i,t-1} \\ + \beta_3 Shock \times \text{T.R.E.}_{i,t-1} + \beta_4 Cash_{t-1} + \varepsilon_{i,t} \end{aligned} \tag{1.9}$$

Similar to equation 1.8, I estimate the model with a placebo test assuming 2019 is the COVID-19 shock. Results of the estimation model for equations 1.8 and 1.9 are reported in tables 1.8 and 1.9 using growth-increasing and growth-reducing pre-pandemic exposures, respectively.

The coefficient estimates reported from the interaction term $Shock \times \text{T.R.E.}_{Pos.}$ in column 1 of table 1.8 show a statistically significant affect of growth-increasing risk exposure levels on the probability of the issuer's call exercise. The estimated odds ratio for a firm with 30% exposure is 1.46 while the odds ratio for a firm with 10% exposure is 0.85. These changes are indeed due to the COVID-19 shock since the placebo test finds no significance for the interaction term. Columns 2 and 3 test for the log maturity of outstanding bonds with and without prior cash levels, respectively. The triple interaction remains consistent and statistically significant at the 10% level while the placebo test finds no significance. Taken together, firms experiencing an increase in growth opportunities after the health pandemic shock are more likely to exercise their call options, as well as extend the overall debt maturity of their bond portfolios.

Columns 4 and 5 in table 1.8 test another characteristic of firms' maturity structure; maturity dispersion or "Granularity" following a positive change in firms' growth prospects. The triple interaction term indicates that maturity towering or, concen-

[21]Note that the sample size is significantly smaller here since I restrict my analysis to only firms with outstanding callable bonds throughout the sample period resulting to roughly 115 issuers.

tration, has decreased, albeit the coefficient is not statistically significant. Finally, Billett et al., 2007 finds evidence of a substitution effect between covenants and the fraction of short-term debt in solving underinvestment problems. Columns 6 and 7 report the estimation results when testing for changes in the covenant index. While the triple interaction term show signs of an increase in covenants for firms with higher exposure to growth-increasing risk factors post COVID-19 shock, the placebo test fails to link the increase is caused by exogenous changes in growth. Perhaps the relation observed here relates to the overall time trend in covenants as documented by Billett et al., 2007.

Table 1.9 replicates table 1.8 when testing for negative changes in growth opportunities. The overall results, as depicted by the triple interaction term, are inline with the previous analysis of this paper. Firms experiencing reductions in their growth opportunities seem to be null in adjusting their debt maturity choices. Thus, supporting the view that an asymmetric relation between growth opportunities and debt maturity choice does exist, at least in the scope following the recent health pandemic shock.

1.6 Concluding Remarks

Earlier research on debt maturity structure and its relation to a borrower's growth prospects have mixed results. While Barclay and Smith, 1995 and Billett et al., 2007 find a positive association between growth opportunities and the fraction of short-term debt, Stohs and Mauer, 1996 finds the opposite. Consequently, the works of Diamond and He, 2014 and Childs et al., 2005 aim to explain what was previously thought to be a straightforward relation. The firm's *characteristic* of growth options plays a an important role in the optimal choice of debt maturity to mitigate the underinvestment problems. This paper examines debt maturity choices after exogenous changes in the firm's growth opportunity set stemming from the recent COVID-19 health pandemic shock. Such a laboratory experiment aid in the understanding of pure changes in growth opportunities, while other characteristics that tend to correlate with growth prospects are likely unchanged. Using firm-level risk exposures inspired by the work of Davis et al., 2021, I find growth opportunities have increased for firms exposed to (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce), while growth opportunities have decreased for firms exposed to (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries). Further, I utilize these factors that fueled the observed changes in growth prospects to examine firm maturity choices. I find firms exposed to growth-inducing factors prior to the pandemic have lengthened their debt maturity and the effect is mainly driven by firms with low cash levels, while firms exposed to growth-reducing factors did not change their debt maturity levels. These results are consistent even after controlling for the endogenous choice of leverage. Further, firms with high exposure to growth-inducing factors are more likely to exercise a call option on their callable bonds, while no opposite relation is observed for firms with high exposure to growth-reducing factors. These results suggest that the relation between growth opportunities and debt maturity structure has an asymmetrical feature similar to that observed for leverage choices (see Admati et al., 2018). And increases in firms' growth opportunities that are likely to be known by market participants leads to longer debt maturity levels, supporting the arguments presented by Diamond and He, 2014. Taken together, debt maturity choices following changes in growth opportunities is more complex than initially thought.

Tables and Figures

Table 1.1: Summary Statistics for Firm-level Risk Exposures

	SD	Mean	Min	Median	Max	N		SD	Mean	Min	Median	Max	N
Firm Characteristics:							Foreign Countries	8.70%	9.90%	0.00%	7.50%	41.40%	26,390
Market-to-Book	1.93	2.05	0.34	1.36	11.34	16,822	Foreign Exchange	0.20%	0.10%	0.00%	0.00%	1.20%	26,390
Total q	2.91	2.57	0.28	1.61	18.41	15,992	Franchising	2.60%	0.50%	0.00%	0.00%	20.50%	26,390
Market-to-Book *(Alt.)*	1.86	2.23	0.60	1.58	11.13	15,643	Gambling	0.80%	0.10%	0.00%	0.00%	7.60%	26,390
Delaware Incorp.	0.47	0.67	0.00	1.00	1.00	26,394	Gold or Silver	0.30%	0.10%	0.00%	0.00%	2.00%	26,390
ln(Assets)	2.13	6.42	2.44	6.48	11.48	26,394	Health Insurance	11.70%	6.60%	0.00%	0.60%	61.80%	26,390
ROA	0.09	-0.03	-0.45	0.00	0.12	26,361	Healthcare Providers	1.10%	0.40%	0.00%	0.00%	8.00%	26,390
Cap. Exp.	0.03	0.02	0.00	0.01	0.19	26,367	Insurance	1.20%	1.20%	0.00%	1.00%	6.50%	26,390
R&D / Sales	5.62	1.06	0.00	0.00	47.94	26,394	Investment Funds	0.30%	0.10%	0.00%	0.00%	2.10%	26,390
R&D Dummy	0.50	0.56	0.00	1.00	1.00	26,394	Metal Products	5.80%	2.80%	0.00%	0.40%	34.60%	26,390
Leverage	0.26	0.29	0.00	0.25	1.29	26,269	Metals and Minerals	1.00%	0.30%	0.00%	0.00%	5.90%	26,390
Firm-level Exposures:							Mortgages	2.40%	1.20%	0.00%	0.50%	16.90%	26,390
Advertising	2.70%	1.10%	0.00%	0.20%	18.00%	26,390	Oil and Gas	9.90%	3.30%	0.00%	0.00%	56.20%	26,390
Airlines or Aircraft	3.50%	0.60%	0.00%	0.00%	28.60%	26,390	Power Generation	3.90%	1.50%	0.00%	0.10%	25.60%	26,390
Alternative Energy	1.40%	0.50%	0.00%	0.00%	9.80%	26,390	REITs	2.70%	1.30%	0.00%	0.60%	18.90%	26,390
Banking	2.40%	1.20%	0.00%	0.60%	16.90%	26,390	Residential Construction	1.20%	0.30%	0.00%	0.00%	10.20%	26,390
Card Payments	2.80%	1.10%	0.00%	0.10%	19.40%	26,390	Restaurants	4.10%	0.60%	0.00%	0.00%	35.60%	26,390
Clearing Houses	0.20%	0.00%	0.00%	0.00%	1.10%	26,390	Semiconductors	2.20%	0.70%	0.00%	0.00%	15.20%	26,390
Commercial Property	3.50%	3.90%	0.00%	3.10%	22.50%	26,390	Shipping Containers	2.30%	0.70%	0.00%	0.00%	17.10%	26,390
Communications	4.20%	1.30%	0.00%	0.10%	28.70%	26,390	Software Services	10.70%	13.40%	0.30%	10.10%	45.50%	26,390
Deposits	0.10%	0.00%	0.00%	0.00%	0.60%	26,390	Software-Hardware Products	5.90%	6.40%	0.00%	4.40%	29.00%	26,390
Display Technology	3.00%	1.60%	0.00%	0.40%	18.30%	26,390	Traditional Media	3.50%	1.30%	0.00%	0.30%	26.00%	26,390
Drug Trials	19.60%	11.30%	0.00%	1.80%	64.60%	26,390	Traditional Retail	6.10%	3.20%	0.00%	0.50%	30.70%	26,390
E-Commerce	3.50%	3.20%	0.00%	1.90%	16.60%	26,390	Transportation	4.40%	1.70%	0.00%	0.50%	35.10%	26,390
Electronics	6.00%	4.20%	0.00%	1.50%	28.70%	26,390	Travel	1.80%	0.70%	0.00%	0.10%	14.10%	26,390
Energy Infrastructure	3.60%	1.20%	0.00%	0.20%	24.30%	26,390	Video Games	2.10%	0.70%	0.00%	0.00%	15.00%	26,390
Financial Management	1.20%	1.00%	0.00%	0.60%	6.90%	26,390	Web Services	4.00%	2.60%	0.00%	0.90%	20.20%	26,390
Food Related Products	4.80%	2.20%	0.00%	0.60%	30.00%	26,390	Workforce	0.10%	0.00%	0.00%	0.00%	0.80%	26,390

This table reports the summary statistics for the sample used to examine changes in growth opportunities around the 2020 health pandemic shock (1/1/2018 to 12/31/2020). Firm financial data is collected from Compustat quarterly filings, and firm-level risk categories follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in all 10-K filings reported in EDGAR; see section 1.3.1 for further details on measuring exposure levels and appendix A.I on the 44 different risk factors. Q^{tot} follows Peters and Taylor, 2017, see section 1.3.2 for detailed information on the construction of this variable. Appendix A.II and A.I provide additional details on the construction of all variables reported in this table. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuos variables are winsorized at the 1st and 99th percentile.

Table 1.2: Descriptive Statistics for the Maturity Structure Choice Test

	SD	Mean	Min	Median	Max	N
Growth Shock Proxies:						
T.R.E.$_{Pos.}$	0.22	0.19	0.00	0.09	0.70	10,879
T.R.E.$_{Neg.}$	0.17	0.13	0.00	0.06	0.67	10,879
Firm Characteristics:						
COVID-19 Shock (fiscal 2020)	0.42	0.23	0.00	0.00	1.00	10,879
Placebo Shock (fiscal 2019)	0.44	0.25	0.00	0.00	1.00	10,879
Fraction of Debt due in 3 Years	0.31	0.33	0.00	0.23	1.00	8,390
Fraction of Debt due in 5 years	0.33	0.54	0.00	0.52	1.00	7,668
Fraction of Debt due after 5 years	0.33	0.46	0.00	0.48	1.00	7,668
Leverage	0.23	0.25	0.00	0.22	0.89	10,879
Market-to-Book	2.07	2.08	0.07	1.36	11.89	10,354
Asset Maturity	8.37	6.07	0.12	3.22	56.07	9,772
ln(Assets)	2.20	6.42	2.43	6.46	11.46	10,879
ln(Assets)^2	29.21	46.08	5.91	41.73	131.33	10,879
Cash Holdings	0.30	0.27	0.00	0.14	1.00	10,878
σ(Profitability)	0.14	0.09	0.00	0.04	0.92	9,124
Profitability	0.35	-0.04	-1.63	0.08	0.45	10,295
FISD Data:						
ln($\overline{Maturity_w}$)	0.49	2.24	1.37	2.17	3.41	2,312
GRAN	5.63	4.51	1.00	2.06	32.50	2,312
Covenant Index	0.16	0.36	0.07	0.33	0.67	2,165
Maturing Bond$_{2020}$	0.43	0.24	0.00	0.00	1.00	2,323
Maturing Bond$_{2019}$ (*Placebo*)	0.43	0.24	0.00	0.00	1.00	2,323
Call Exercise	0.32	0.11	0.00	0.00	1.00	2,323

This table reports the summary statistics for the sample used to examine firm maturity structure choice around the 2020 health pandemic shock (1/1/2018 to 12/31/2020). The sample is constructed by the intersection of Compustat annual data and EDGAR 10-K filings. Supplementary data on debt comes from Mergent FISD. T.R.E.$_{Pos.}$ is the sum of eight growth-inducing firm-level risk exposures. T.R.E.$_{Neg.}$ is the sum of eight growth-reducing firm-level risk exposures. See section 1.4 for additional details. *COVID-19 Shock* is an indicator for financial data reported after June, 2020. *Placebo Shock* is an indicator taking the value of 1 if the fiscal reporting year is 2019. Appendix A.II provides additional details on the construction of all variables reported in this table. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuos variables are winsorized at the 1st and 99th percentile.

Table 1.3: Growth Opportunities on Firm-Level Risk Exposures (Positive)

	Market-to-Book		Total q		Market-to-Book *(Alt.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	-0.30***	-0.56***	-0.33***	-0.69***	-0.29***	-0.53***
	(0.04)	(0.08)	(0.07)	(0.13)	(0.04)	(0.08)
T.R.E.$_{Pos.}$	0.49	0.33	-0.94	-1.66	1.02	0.88
	(0.68)	(0.65)	(1.69)	(1.75)	(0.75)	(0.72)
Shock×T.R.E.$_{Pos.}$	0.44***	0.92***	0.77***	1.40***	0.40***	0.80***
	(0.15)	(0.21)	(0.28)	(0.34)	(0.14)	(0.20)
Delaware Incorp.		0.09		0.15		0.03
		(0.16)		(0.25)		(0.18)
ln(Assets)		-0.51***		1.13***		-0.49***
		(0.09)		(0.20)		(0.10)
ROA		-0.47		1.11***		-0.55*
		(0.30)		(0.41)		(0.29)
Cap. Exp.		0.47		0.41		0.47
		(0.50)		(0.75)		(0.52)
R&D / Sales		-0.00		0.00		-0.00
		(0.00)		(0.01)		(0.00)
R&D Dummy		-0.02		0.10		-0.03
		(0.04)		(0.08)		(0.04)
Leverage		-0.31		-1.65***		-1.06***
		(0.21)		(0.31)		(0.22)
Constant	1.92***	5.44***	2.87***	-4.24***	1.93***	5.57***
	(0.21)	(0.61)	(0.53)	(1.44)	(0.24)	(0.64)
Observations	16,595	16,553	15,793	15,754	15,406	15,363
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE		Yes		Yes		Yes
Number of Firms	2,371	2,370	2,223	2,222	2,239	2,236
R-squared	0.85	0.86	0.84	0.86	0.85	0.86

This table reports estimation results for regressing growth opportunities on the sum of eight growth-inducing firm-level risk exposures (T.R.E.$_{Pos.}$) around the COVID-19 health pandemic shock. Risk factors are (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce). Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The regression model follows equation 1.4. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. Quarterly reports covering months March - May of 2020 are dropped from the final sample. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 1.4: Growth Opportunities on Firm-Level Risk Exposures (Negative)

	Market-to-Book		Total q		Market-to-Book *(Alt.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	-0.05	-0.14**	0.05	-0.13	-0.05	-0.15**
	(0.04)	(0.07)	(0.07)	(0.12)	(0.04)	(0.07)
T.R.E.$_{Neg.}$	-0.60	-0.67	-0.26	-0.67	-0.82	-0.87*
	(0.53)	(0.48)	(1.11)	(1.17)	(0.54)	(0.51)
Shock×T.R.E.$_{Neg.}$	-0.42***	-0.77***	-0.54**	-0.82**	-0.42***	-0.73***
	(0.14)	(0.21)	(0.26)	(0.37)	(0.15)	(0.22)
Delaware Incorp.		0.10		0.16		0.05
		(0.17)		(0.25)		(0.18)
ln(Assets)		-0.51***		1.13***		-0.49***
		(0.09)		(0.20)		(0.10)
ROA		-0.46		1.12***		-0.54*
		(0.30)		(0.41)		(0.29)
Cap. Exp.		0.48		0.44		0.49
		(0.49)		(0.75)		(0.51)
R&D / Sales		-0.00		0.00		-0.00
		(0.00)		(0.01)		(0.00)
R&D Dummy		-0.02		0.10		-0.03
		(0.04)		(0.08)		(0.04)
Leverage		-0.32		-1.65***		-1.06***
		(0.21)		(0.32)		(0.22)
Constant	2.21***	5.74***	2.64***	-4.60***	2.45***	6.09***
	(0.12)	(0.64)	(0.26)	(1.43)	(0.12)	(0.66)
Observations	16,595	16,553	15,793	15,754	15,406	15,363
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Time FE		Yes		Yes		Yes
Number of Firms	2,371	2,370	2,223	2,222	2,239	2,236
R-squared	0.85	0.86	0.84	0.86	0.85	0.86

This table reports estimation results for regressing growth opportunities on the sum of eight growth-reducing firm-level risk exposures (T.R.E.$_{Neg.}$) around the COVID-19 health pandemic shock. Risk factors are (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries). Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The regression model follows equation 1.4. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. Quarterly reports covering months March - May of 2020 are dropped from the final sample. All continuos variables are winsorized at the 1^{st} and 99^{th} percentile. Standard errors are clustered at the firm level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 1.5: Regression of Debt Maturity Structure on Growth Opportunities (Growth-inducing Factors)

	$\leq$ 3 yrs		$\leq$ 5 yrs	> 5 yrs	High Cash$_{t-1}$	Low Cash$_{t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)
T.R.E.$_{Pos.}$	-0.05**	0.04	0.14**	-0.14**	0.04	-0.01
	(0.02)	(0.04)	(0.06)	(0.06)	(0.09)	(0.05)
Shock$\times$T.R.E.$_{Pos.}$	-0.11***	-0.09**	-0.10**	0.10**	-0.00	-0.12**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Leverage		0.06	-0.09	0.09	0.15	0.05
		(0.07)	(0.09)	(0.09)	(0.13)	(0.09)
Asset Maturity		-0.00**	-0.00	0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Assets)		-0.15*	-0.11	0.11	-0.18	-0.15
		(0.09)	(0.10)	(0.10)	(0.15)	(0.11)
ln(Assets)^2		0.01*	0.01	-0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
σ(Profitability)		-0.09	-0.22***	0.22***	0.12	-0.26***
		(0.08)	(0.06)	(0.06)	(0.23)	(0.07)
Constant	0.35***	0.78**	0.95**	0.05	0.84	0.77*
	(0.01)	(0.30)	(0.36)	(0.36)	(0.54)	(0.41)
Observations	7,740	4,167	3,759	3,759	1,507	2,050
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2,533	1,581	1,426	1,426	623	813
R-squared	0.44	0.44	0.51	0.51	0.47	0.37

This table reports estimation results for regressing debt maturity structure choice on firm's total level of exposure to eight *growth-inducing* risk factors (T.R.E.$_{Pos.}$) around the COVID-19 health pandemic shock. The regression model estimates equation 1.5. Columns 1 and 2 use the fraction of short-term debt maturing in 3 years or less as the dependent variable. Column 3 uses the fraction of short-term debt maturing in 5 years or less while column 4 uses the fraction of debt maturing after 5 years as the dependent variable. Columns 5 and 6 replicates the estimation for column 2 when using subsamples of cash levels at period $t-1$. High Cash$_{t-1}$ = 1 if the firm's cash to asset ratio is higher than its industry median while Low Cash$_{t-1}$ = 1 if it is lower than the median. Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The eight risk factors are (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce). *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All independent variables, except (*Shock*), are lagged one period. Detailed descriptions of all the variables used in this table are available in appendix A.II. Industry classifications follows the Fama-French 49 method. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the Fama-French 49 industry level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 1.6: Regression of Debt Maturity Structure on Growth Opportunities (Growth-reducing Factors)

	$\leq$ 3 yrs		$\leq$ 5 yrs	> 5 yrs	High Cash$_{t-1}$	Low Cash$_{t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)
T.R.E.$_{Neg.}$	0.02	0.07	0.13**	-0.13**	0.13	-0.04
	(0.03)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)
Shock×T.R.E.$_{Neg.}$	-0.07**	-0.02	0.05	-0.05	-0.12	-0.00
	(0.03)	(0.04)	(0.05)	(0.05)	(0.08)	(0.08)
Leverage		0.06	-0.09	0.09	0.15	0.06
		(0.07)	(0.09)	(0.09)	(0.13)	(0.09)
Asset Maturity		-0.00***	-0.00	0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Assets)		-0.16*	-0.12	0.12	-0.18	-0.16
		(0.09)	(0.09)	(0.09)	(0.15)	(0.11)
ln(Assets)^2		0.01*	0.01	-0.01	0.01	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
σ(Profitability)		-0.07	-0.18***	0.18***	0.12	-0.23**
		(0.08)	(0.05)	(0.05)	(0.22)	(0.09)
Constant	0.33***	0.79**	1.01***	-0.01	0.84	0.80*
	(0.01)	(0.31)	(0.34)	(0.34)	(0.55)	(0.44)
Observations	7,740	4,167	3,759	3,759	1,507	2,050
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	2,533	1,581	1,426	1,426	623	813
R-squared	0.43	0.43	0.51	0.51	0.47	0.37

This table reports estimation results for regressing debt maturity structure choice on firm's total level of exposure to eight *growth-reducing* risk factors (T.R.E.$_{Neg.}$) around the COVID-19 health pandemic shock. The regression model estimates equation 1.5. Columns 1 and 2 use the fraction of short-term debt maturing in 3 years or less as the dependent variable. Column 3 uses the fraction of short-term debt maturing in 5 years or less while column 4 uses the fraction of debt maturing after 5 years as the dependent variable. Columns 5 and 6 replicates the estimation for column 2 when using subsamples of cash levels at period $t-1$. High Cash$_{t-1}$ = 1 if the firm's cash to asset ratio is higher than its industry median while Low Cash$_{t-1}$ = 1 if it is lower than the median. Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The eight risk factors are (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries). *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All independent variables, except (*Shock*), are lagged one period. Detailed descriptions of all the variables used in this table are available in appendix A.II. Industry classifications follows the Fama-French 49 method. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the Fama-French 49 industry level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 1.7: 2SLS Regression of Debt Maturity Structure on Growth Opportunities

	2SLS (3 yrs)		2SLS (5 yrs)		2SLS (3 yrs)		2SLS (5 yrs)	
	(1) Maturity	(2) Leverage	(3) Maturity	(4) Leverage	(5) Maturity	(6) Leverage	(7) Maturity	(8) Leverage
$\widehat{\text{Leverage}}$	-0.59		0.17		-0.64		0.15	
	(0.49)		(0.55)		(0.49)		(0.54)	
T.R.E.$_{Pos.}$	0.02	0.04	0.15**	0.15***				
	(0.05)	(0.05)	(0.06)	(0.06)				
Shock×T.R.E.$_{Pos.}$	-0.11***	-0.09**	-0.09*	-0.09**				
	(0.04)	(0.04)	(0.05)	(0.04)				
T.R.E.$_{Neg.}$					0.06	0.07	0.13**	0.14**
					(0.07)	(0.07)	(0.06)	(0.06)
Shock×T.R.E.$_{Neg.}$					-0.05	-0.02	0.06	0.05
					(0.05)	(0.05)	(0.05)	(0.05)
Asset Maturity	-0.00*	-0.00	-0.00	-0.00	-0.00*	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Assets)		-0.15**		-0.11		-0.16**		-0.12*
		(0.07)		(0.07)		(0.07)		(0.07)
ln(Assets)^2	0.00	0.01**	-0.00	0.01	0.00	0.01**	-0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Profitability		0.06		-0.11		0.05		-0.12
		(0.06)		(0.08)		(0.06)		(0.08)
σ(Profitability)		-0.10		-0.20		-0.07		-0.16
		(0.10)		(0.18)		(0.10)		(0.18)
Fixed Assets		0.01		0.11		0.02		0.12
		(0.11)		(0.12)		(0.11)		(0.12)
Observations	4,167	4,167	3,759	3,759	4,167	4,167	3,759	3,759
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	1,581	1,581	1,426	1,426	1,581	1,581	1,426	1,426

This table estimates a 2SLS regression (equations 1.6 and 1.7) around the COVID-19 health pandemic shock. The dependent variable in columns 1 and 3 (5 and 7)is the fraction of debt maturing in 3 (5) years or less, respectively. Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All independent variables, except (*Shock*), are lagged one period. Detailed descriptions for the rest of the variables are in appendix A.II. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the firm level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 1.8: Maturity Structure Choices and Growth-inducing Risk Factors (FISD Sample)

	Call	$\ln(\overline{Maturity_w})$		GRAN		Cov. Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock	-0.43	-0.04**	-0.07***	0.33**	0.18	-0.01	-0.01**
	(0.34)	(0.02)	(0.02)	(0.13)	(0.11)	(0.01)	(0.01)
Maturing Bond_{2020}		0.12***	0.10*	5.91***	5.83***	0.04***	0.03**
		(0.04)	(0.06)	(0.61)	(0.71)	(0.01)	(0.01)
$\text{T.R.E.}_{Pos.}$	0.24	-0.08	-0.07	-1.88***	-2.26*	-0.13***	-0.13***
	(1.02)	(0.07)	(0.10)	(0.65)	(1.16)	(0.02)	(0.03)
$\text{Shock}\times\text{T.R.E.}_{Pos.}$	2.48**						
	(1.21)						
$\text{Shock}\times\text{Maturing Bond}_{2020}$		0.00	0.00	0.22	0.16	-0.04*	-0.03**
		(0.07)	(0.06)	(1.11)	(0.91)	(0.02)	(0.02)
$\text{Shock}\times\text{Maturing Bond}_{2020}$ $\times\text{T.R.E.}_{Pos.}$		0.44*	0.35*	2.53	2.09	0.20***	0.17***
		(0.23)	(0.20)	(3.81)	(3.84)	(0.07)	(0.06)
Cash Holdings_{t-1}	-1.21		-0.53***		-2.73*		-0.23***
	(2.26)		(0.09)		(1.57)		(0.04)
Constant		2.23***	2.34***	3.32***	4.03***	0.37***	0.42***
		(0.02)	(0.03)	(0.20)	(0.45)	(0.01)	(0.010)
Observations	440	2,310	1,840	2,310	1,840	2,163	1,726
Firm FE	Yes						
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.14	0.18	0.29	0.29	0.20	0.26

(Placebo)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock	0.41	-0.02*	-0.01	0.15	0.13*	0.01***	0.01**
	(0.30)	(0.01)	(0.01)	(0.10)	(0.07)	(0.00)	(0.00)
Maturing Bond_{2019}		0.16***	0.15***	6.44***	6.32***	0.01	0.00
		(0.04)	(0.04)	(0.60)	(0.82)	(0.01)	(0.02)
$\text{T.R.E.}_{Pos.}$	0.90	-0.06	-0.07	-1.25	-1.70	-0.14***	-0.14***
	(1.03)	(0.07)	(0.10)	(0.77)	(1.21)	(0.02)	(0.03)
$\text{Shock}\times\text{T.R.E.}_{Pos.}$	-1.17						
	(1.10)						
$\text{Shock}\times\text{Maturing Bond}_{2019}$		0.02	-0.00	-0.70	-0.68	-0.02	-0.03**
		(0.06)	(0.04)	(0.88)	(0.74)	(0.02)	(0.01)
$\text{Shock}\times\text{Maturing Bond}_{2019}$ $\times\text{T.R.E.}_{Pos.}$		0.19	0.21	2.57	2.83	0.12*	0.15***
		(0.21)	(0.22)	(3.24)	(2.62)	(0.06)	(0.05)
Cash Holdings_{t-1}	-1.16		-0.55***		-4.29**		-0.25***
	(2.30)		(0.08)		(1.78)		(0.04)
Constant		2.21***	2.31***	3.15***	4.07***	0.38***	0.42***
		(0.02)	(0.03)	(0.20)	(0.47)	(0.01)	(0.01)
Observations	440	2,310	1,840	2,310	1,840	2,163	1,726
Firm FE	Yes						
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.15	0.18	0.31	0.31	0.19	0.25

This table reports the estimation results for regressing debt maturity structure choice on firm's total level of exposure to eight *growth-inducing* risk factors ($\text{T.R.E.}_{Pos.}$) around the COVID-19 health pandemic shock. The logit regression in column 1 estimates equation 1.9 while columns 2-7 estimates equation 1.8. *Shock* takes the value of 1 if the time period is after June 1^{st}, 2020, and 0 otherwise. Detailed descriptions of all the variables used in this table are available in appendix A.II. All continuos variables are winsorized at the 1^{st} and 99^{th} percentile. Standard errors are clustered at the firm level (Except for column 1). * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table 1.9: Maturity Structure Choices and Growth-reducing Risk Factors (FISD Sample)

	Call	$\ln(\overline{Maturity_w})$		GRAN		Cov. Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shock	0.24	-0.05***	-0.07***	0.19	0.11	-0.02***	-0.02***
	(0.30)	(0.02)	(0.02)	(0.14)	(0.13)	(0.01)	(0.01)
Maturing Bond$_{2020}$		0.12***	0.10*	5.93***	5.84***	0.04***	0.03**
		(0.04)	(0.06)	(0.61)	(0.71)	(0.01)	(0.01)
T.R.E.$_{Neg.}$	1.79	0.06	0.01	-0.28	-0.60	0.01	-0.00
	(1.32)	(0.09)	(0.16)	(0.82)	(1.53)	(0.03)	(0.04)
Shock×T.R.E.$_{Neg.}$	-0.49						
	(1.07)						
Shock×Maturing Bond$_{2020}$		0.06	0.05	0.73	0.68	0.01	0.00
		(0.06)	(0.06)	(1.03)	(1.22)	(0.02)	(0.02)
Shock×Maturing Bond$_{2020}$		0.22	0.17	0.58	0.09	0.03	0.02
×T.R.E.$_{Neg.}$		(0.18)	(0.16)	(3.74)	(4.64)	(0.06)	(0.10)
Cash Holdings$_{t-1}$	-1.25		-0.54***		-3.20*		-0.26***
	(2.26)		(0.09)		(1.69)		(0.04)
Constant		2.20***	2.32***	3.01***	3.70***	0.35***	0.39***
		(0.02)	(0.05)	(0.20)	(0.45)	(0.01)	(0.010)
Observations	440	2,310	1,840	2,310	1,840	2,163	1,726
Firm FE	Yes						
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.14	0.18	0.28	0.29	0.18	0.24

			(Placebo)				
Shock	0.10	-0.03***	-0.01	0.00	0.06	0.00	0.00
	(0.28)	(0.01)	(0.01)	(0.09)	(0.08)	(0.00)	(0.00)
Maturing Bond$_{2019}$		0.16***	0.15***	6.48***	6.35***	0.01	0.01
		(0.04)	(0.04)	(0.61)	(0.81)	(0.01)	(0.02)
Total R.E.$_{Neg.}$	1.65	0.11	0.07	0.74	0.28	0.00	-0.01
	(1.34)	(0.08)	(0.14)	(0.73)	(1.51)	(0.03)	(0.05)
Shock×Total R.E.$_{Neg.}$	0.18						
	(0.98)						
Shock×Maturing Bond$_{2019}$		0.15***	0.17***	0.11	0.48	-0.01	-0.00
		(0.05)	(0.05)	(0.82)	(0.95)	(0.02)	(0.02)
Shock×Maturing Bond$_{2019}$		-0.36*	-0.50**	-0.79	-1.92	0.08	0.04
×Total R.E.$_{Neg.}$		(0.19)	(0.19)	(3.19)	(4.19)	(0.06)	(0.06)
Cash Holdings$_{t-1}$	-1.15		-0.56***		-4.53**		-0.27***
	(2.30)		(0.09)		(1.83)		(0.04)
Constant		2.19***	2.29***	2.80***	3.65***	0.35***	0.39***
		(0.02)	(0.04)	(0.17)	(0.41)	(0.01)	(0.01)
Observations	440	2,310	1,840	2,310	1,840	2,163	1,726
Firm FE	Yes						
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.15	0.18	0.31	0.31	0.17	0.23

This table reports the estimation results for regressing debt maturity structure choice on firm's total level of exposure to eight *growth-reducing* risk factors (T.R.E.$_{Pos.}$) around the COVID-19 health pandemic shock. The logit regression in column 1 estimates equation 1.9 while columns 2-7 estimates equation 1.8. *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Detailed descriptions of all the variables used in this table are available in appendix A.II. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the firm level (Except for column 1. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

	Software–Hardware Products	Software Services	Web Services	E–Commerce	Electronics	Video Games	Semiconductors	Display Technology	Healthcare Providers	Drug Trials	Oil and Gas	Energy Infrastructure	Power Generation	Alternative Energy	Airlines or Aircraft	Travel	Traditional Retail	Commercial Property	Residential Construction
Software Services	0.649																		
Web Services	0.551	0.508																	
E–Commerce	0.282	0.131	0.410																
Electronics	0.025	0.203	−0.049	−0.082															
Video Games	0.123	0.063	0.255	0.208	−0.050														
Semiconductors	0.106	0.244	0.039	−0.067	0.419	−0.000													
Display Technology	0.139	0.156	0.226	0.222	0.044	0.363	0.070												
Healthcare Providers	−0.064	−0.022	−0.124	−0.135	−0.063	−0.090	−0.067	−0.104											
Drug Trials	−0.283	−0.252	−0.289	−0.386	−0.242	−0.175	−0.135	−0.228	0.087										
Oil and Gas	−0.221	−0.227	−0.165	−0.171	−0.073	−0.107	−0.083	−0.131	−0.097	−0.172									
Energy Infrastructure	−0.218	−0.229	−0.158	−0.159	−0.078	−0.095	−0.083	−0.127	−0.087	−0.130	0.758								
Power Generation	−0.180	−0.167	−0.168	−0.124	0.064	−0.107	−0.053	−0.133	−0.089	−0.182	0.279	0.266							
Alternative Energy	−0.138	−0.136	−0.130	−0.082	0.022	−0.095	−0.036	−0.114	−0.092	−0.161	0.218	0.269	0.354						
Airlines or Aircraft	−0.080	−0.054	−0.066	−0.013	0.008	−0.043	0.007	−0.031	−0.054	−0.091	−0.028	−0.027	−0.032	−0.005					
Travel	−0.034	−0.084	0.056	0.198	−0.112	0.042	−0.055	0.047	−0.088	−0.179	−0.080	−0.053	−0.060	−0.011	0.483				
Traditional Retail	−0.007	−0.184	−0.050	0.360	−0.044	0.033	−0.069	0.081	−0.111	−0.232	−0.113	−0.103	−0.068	−0.012	−0.060	0.133			
Commercial Property	−0.011	−0.080	−0.056	−0.032	−0.051	0.029	−0.025	−0.053	−0.086	−0.148	0.194	0.103	0.084	−0.017	−0.058	0.134	0.007		
Residential Construction	−0.021	−0.086	−0.063	0.041	0.037	−0.003	−0.042	−0.047	−0.033	−0.105	−0.032	−0.038	0.075	−0.002	−0.029	−0.017	0.084	0.112	
REITs	−0.107	−0.142	−0.073	−0.036	−0.050	−0.059	−0.040	−0.056	−0.056	−0.155	0.121	0.218	0.179	0.133	−0.035	0.008	−0.010	0.135	0.042

Figure 1.1: Correlation Matrix for Firm-level Risk Exposures (1/1/2018 to 12/31/2020)

Categories follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in the 10-K filings reported in EDGAR; see section 1.3.1 and appendix A.I for further details.

	Metal Products	Gold or Silver	Metals and Minerals	Financial Management	Investment Funds	Banking	Deposits	Insurance	Mortgages	Card Payments	Clearing Houses	Communications	Traditional Media	Restaurants	Food Related Products	Franchising	Workforce	Foreign Exchange
Gold or Silver	0.153																	
Metals and Minerals	0.259	0.377																
Financial Management	0.051	0.035	0.017															
Investment Funds	−0.052	−0.024	−0.058	0.272														
Banking	−0.040	−0.007	−0.036	0.087	0.188													
Deposits	−0.028	0.001	0.002	−0.021	0.021	0.378												
Insurance	−0.065	−0.034	−0.062	0.103	0.112	0.014	−0.038											
Mortgages	0.033	0.039	−0.024	0.222	0.186	0.277	0.103	0.159										
Card Payments	−0.111	0.001	−0.077	0.034	0.144	0.386	0.169	−0.065	0.056									
Clearing Houses	−0.016	0.001	−0.035	0.038	0.102	0.193	0.182	−0.017	0.057	0.134								
Communications	−0.074	−0.017	−0.030	−0.054	−0.024	−0.058	−0.020	−0.099	−0.054	−0.048	−0.038							
Traditional Media	−0.083	−0.004	−0.061	−0.023	−0.014	−0.042	−0.038	−0.089	−0.030	0.028	−0.048	0.515						
Restaurants	−0.051	0.001	−0.048	−0.043	0.004	−0.041	−0.018	−0.052	−0.031	0.139	−0.023	−0.036	0.015					
Food Related Products	0.136	0.025	0.034	0.115	−0.026	−0.071	−0.037	−0.017	−0.035	−0.030	0.098	−0.099	−0.053	0.076				
Franchising	−0.071	−0.023	−0.056	−0.005	0.023	0.007	−0.006	0.004	0.035	0.153	−0.003	−0.013	0.023	0.528	0.011			
Workforce	0.075	0.017	0.033	0.082	0.045	0.030	−0.005	0.142	0.147	−0.033	−0.004	−0.029	−0.043	−0.027	−0.005	0.008		
Foreign Exchange	0.140	−0.003	0.046	0.101	−0.004	0.019	−0.008	0.018	0.004	−0.014	−0.014	−0.037	−0.035	−0.024	0.041	−0.021	0.108	
Foreign Countries	0.231	0.069	0.143	0.081	−0.062	−0.020	−0.028	−0.056	−0.095	−0.099	−0.071	−0.133	−0.122	−0.082	0.079	−0.075	0.006	0.216

Figure 1.2: Correlation Matrix for Firm-level Risk Exposures (1/1/2018 to 12/31/2020)

Categories follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in the 10-K filings reported in EDGAR; see section 1.3.1 and appendix A.I for further details.

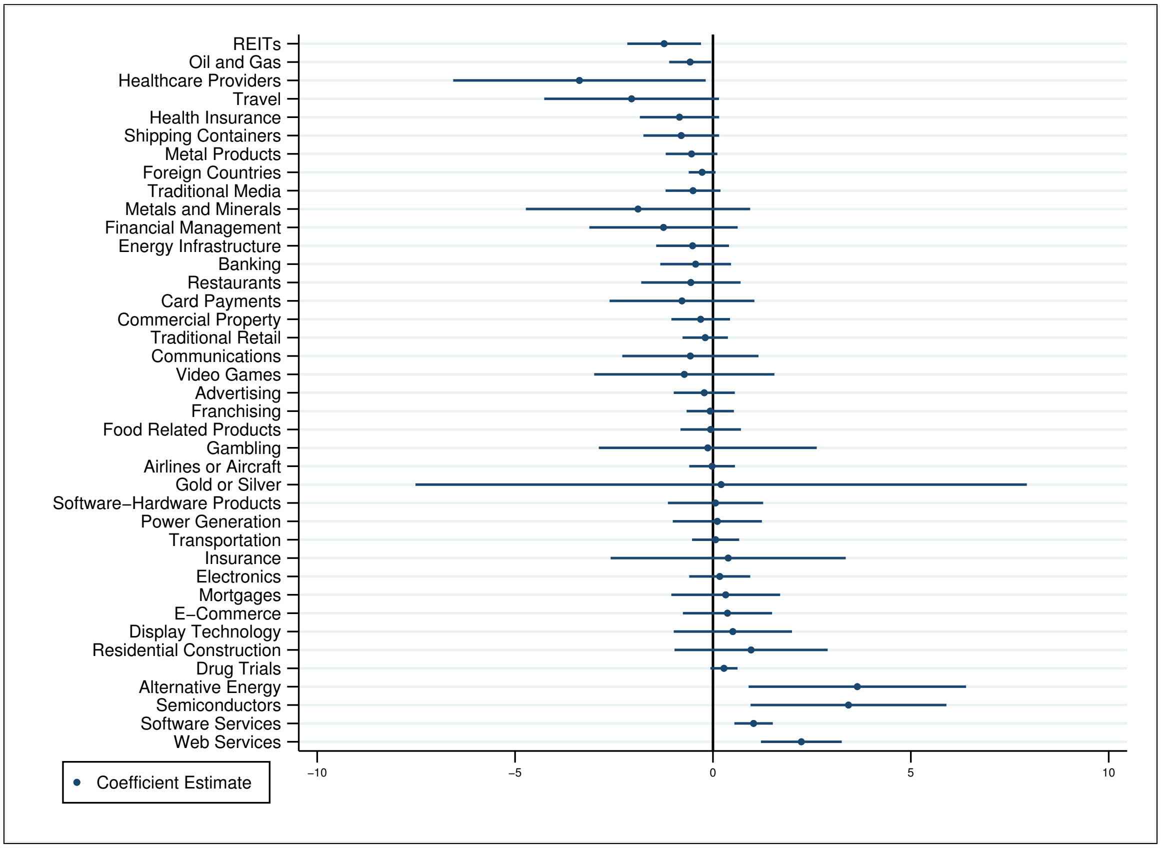

Figure 1.3: Firm-level Risk Exposures on Growth Opportunities Post COVID-19 Pandemic

This figure reports the estimated coefficient (β_3) and the confidence interval when running the following regression separately for each risk factor y:

$$Q_{i,t} = \alpha_i + \beta_1 Shock + \beta_2 R.E._{i,t-1,y} + \beta_3 Shock \times R.E._{i,t-1,y} + \beta_4 X_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}$$

where $R.E._{i,t-1,y}$ is firm i's pre-pandemic exposure to risk factor y. Factors follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in the 10-K filings reported in EDGAR; see section 1.3.1 and appendix A.I for further details. The dependent variable $Q_{i,t}$ is the firm's Market-to-book ratio during the quarter-year period t, and $\delta_{j,t}$ is an industry-time fixed effects (Fama-French 49 industries). $Shock$ takes the value of 1 if the time period is after 3/1/2020, and X is a host of control variables; see section 1.4 for additional details. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuos variables are winsorized at the 1st and 99th percentile.

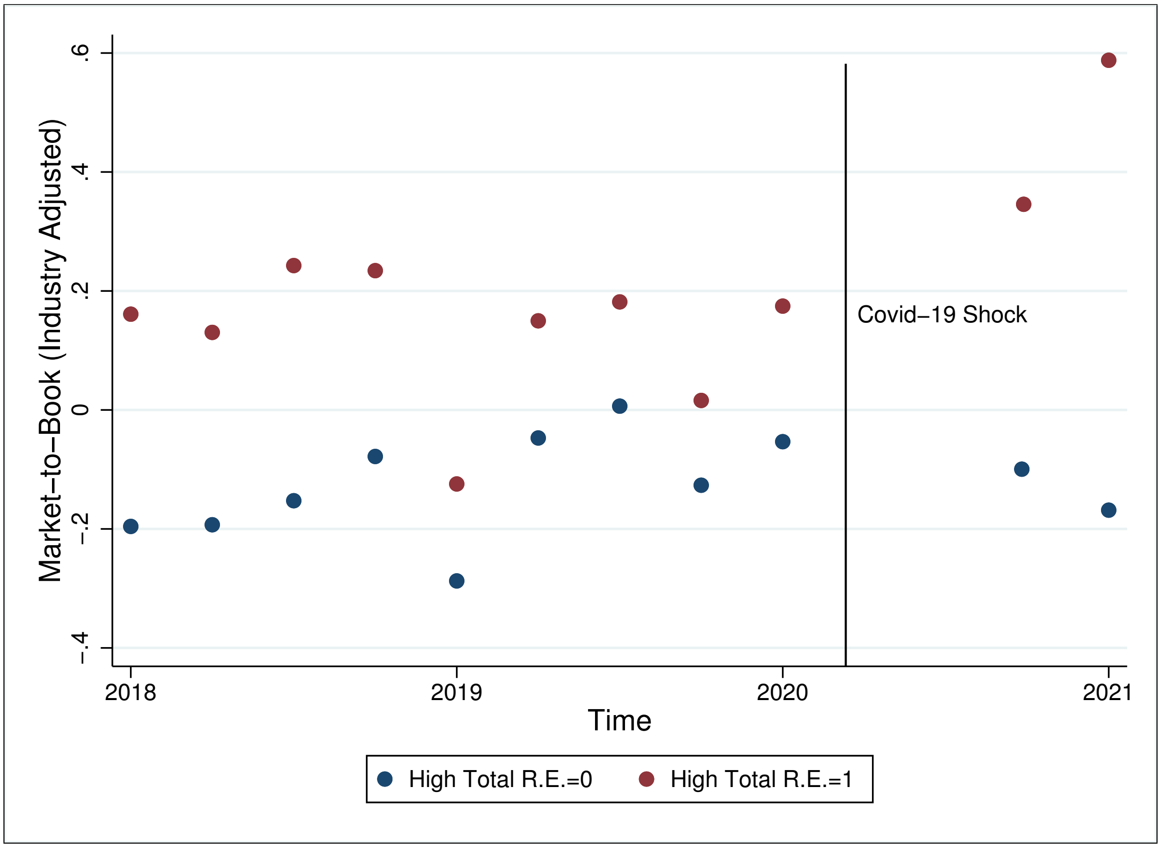

Figure 1.4: Firm Total Growth-inducing Risk Exposure and Growth Opportunities Around the COVID-19 Pandemic Shock

This figure plots the time trend for the average level of firm growth opportunities proxied by the Market-to-Book ratio for firms having either high or low exposure to Total R.E.$_{Pos.}$. The Market-to-Book ratio is industry adjusted using the Fama-French 49 industry classifications. Total R.E.$_{Pos.}$ is the firm's total level of exposure to the following eight risk factors (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce). High Total R.E.$_{Pos.}$ is an indicator taking the value of 1 if the firm has a total exposure level higher than it's industry average, and 0 otherwise. The construction and the number of factors follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in the 10-K filings reported in EDGAR; see section 1.3.1 and appendix A.I for further details. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuos variables are winsorized at the 1st and 99th percentile.

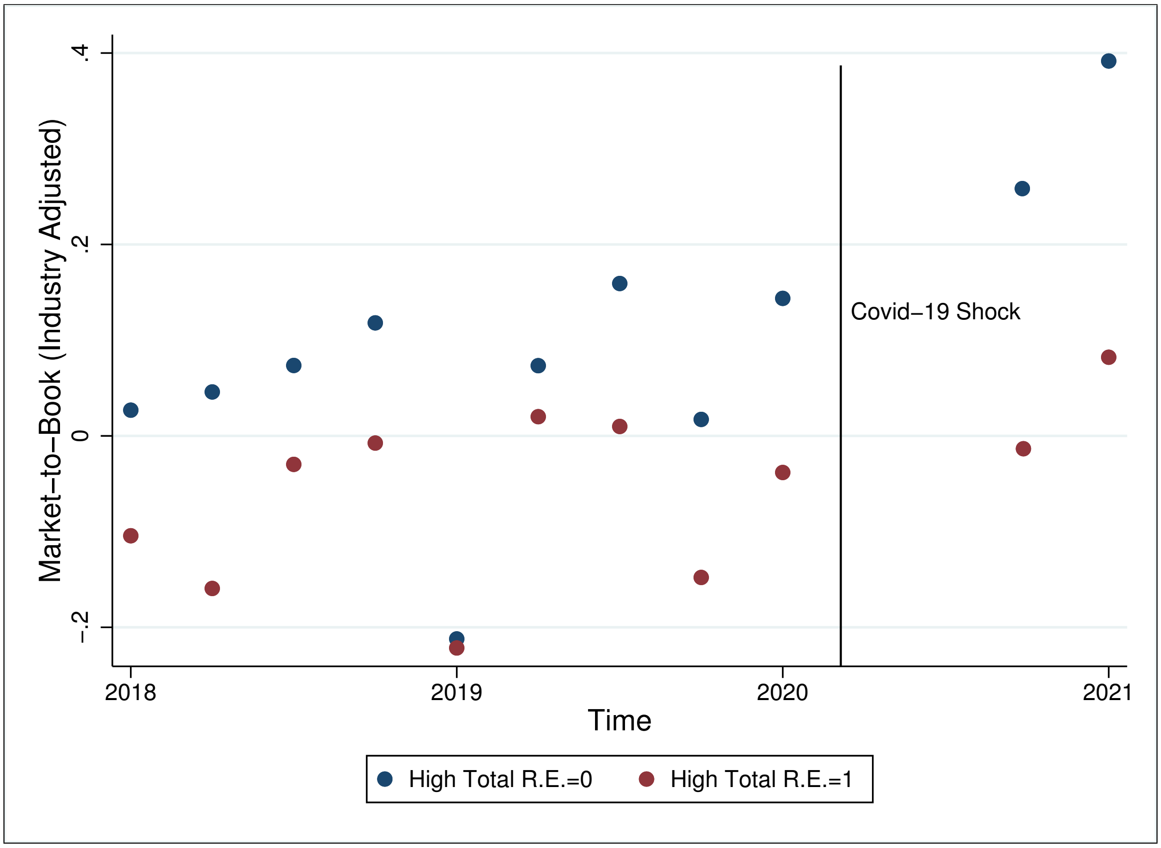

Figure 1.5: Firm Total Growth-reducing Risk Exposure and Growth Opportunities Around the COVID-19 Pandemic Shock

This figure plots the time trend for the average level of firm growth opportunities proxied by the Market-to-Book ratio for firms having either high or low exposure to Total R.E.$_{Neg.}$. The Market-to-Book ratio is industry adjusted using the Fama-French 49 industry classifications. Total R.E.$_{Neg.}$ is the firm's total level of exposure to the following eight risk factors (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries). High Total R.E.$_{Neg.}$ is an indicator taking the value of 1 if the firm has a total exposure level higher than it's industry average, and 0 otherwise. The construction and the number of factors follow the work of Davis et al., 2021. Risk exposure levels are measured by scraping all terms under "Item 1" in the 10-K filings reported in EDGAR; see section 1.3.1 and appendix A.I for further details. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuos variables are winsorized at the 1st and 99th percentile.

CHAPTER 2

FIRM RISK EXPOSURE CONCENTRATION AND DEBT STRUCTURE CHOICE[22]

JEL Code : G30; G32

Keywords : Maturity Structure, Agency Costs of Debt, Asset Substitution, Risk Shifting, Text Analysis, 10-K filings, Firm-level Risk Exposures

---

[22]Authors: Eyad Alhudhaif, Allen Berger, and Hugh Kim. To be submitted to the Review of Financial Studies.

CHAPTER 2

Firm Risk Exposure Concentration and Debt Structure Choice

Abstract

Firms with more risk shifting problems due to the high-risk exposure concentration are likely to include more short-term debt in their capital structures and less covenants in their outstanding bonds. Using a firm's risk exposure concentration derived from the written text in 10-K filings, we find this effect is more pronounced among companies with strong managerial incentive alignment with shareholders. The findings suggest maintaining future investment flexibility is important for firms with high-risk exposure concentration, even at the expense of a higher liquidity risk associated with the use of short-term debt.

2.1 Introduction

When a firm decides to issue debt to fund its operational and investment needs, among the key elements accompanying this choice are covenants and the maturity of the new issued security. Both aid in mitigating agency costs of debt arising from the underinvestment problem (see Billett et al., 2007; Jensen and Meckling, 1976; Myers, 1977). However, the mechanism to which they minimize these conflicts is different. Short-term debt permits a more frequent adjustment to the cost of debt, and thus, strict monitoring by creditors but at the cost of a higher liquidity risk for the firm (Diamond, 1991). Restrictive covenants on the other hand grant control rights to lenders following covenant violations but at the cost of restricting future financing and investment decisions by shareholders (Chava and Roberts, 2008; Nini et al., 2009; Press and Beneish, 1993; Smith and Warner, 1979). While both alternatives mitigate the underinvestment problem, the net benefit of these alternatives are likely to be different in reducing asset substitution issues, another major contractual problem of debt.

Companies that have their operations, investments, and future earnings exposed to a narrow set of risk factors, i.e., concentrated risk exposure, are likely to suffer from higher asset substitution costs relative to firms with a more diverse risk exposure. In this paper, we examine whether a firm's risk exposure concentration leads to more short-term debt in its capital structure as appose to covenants, since future investment flexibility is more important for such firms. Further, we examine whether asset substitution problems can affect new bond-offering yields.

Unlike previous studies that rely on business segment reporting, which may not be an accurate estimate of diversification[1], we use the concentration of risk exposure topics declared in a firm's 10-K filings. More specifically, the U.S. Securities and Exchange Commission (SEC) requires all public firms to disclose any relevant risks affecting their future earnings. Thus, inspired by the work of Davis et al., 2021, we first construct firm-level estimates of risk exposures[2] derived from the written text under "Item 1" to measure a firm's diversification level through its risk exposure concentration (REC hereafter). Consistent with our hypothesis, we find firms'

[1]In many cases firm segments can share the same underlying risk exposures and/or customer base. Thus, using reported business segments as the base of diversification may inflate the firm's true level of diversification.

[2]There are 44 risk factors. The type, and term dictionaries, of these factors are presented in greater detail in section 2.3.1.

degree of REC is an important determinant of short-term debt. REC increases the fraction of short-term debt by roughly 8%, while the covenant index increases by 15%. However, when managerial incentives are well aligned with shareholders, short-term debt is preferred over covenants, and the effect is more pronounced. A one unit increase in the REC leads to 28% increase in the fraction of short-term debt and -26% in the covenant index. These results are consistent while using alternative measures of short-term debt or managerial incentive alignment. Further, the results are robust after including industry, time, and firm fixed effects. We also control for the effect of each risk factor on the debt structure choice, and our findings remain unchanged.

The results overall demonstrate that similar to previous studies, short-term debt and covenants are used to mitigate agency costs of debt. However, when such costs arise due to risk shifting problems, short-term debt seems to be the preferred option by shareholders, especially among firms with high managerial alignment with shareholders. The revealed preference suggests that costs of investment restrictions are higher relative to repayment risks of short-term debt[3] for firms with high REC levels. Our paper is also related to Chen et al., 2021. They find firms with high systematic risk exposure prefer longer-term debt if external financing costs are high, and the opposite is true for firms with low external financing costs. In their model, firm's maturity structure choice reflect tradeoffs of liquidity discounts (With the use of long-term debt), repayment risks of short-term debt, and the benefit of short-term debt as a commitment device for timely leverage adjustments. We add to these consideration the costs of risk shifting, which can impact a firm's debt maturity choice.

[3] Also referred as Refinancing Risk of short-term debt; see Diamond, 1991; Harford et al., 2014.

The remainder of this article is organized as follows. Section 2.2 develops our hypotheses, while section 2.3 describes the data collection process and measures of firm-level risk exposures. Section 2.4 examines the effect of REC on debt structure choices. Section 2.5 examines the effect of managerial ownership on the relation between REC and debt structure choice, section 2.6 preforms additional robustness checks, and section 2.7 concludes.

2.2 Hypothesis Development

There are mixed evidence on whether diversified firms are efficient relative to stand alone firms. Costs associated with diversification include valuation discounts and inefficient allocation of capital among divisions (e.g., see P. G. Berger and Ofek, 1995; Lamont, 1997; Rajan et al., 2000; Servaes, 1996). Examples of diversification benefits on the other hand include an increase in productivity and the presence of specific assets (Khanna and Palepu, 2000; Wernerfelt and Montgomery, 1988). Our analysis sits on the intersection of diversification and the agency costs of debt.

Neoclassical theories, such as Jensen and Meckling, 1976 and Myers, 1977, demonstrate how short-term debt can be a valuable tool in mitigating debt agency costs. Our examination focuses on one particular agency issue; the *risk-shifting* (or asset-substitution) problem. We argue that firms high in REC are likely to have stronger risk-shifting agency issues compared to firms low in REC for two main reasons. First, firms high in their REC are expected to specialize in a narrow field of business, and their knowledge of future available investment projects are likely within the boundaries of this narrow field. Thus, if asset substitution occurs, the consequences are dire (in the eyes of lenders) because any future riskier investment managers may pursue will possibly have a high positive correlation with the firm's existing assets. Second, companies that choose to have a concentrated risk exposure are plausibly firms that also have a high risk tolerance, and thus, the incentive for asset substitution is likely to be high.

Smith and Warner, 1979 theorize that covenants restricting certain firm activities in new debt issues can aid in reducing shareholder-debtholder conflicts, and maximize shareholder value. Billett et al., 2007 empirically tests whether covenants are used by firms with high growth opportunities. Such firms are likely to have strong shareholder-debtholder conflicts stemming from the debt-overhang problem. They find covenants tend to increase for firms with high growth options, and short-term debt and covenants act as substitutes in reducing agency costs of debt overhang. However, restrictive covenants may not be as valuable as short-term debt in reducing risk shifting costs of high REC firms. Such firms are likely to preserve future investment flexibility given the narrow set of future investments they can pursue[4]. Additionally, the mere existence of covenants in the firm's outstanding debt pose the threat for the transfer of control rights to creditors, which may not be an optimal choice for lenders. First, firms with high REC would require a decision maker who has deep and specific knowledge in the investment opportunities available within the scope of projects available for the firm. Lenders are likely to have general knowledge as appose to specific knowledge in assessing risks. As such, if control rights are transferred to creditors, they are likely to make sub-optimal investment choices for stand alone firms (i.e., high REC firms), and as a result, both shareholders and debtholders would benefit if the firm is actually run by existing managers. For example, Chava and Roberts, 2008 provide evidence of investment distortions following covenant violations due to the transfer of control rights. Leland, 1994 shows that covenants can mitigate the risk shifting incentives borne

[4]As Smith and Warner, 1979 points out. Due to the cash flow identity, covenants restricting dividends and financing policy will also restrict investment policy.

by shareholders. However, his analysis demonstrate that in some anomaly states, unprotected debt can benefit both shareholders and stockholders, because in those circumstances both stakeholders prefer to increase firm risk. Finally, bankruptcy costs are likely high for firms with concentrated risk exposure. The assets they hold are presumably specialized assets that have high liquidation costs or require special knowledge and skill to manage, and it is in the interest of shareholders and debtholders to keep the firm as an ongoing concern. Thus we state the following hypotheses:

Hypothesis 1 : Firms with high risk exposure concentration are likely to mitigate their risk shifting agency costs through short-term debt.

Hypothesis 2 : Firms with high risk exposure concentration are likely to mitigate their risk shifting agency costs through more covenant restrictions.

Most of the theories discussing agency costs of debt assume managerial incentives are aligned with shareholders (Leland, 1994; Myers, 1977; Smith and Warner, 1979). When incentives are aligned, managers are likely to choose the value maximizing option to reduce risk shifting problems. Thus, we state the following:

Hypothesis 3 : When managerial incentives are well aligned with shareholders, firms with high risk exposure concentration are likely to mitigate their risk shifting agency costs through short-term debt as appose to covenant restrictions.

2.3 Data

Our sample comes from several sources. Firm-level risk exposures are obtained from the written text in 10-K filings, executive ownership comes from ExecuComp, public debt information is from Mergent FISD, and other firm characteristics is obtained from Compustat. Section 2.3.1 describes our methodology of measuring risk exposure concentration, while section 2.3.2 describes the rest of the variables used in this research.

2.3.1 Risk Exposure Concentration

To measure a firm's concentration in risk exposures, one needs to define the set of risk factors as well as the level of exposure to each of those factors. We develop our REC measure from the information discussed under (Item 1) in firms' 10-K filings. Item 1 in the annual 10-K filing typically includes three sections; Business Description, Risk Factors, and Unresolved Staff Comments. Although corporation are required by the Securities and Exchange Commission to disclose all risk factors that are relevant to their future earnings under item 1.A, our manual screening of 10-K filings suggests that many companies discuss their operational and/or non-operational risks under the business section as well. Thus, our initial step is extracting all the readable text under (Item 1) from 10-K filings between calendar years 2006 and 2018[5]. We then process the text through an algorithm to insure the extracted raw terms are following the standard procedure in the text-analysis literature; i.e., the text is cleaned from abbreviations, headings, plurals, stop words, and numbers, leaving only relevant lower-cased terms (Baker et al., 2016; Davis et al., 2021; Loughran and Mcdonald, 2011, 2014).

However, the information captured from the filings is qualitative in nature. As such, the process of determining the number of risk categories (*factors, or topics*) and quantifying a firm's exposure to each one is a crucial step for our analysis. A common practice used in the literature is the dictionary approach (Baker et al., 2016;

[5]The data for the complete raw text of all EDGAR filings are made available by Bill McDonald at the University of Notre Dame - The Software Repository for Accounting and Finance, we thank him and the University of Notre Dame for their contribution to the academic community.

Loughran and Mcdonald, 2011; Tetlock, 2007), where a predetermined set of terms are grouped to define a dictionary category. Firm-level exposure to each category is then estimated by some proxy, e.g., counting the number of sentences containing any term in the dictionary set (Davis et al., 2021), or the ratio of terms belonging to the dictionary set to the total number of terms in the document (Loughran and Mcdonald, 2011). However, dictionary methods rely heavily on expert-curated terms, which in some cases can be subjective and limited. Further, such an approach may not guarantee a set of *distinct* topics or categories. A newer approach to quantify information from content is Supervised Machine Learning (ML), where an algorithm identify and group text terms sharing similar topics. This methodology requires the examination of all the terms appearing in the text corpus. The set of terms can be large, depending on the number of distinct categories or topics set at priori. Davis et al., 2021 apply a hybrid approach by first using (ML) to identify the most important and distinctive seed terms in explaining firm-level abnormal returns during COVID-19 pandemic, then systematically expanding each dictionary set with terms from the corpus based on similarity in both content and effect on abnormal daily returns. The categories produced by the authors contain a finite set of terms for a finite set of categories that are sufficient to distinguish firms' varying response to economic crisis.

Our paper uses the 44 risk categories constructed by Davis et al., 2021[6]. Factors include Commercial Property, Display Technology, Traditional Retail, E-commerce, and Franchising. All 44 risk factors, and their terms, are obtained from the authors' article and re-listed in the appendix A.I. To estimate firm i's exposure to risk factor

[6]The authors construct 45 categories. However, following their approach, we drop the manufacturing category due to its high correlation with the other categories, leaving 44 in total. The Python for code for measuring the risk exposures, and the risk exposure measures are available by the authors upon request.

j, we use the following approach:

$$re_{i,j} = \frac{\sum_{yj=1}^{Yj} term_{yj}}{\sum_{j=1}^{J=44} \sum_{yj=1}^{Yj} term_{yj}} \tag{2.1}$$

Equation 2.1 estimates firm i's risk exposure to factor j as the total number of terms (y) extracted from Item 1 that belongs to risk factor j, divided by the total number of terms captured for all the 44 risk factors. Alternatively, $R.E._{i,j}$ can be measured as the total number of terms for factor j over the *total* number of terms in item 1, or using sentences as appose to terms. However, the approach in equation 2.1 insures the proxy is not influenced by either the size or the readability of the document itself (Loughran and Mcdonald, 2014). Firm-level risk exposures are then merged with firm fundamentals from Compustat using (CIK) keys. Table 2.2 presents the summary statistics for each risk topic. Note that some of the categories have means that tend to deflate their true economic importance, such as Investment Funds, Banking, and Deposits. Such factors are likely not representing the true population mean for all public firms in the economy due to excluding regulated industries from our sample[7].

Our primary proxy for the firm's REC is the Herfindahl–Hirschman index from the 44 risk exposures. Specifically:

$$\mathrm{REC}_{i,t} = \sum_{j=1}^{J=44} re_1^2 + re_2^2 + \ldots + re_{44}^2 \tag{2.2}$$

Where firm i's risk exposure concentration at time t is the aggregated exposure levels squared. A high REC level indicates a strong concentration of risk exposure, while low levels of REC demonstrate a more diverse risk exposure affecting the

[7]Firms operating in the financial and utilities sectors are dropped from our sample. Such firms are likely to have significant constraints on their capital and debt structure choices.

firm's future earnings. Albeit its simplicity, our measure does not account for the varying effect of each risk factor composing the REC measure, and assumes homogeneity across the 44 factors. We address this issue in the robustness section of our paper. Figure 2.1 plots the time trend for the cross sectional average of REC. Note that concentration levels tend to have a downward trend after the 2007-2008 financial crisis then increases slightly years thereafter. One explanation for the downward trend could be due to the waive of mergers and acquisitions that occur post the financial crisis period. Such M&A activities could potentially diversify a firm's risk concentration, especially if the firms involved operate in different industries or business segments.

2.3.2 Firm Financial Data

The rest of the variables are obtained from Compustat, ExecuComp, and Mergent FISD. Firm characteristics come from Compustat. Specifically, we follow the literature in measuring short-term debt as the fraction of debt that matures in three years or less (dd1 + dd2 + dd3 / dlc + dltt). Alternatively, we use the fraction of debt maturing in 5 years or less (dd1 + dd2 + dd3 + dd4 + dd5 / dlc + dltt). We construct other essential variables that have been documented to effect debt maturity choices, such as the natural log of size and size squared after adjusting for inflation; Ln(Total Assets), Ln(Total Assets)^2, Book Leverage (dlc + dltt / at), Market-to-Book (csho*prcc_f + dlc + dltt + pstkl - txditc / at), Profitability (oibdp/ at), and Cash (che/at) (Barclay and Smith, 1995; Billett et al., 2007; Datta et al., 2005; Johnson, 2003).

Managerial-Shareholder agency issues are proxied by insider ownership. We obtain data from Execucomp on CEO and total executive share ownership in the firm. Share ownership is measured as the total number of shares including restricted stock (shrown_tot + stock_unvest_num) divided by the total number of shares outstanding. We create two indicators *High CEO Ownership* and *High Exec. Ownership*, both take the value of 1 if the ownership level is in the top quartile of the industry distribution (Fama-French 49 industry classification), and zero otherwise. Finally, we supplement the data with public debt information from FISD. Specifically, we measure the firm's covenant index at a given year following the approach of Billett et al., 2007, and obtain data on new bond issues. Further, we gather information on new public debt issues that have the following characteristics: denominated in US dollars, offering amount of at least $10 million, fixed semi-annual coupon, not asset-backed, not putable, no sinking fund, not a Yankee bond, not a unit offering, and not convertible. For the purposes of our study, we construct three variables for the new bond issues; Ln(1 + Offering Yield) , Ln(Offering Amount "inflation adjusted"), Ln(Years to Maturity). We merge the FISD sample with Compustat following the methodology presented by Brown and Powers, 2020[8]. Finally, we drop firm-years operating in regulated industries or reporting unrealistic information, such as a fraction of short-term debt outside the interval $(0, 1]$. All variables are winsorized at the 1st and 99th percentile to reduce the effect of outliers on our empirical tests. The final sample includes around 31 thousand firm-year observations for 5,890 firms from 2006 - 2018. Table 2.1 reports the descriptive statistics for the final sample.

2.4 Risk Exposure Concentration and Debt Structure

We begin our analysis by examining firm debt maturity choice. We then investigate whether debt covenants may serve as an alternative mechanism in mitigating the

[8]Specifically, we use the historic CUSIP to create a matching index between FISD and Compustat. Issuers in FISD have a unique permanent identifier (Issuer_Id). Because an (Issuer_Id) can use multiple "Issuer Cusip" identifiers for new notes, any new bond issued is matched with a corresponding firm in Compustat if either its issuer cusip number or any sibling issuer cusips belonging to the same permanent identifier issuer_id finds a match during the calendar year.

risk-shifting problem. Finally, we examine the price of new bond issues.

Barnea et al., 1980 argue that the value of short-term debt, compared to long-term debt, is less sensitive to changes in asset volatility, and therefore, short-term debt can be used to mitigate agency costs of debt when the costs of risk-shifting are high. We test this prediction by estimating the following regression:

$$\text{Fraction of S.T. Debt}_{itj} = \beta_0 + \beta_1 REC_{t-1} + \delta^{'} X_{t-1} + \lambda_t + \gamma_j + \varepsilon_i \qquad (2.3)$$

where REC is firm i's risk exposure concentration at time $t-1$, $\delta^{'}$ is a vector of control variables used in the literature (Barclay and Smith, 1995; Harford et al., 2014; Johnson, 2003), λ is a fiscal year fixed effect, and γ is an industry fixed effect using the Fama-French 49 industry classification.

Table 2.3 reports the regression results. The coefficient on the REC variable is positive and statistically significant across all different regression specifications. According to column 3, a one unit increase in the firm's risk exposure concentration is related to an average of 8% increase in the firm's fraction of short-term debt, after controlling for year, industry, and other debt maturity determinants. Table 2.4 reports the regression estimation of equation 2.3 when using the standard deviation of the risk exposures as an alternative proxy to REC. The coefficient remains positive and mostly significance across the different models. These results are inline with our hypothesis; firms with concentrated risk exposure tend to choose shorter-term debt to mitigate agency costs stemming from the potential risk shifting behavior by shareholders.

Smith and Warner, 1979 show debt covenants can aid in reducing shareholder-debtholder conflicts, including the issue of asset substitution. Billett et al., 2007 examine whether covenants are used by firms with high growth opportunities. Such firms are likely to have strong shareholder-debtholder conflicts stemming from the debt-overhang problem. They find covenants tend to increase for firms with high growth options, and short-term debt and covenants act as substitutes in reducing agency costs of debt overhang. Therefore, we examine whether covenant intensity increases for firms with high risk-shifting problems, another major component of debt related agency issues. Table 2.5 reports the estimation results of equation 2.3 while using the covenant index as the dependent variable. The covenant index we use follow the methodology of Billett et al., 2007. Specifically, an issuer's covenant index during the period is calculated by counting the occurrences of 15 covenant categories in the firm's outstanding public bonds during the calendar year, then dividing the sum by 15. The results reported in table 2.5 suggest a positive association between REC and the covenant index, but the statistical significance only occurs when other firm characteristics are introduced in the regression model. Note that the sample size for our covenant analysis is relatively small due to the loss of data after merging Compustat with FISD.

Our last examination is the offering price of new bond issues. Franco et al., 2016 finds firm diversification leads to lower bond-offering yields, and such a relation is more pronounced among firms with high quality business segment disclosure due to the better assessment of risk by bond investors. However, measuring diversification via the number and quality of business segments is likely influenced by the firm's endogenous choice to report such information. For example the choice might be effected by whether the proprietary costs are high if the information is relevant to a firm's competitors (Bens et al., 2011; P. G. Berger and Hann, 2007; Nagarajan and Sridhar, 1996). Olibe et al., 2019 finds the cost of debt to be lower for geographically diversified firms. By measuring diversification through the firm's risk exposure discussion in 10-K filings, which are mandated by the SEC and managers are legally liable for any misinformation, we are able to verify and complement previous studies on the effect of diversification on the cost of debt. Thus, we estimate the following model:

$$\text{Ln(1+Offering Yield)}_{itj} = \beta_0 + \beta_1 REC_{t-1} + \delta' X_{t-1} + \lambda' Y_t + \lambda_t + \gamma_j + \varepsilon_i \qquad (2.4)$$

X is a vector of firm characteristics at time $t-1$ while Y_t is a vector of issue characteristics, including Ln(Amount), Covenant Index of the new issue, and the natural log of years to maturity; Ln(Maturity). We also control for year and industry fixed effects; λ and γ_j, respectively.

Table 2.6 reports the estimation results for equation 2.4. Using both proxies of risk exposure concentration, the primary measure (REC) and the standard deviation of risk exposure, creditors seem to demand a higher price from issuers who tend to have high risk exposure concentration. These findings shed some light on some of the consequences of the higher agency costs in firms with high risk exposure concentration due to the asset substitution problem.

2.5 The Managerial Ownership Channel

In this section, we focus our analysis on debt maturity choices and covenants for firms that are considered to have severe risk shifting problems. When manager-shareholder interests are more aligned and the firm has a high risk exposure concentration, our hypothesis predict a stronger preference for short-term debt over covenants, since managers will have the right incentives to minimize debt-agency costs of risk shifting while maximizing shareholder value. We measure the degree of manager-shareholder incentive alignment by managerial equity ownership in the firm. Self-interested managers that have low or no equity ownership are likely to make sub-optimal choices. That is, they are likely to choose covenants, or other alternatives, over short-term debt since the latter alleviates the self-interested manager from the pressure arising due to frequent monitoring by creditors. Thus, we estimate the following model:

$$\begin{aligned}\text{Frac. ST Debt / Covenant}_{itj} = \beta_0 + \beta_1 REC_{t-1} + \beta_2 Ownership_{t-1} \\ + \beta_3 REC_{t-1} \times Ownership_{t-1} + \delta' X_{t-1} \\ + \lambda_t + \gamma_j + \varepsilon_i\end{aligned} \tag{2.5}$$

The coefficient of interest in equation 2.5 is β_3, which estimates the effect of high substitution problems arising from the REC for firms with strong manager-shareholder alignment. The $Ownership$ variable in the estimation model is an indicator taking the value of unity if the firm's CEO (Total executive) ownership is in the top quartile of its industry, and zero otherwise. Industry classifications follow the Fama-French 49 method, and the rest of the variables follow the definitions in equation 2.3.

Table 2.7 reports the regression estimates. Consistent with our prediction of a higher risk shifting agency problem for firms with concentrated risk exposures, the coefficient on the interaction term is positive and statistically significant in columns 1-4. Note that the effect is even stronger when total executives at the firm are well aligned with shareholders (columns 2 and 4). In economic terms, a one unit increase in our measure of REC for firms with high executive share ownership is associated with an average of 28% increase in the firm's fraction of debt maturing in 3 years or less. Moreover, the effect of REC on debt maturity choice is mainly driven by managerial ownership. That is, firms that have a strong risk exposure concentration but tend to have self-interested managers are likely to choose sub-optimal alternatives in controlling the asset substitution issue; e.g., foregoing future financial flexibility by accepting stricter covenants as observed in columns 5 and 6[9]. Further, consistent with our hypothesis, the interaction terms in columns 5 and 6 are negative, albeit the statistical significance is weak. We address this issue in the next section. Note that according to our estimates, managerial ownership in itself does not necessarily increase the firm's fraction of short-term debt as reported by Datta et al., 2005. Rather, if the incentive alignment between managers and shareholders may lead the firm to easily increase its risk, firms then prefer shorter debt maturity to reduce the higher debt-agency costs[10].

2.6 Additional Robustness Tests

2.6.1 Adjusting for Risk-Factor Composition

In our earlier analysis, risk categories are assumed to have a homogeneous effect on the firm's choice of debt maturity or covenant intensity. For example, a firm that has 100% exposure to E-commerce and another with 100% exposure to Travel will both have a strong risk exposure concentration (REC = 1). However, both firms' choices of debt maturity or covenant intensity is likely influenced by the *type* of risk exposure as well. Moreover, a firm's choice of risk exposures is likely correlated with unobservable characteristics, such as management quality. In this section, we attempt to address these issues to confirm our findings.

In order to account for the effect of firm's composition of risk exposures on debt

[9]However, the coefficient estimate of REC in columns 5 and 6 is not statistically significant in table 2.7. Section 2.6 presents an alternative specification and shows the coefficient is indeed statistically positive.

[10]In our analysis, the shareholder-debtholder conflict we examine is the risk-shifting problem. However, there are other potential agency costs of debt, for example the underinvestment problem. The interaction of managerial ownership and debt overhang is examined in greater detail by Datta et al., 2005.

structure choices, we estimate the beta for each risk category on debt maturity (covenants). Specifically, we run 44 individual regressions and obtain the estimated beta coefficients. We then examine whether the unexplained portion of the observed debt maturity (covenant intensity) is explained by the firm's risk exposure concentration while including firm fixed effects. In formal terms, we first estimate the following equation:

$$\text{Frac. ST Debt / Covenant Index}_{it} = \beta_0 + \beta_{1,y} re_{t-1,y} + \varepsilon_i \qquad \text{for } y \in [1, \ldots, 44] \tag{2.6}$$

Where $\beta_{1,y}$ is the estimated coefficient for each risk factor y. Then we measure the unexplained portion of debt maturity (Covenant Index) by measuring the weighted average of the predicted dependent variable[11]:

$$\text{Unex. ST Debt (Cov.)}_{i,t} = \text{ST Debt (Cov.)}_{i,t} - \sum_{y=1}^{Y=44} \widehat{\text{ST Debt (Cov.)}}_{i,y,t} \times re_{i,y,t-1} \tag{2.7}$$

from 2.6 and 2.7, we estimate the following equation to determine whether a firm's risk exposure concentration affects the fraction of short-term debt (Covenant Index):

$$\begin{aligned} \text{Unex. ST Debt (Cov.)}_{i,t,j} = {} & \alpha_i + \beta_1 REC_{t-1} + \beta_2 Ownership_{t-1} \\ & + \beta_3 REC_{t-1} \times Ownership_{t-1} + \delta' X_{t-1} \\ & + \lambda_t + \gamma_j + \varepsilon_{i,t,j} \end{aligned} \tag{2.8}$$

Where α_i is a firm fixed effect, X_{t-1} is a vector of controls, λ_t is a fiscal year fixed effect, and γ_j is an industry fixed effect. The coefficient on the interaction term β_3 estimates the effect of the *change* in a firm's risk exposure concentration, for firms

[11]We use the weighted average in order to give more weight to the estimated coefficients that the firm has more exposure to, and less weight to coefficients that seem unimportant to the firm's risk composition. Note that by construction, firm-level risk exposures sum up to 1, i.e., $\sum_{y=1}^{Y=44} re_y = 1$ for each firm at time t.

with high managerial ownership, on the fraction of short-term debt (Covenant Index). Table 2.8 reports the estimates for equation 2.8. In all alternative proxies for either short-term debt (except column 1) or the degree of management alignment with shareholders, the interaction term is positive and statistically significant. Further, columns 7 and 8 show the interaction term for the covenant index choice is negative and statistically significant, while the the coefficient on REC is positive and significant. That is, firms with strong risk exposure concentration but have self-serving managers are more likely to have stronger covenants. The results here confirm our earlier findings. Short-term debt mitigates debt-agency problems arising from asset substitution, and it is preferred over covenants for firms with high manager-shareholder incentive alignment.

2.7 Concluding Remarks

Traditional theories on agency costs, such as Jensen and Meckling, 1976 and Myers, 1977, show how the use of short-term debt can mitigate contractual problems arising from debt financing. This paper examines firms' choices of short-term debt and covenants, which is argued to be substitutes in reducing shareholder-debtholder conflicts. However, we focus on a particular debt agency issue; the risk-shifting (or asset-substitution) problem. Using a firm's risk exposure concentration derived from the written text in 10-K filings, we find firms who are likely to have severe risk shifting problems due to high risk exposure concentration are likely to have more short-term debt in their capital structure, and less covenants intensity in their outstanding bonds. This effect is more pronounced for firms with managers that have stronger alignment with shareholders. Further, issuing costs of public debt tend to increase with the firm's risk exposure concentration.

Tables and Figures

Table 2.1: Descriptive Statistics

	SD	Mean	Min	Median	Max	N
EDGAR:						
REC	0.10	0.21	0.08	0.17	0.54	31,454
σ(Risk Expo.)	0.02	0.06	0.04	0.06	0.11	31,454
Compustat:						
Fraction of ST Debt (3yrs)	0.35	0.38	0	0.26	1	33,691
Fraction of ST Debt (5yrs)	0.36	0.56	0	0.55	1	35,328
Leverage	0.23	0.23	0	0.17	0.90	50,886
Ln(Assets)	2.69	5.47	0.01	5.66	10.95	54,704
Ln(Assets)^2	29.36	37.15	0	32.02	119.89	54,704
Market-to-Book	2.66	2.09	0	1.24	17.60	48,684
Profitability	0.41	-0.05	-2.17	0.08	0.41	50,738
Cash	0.27	0.25	0	0.14	0.97	50,877
ExecuComp:						
High CEO Ownership	0.43	0.25	0	0	1	16,335
High Total Exec. Ownership	0.43	0.25	0	0	1	17,187
Mergent FISD:						
Cov. Index (Normalized)	0.19	0.36	0.07	0.33	0.73	6,205
Ln(Maturity)	0.69	2.1	0	2.08	4.60	5,735
Ln(Yield)	0.46	1.61	0	1.66	4.13	4,191
Ln(Amount)	0.93	13.16	0.13	13.20	18.58	5,738

This table reports the descriptive statistics for the final sample used to examine risk exposure concentration on debt maturity structure choices. REC is the Herfindahl–Hirschman index of the 44 risk exposures measured at the firm-year level; see section 2.3.1. σ(Risk Expo.) is the standard deviation of the 44 risk exposures. Fraction of ST Debt is the ratio of debt maturing in 3 years or less, or five years or less, over total debt, respectively. Ln(Assets) and Ln(Assets)^2 is the natural log of firm size and size squared after adjusting for inflation, respectively. Profitability is (oibdp / at), and Cash is (che /at). High CEO Ownership and High Total Exec. Ownership are indicators taking the value of 1 if the percentage ownership (including restricted stocks) is in the top quartile of the industry distribution (Fama-French 49 industry classification), and zero otherwise. Cov. Index is the firm's covenant index measure for its total public debt outstanding using the method presented by Billett et al., 2007. Ln(Maturity) is the natural log of years to maturity for the new debt issue. Ln(Yield) is the natural log of (1+ offering yield). Ln(Amount) is the natural log of the issue amount after adjusting for inflation. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile.

Table 2.2: Summary Statistics for Firm-level Risk Exposures

Firm-level Risk Exposures	SD	Mean	Min	Median	Max	N	Firm-level Risk Exposures	SD	Mean	Min	Median	Max	N
Advertising	3.10%	1.10%	0.00%	0.20%	48.10%	23,672	Traditional Media	4.70%	1.70%	0.00%	0.40%	50.80%	23,672
Alternative Energy	4.00%	0.80%	0.00%	0.00%	77.20%	23,672	Energy Infrastructure	6.30%	1.90%	0.00%	0.10%	59.90%	23,672
Card Payments	3.70%	1.10%	0.00%	0.00%	72.50%	23,672	Oil and Gas	12.00%	4.40%	0.00%	0.00%	89.50%	23,672
Clearing Houses	0.30%	0.10%	0.00%	0.00%	8.30%	23,672	Drug Trials	16.40%	8.10%	0.00%	1.60%	86.00%	23,672
Commercial Property	5.10%	4.00%	0.00%	2.70%	80.00%	23,672	E-Commerce	3.80%	3.20%	0.00%	1.80%	60.00%	23,672
Display Technology	4.20%	1.80%	0.00%	0.40%	56.00%	23,672	Electronics	7.50%	5.30%	0.00%	1.90%	62.80%	23,672
Financial Management	1.40%	0.90%	0.00%	0.50%	37.00%	23,672	Food Related Products	6.30%	2.60%	0.00%	0.60%	66.90%	23,672
Foreign Exchange	0.30%	0.10%	0.00%	0.00%	5.10%	23,672	Foreign Countries	9.50%	9.80%	0.00%	7.20%	71.40%	23,672
Franchising	3.60%	0.60%	0.00%	0.00%	81.50%	23,672	Health Insurance	11.50%	5.10%	0.00%	0.40%	86.40%	23,672
Gambling	4.40%	0.50%	0.00%	0.00%	78.70%	23,672	Investment Funds	0.50%	0.10%	0.00%	0.00%	13.20%	23,672
Gold or Silver	2.00%	0.30%	0.00%	0.00%	60.20%	23,672	Metal Products	7.50%	3.40%	0.00%	0.50%	81.60%	23,672
Healthcare Providers	2.40%	0.50%	0.00%	0.00%	56.50%	23,672	Power Generation	6.10%	1.90%	0.00%	0.10%	85.90%	23,672
Insurance	1.50%	1.20%	0.00%	0.80%	41.90%	23,672	Metals and Minerals	1.60%	0.50%	0.00%	0.00%	37.20%	23,672
Mortgages	4.20%	1.30%	0.00%	0.40%	73.30%	23,672	Semiconductors	3.20%	1.00%	0.00%	0.00%	49.40%	23,672
REITs	3.70%	1.20%	0.00%	0.40%	76.20%	23,672	Video Games	3.10%	0.90%	0.00%	0.00%	61.50%	23,672
Residential Construction	2.30%	0.40%	0.00%	0.00%	39.00%	23,672	Web Services	4.80%	2.90%	0.00%	0.90%	57.10%	23,672
Restaurants	5.40%	0.70%	0.00%	0.00%	69.90%	23,672	Banking	4.30%	1.50%	0.00%	0.50%	65.10%	23,672
Traditional Retail	7.60%	3.90%	0.00%	0.60%	59.70%	23,672	Deposits	0.30%	0.00%	0.00%	0.00%	16.50%	23,672
Workforce	0.20%	0.00%	0.00%	0.00%	10.00%	23,672	Shipping Containers	3.80%	1.00%	0.00%	0.00%	60.70%	23,672
Airlines or Aircraft	5.30%	0.90%	0.00%	0.00%	77.30%	23,672	Transportation	5.40%	2.00%	0.00%	0.50%	67.60%	23,672
Travel	2.60%	0.80%	0.00%	0.00%	59.60%	23,672	Software Services	10.70%	12.70%	0.00%	9.50%	100.00%	23,672
Communications	5.30%	1.60%	0.00%	0.20%	65.80%	23,672	Software-Hardware Products	6.90%	6.10%	0.00%	3.80%	58.60%	23,672

This table reports the summary statistics for the sample used to measure firms' risk exposure concentration (REC). Measures of risk exposure are obtained from the readable text under Item 1 in company 10-K filings for years 2006-2018, and the categories of risk follow the work of Davis et al., 2021; see section 2.3.1 and appendix A.I for further details. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample.

Table 2.3: Risk Exposure Concentration and Debt Maturity

	≤ 3 yrs			≤ 5 yrs		
	(1)	(2)	(3)	(4)	(5)	(6)
REC	0.22***	0.09***	0.08**	0.17***	0.11***	0.07**
	(8.29)	(3.68)	(2.49)	(6.69)	(4.49)	(2.23)
Leverage		-0.23***	-0.23***		-0.15***	-0.15***
		(-17.91)	(-17.43)		(-11.04)	(-11.18)
Ln(Assets)		-0.08***	-0.08***		0.03***	0.04***
		(-12.75)	(-11.74)		(5.03)	(5.49)
Ln(Assets)^2		0.00***	0.00***		-0.01***	-0.01***
		(5.30)	(4.31)		(-12.22)	(-12.61)
Market-to-Book		-0.01***	-0.00		-0.00	0.00
		(-2.88)	(-1.45)		(-0.32)	(0.55)
Profitability		0.02	0.02		0.02	0.02
		(1.14)	(1.14)		(1.55)	(1.36)
Cash		0.10***	0.11***		-0.02	-0.01
		(5.91)	(5.50)		(-1.06)	(-0.74)
Constant	0.34***	0.85***	0.83***	0.55***	0.66***	0.65***
	(58.32)	(37.76)	(36.23)	(98.79)	(29.73)	(29.06)
Observations	18,549	17,545	17,545	19,763	18,691	18,691
Industry FE			Yes			Yes
Year FE			Yes			Yes
R-squared	0.00	0.16	0.18	0.00	0.07	0.09

This table reports the OLS regression from estimating equation 2.3. The dependent variable in columns 1-3 is the fraction of debt maturing in 3 years or less (dd1 + dd2 + dd3 / dlc + dltt), while the dependent variable in columns 4 - 5 is the fraction of debt maturing in 5 years or less. REC is the Herfindahl–Hirschman index of the 44 risk exposures measured at the firm-year level; see section 2.3.1. Ln(Assets) and Ln(Assets)^2 is the natural log of firm size and size squared after adjusting for inflation, respectively. Profitability is (oibdp / at), and Cash is (che / at). All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are robust for heteroscedasticity.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 2.4: Variation in Risk Exposures and Debt Maturity

	≤ 3 yrs			≤ 5 yrs		
	(1)	(2)	(3)	(4)	(5)	(6)
σ(Risk Expo.)	1.33***	0.55***	0.37**	0.94***	0.62***	0.27
	(8.25)	(3.60)	(1.97)	(6.24)	(4.13)	(1.43)
Leverage		-0.23***	-0.23***		-0.15***	-0.15***
		(-17.89)	(-17.39)		(-11.00)	(-11.12)
Ln(Assets)		-0.08***	-0.08***		0.03***	0.04***
		(-12.71)	(-11.71)		(5.09)	(5.53)
Ln(Assets)^2		0.00***	0.00***		-0.01***	-0.01***
		(5.26)	(4.27)		(-12.28)	(-12.66)
Market-to-Book		-0.01***	-0.00		-0.00	0.00
		(-2.89)	(-1.48)		(-0.34)	(0.50)
Profitability		0.02	0.02		0.02	0.02
		(1.11)	(1.08)		(1.49)	(1.28)
Cash		0.10***	0.11***		-0.02	-0.01
		(5.93)	(5.58)		(-1.01)	(-0.63)
Constant	0.30***	0.83***	0.82***	0.52***	0.64***	0.65***
	(29.73)	(34.96)	(33.18)	(54.48)	(27.37)	(26.58)
Observations	18,549	17,545	17,545	19,763	18,691	18,691
Industry FE			Yes			Yes
Year FE			Yes			Yes
R-squared	0.00	0.16	0.18	0.00	0.07	0.09

This table reports the OLS regression from estimating equation 2.3. The dependent variable in columns 1-3 is the fraction of debt maturing in 3 years or less (dd1 + dd2 + dd3 / dlc + dltt), while the dependent variable in columns 4 - 5 is the fraction of debt maturing in 5 years or less. σ(Risk Expo.) is the standard deviation of the 44 risk exposures measured at the firm-year level; see section 2.3.1. Ln(Assets) and Ln(Assets)^2 is the natural log of firm size and size squared after adjusting for inflation, respectively. Profitability is (oibdp / at), and Cash is (che / at). All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are robust for heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 2.5: Risk Exposure Concentration and Debt Covenants

	(1)	(2)	(3)
REC	0.05	0.15**	0.17***
	(0.54)	(2.17)	(2.60)
Leverage		0.09***	0.09***
		(6.74)	(6.47)
Ln(Assets)		-0.05**	-0.04**
		(-2.40)	(-1.98)
Ln(Assets)^2		0.00***	0.00**
		(3.50)	(2.40)
Market-to-Book		0.00	-0.00
		(0.21)	(-0.37)
Profitability		0.03**	0.03**
		(2.20)	(2.17)
Cash		0.03	0.02
		(1.55)	(0.97)
Constant	0.35***	0.40***	0.42***
	(18.01)	(4.65)	(4.78)
Observations	4,464	3,964	3,964
Firm FE	Yes	Yes	Yes
Industry FE		Yes	
Year FE			Yes
R-squared	0.00	0.83	0.83

This table reports the OLS regression from estimating equation 2.3. The dependent variable in the regression models of this table is the covenant index. We follow Billett et al., 2007 in constructing the covenant index for each firm at time t. Specifically, an issuer's covenant index during the period is calculated by counting the occurrences of 15 covenant categories in the firm's outstanding public bonds during the calendar year, then dividing the sum by 15. REC is the Herfindahl–Hirschman index of the 44 risk exposures measured at the firm-year level; see section 2.3.1. Ln(Assets) and Ln(Assets)^2 is the natural log of firm size and size squared after adjusting for inflation, respectively. Profitability is (oibdp / at), and Cash is (che / at). All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are robust for heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 2.6: Risk Exposure Concentration and Debt Offering Price

	Concentration			Variation		
	(1)	(2)	(3)	(4)	(5)	(6)
REC	0.95***	0.56***	0.19**			
	(14.47)	(8.40)	(2.15)			
σ(Risk Expo.)				5.37***	3.31***	1.08**
				(13.19)	(8.31)	(2.07)
Ln(Amount)		0.01	0.04**		0.01	0.04**
		(1.09)	(2.53)		(1.08)	(2.53)
Covenant Index		-0.08*	-0.00		-0.08*	-0.00
		(-1.91)	(-0.03)		(-1.92)	(-0.04)
Leverage		0.39***	0.44***		0.39***	0.44***
		(10.26)	(10.93)		(10.38)	(11.00)
Ln(Size)		-0.09***	-0.08***		-0.09***	-0.08***
		(-15.78)	(-12.32)		(-15.88)	(-12.33)
Market-to-Book		-0.10***	-0.08***		-0.10***	-0.08***
		(-7.65)	(-6.34)		(-7.65)	(-6.34)
Ln(Maturity)		0.22***	0.22***		0.22***	0.22***
		(24.61)	(24.72)		(24.60)	(24.72)
Profitability		0.06	-0.08		0.06	-0.08
		(0.76)	(-1.11)		(0.77)	(-1.13)
Cash		-0.33***	-0.11*		-0.33***	-0.11*
		(-5.98)	(-1.79)		(-6.07)	(-1.78)
σ(Profitability)		0.08*	0.06		0.08*	0.06
		(1.93)	(1.63)		(1.95)	(1.64)
Constant	1.43***	1.80***	1.36***	1.29***	1.71***	1.33***
	(98.46)	(13.08)	(8.97)	(50.11)	(12.40)	(8.71)
Observations	4,191	3,777	3,775	4,191	3,777	3,775
Industry FE			Yes			Yes
Year FE			Yes			Yes
R-squared	0.04	0.36	0.47	0.03	0.36	0.47

This table reports the OLS regression from estimating equation 2.4. The dependent variable is the natural log of (1 + offering yield). REC is the Herfindahl–Hirschman index of the 44 risk exposures while σ(Risk Expo.) is the standard deviation of the risk exposures; see section 2.3.1. Definitions for the rest of the variables are reported in sectio 2.3.2. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are robust for heteroscedasticity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 2.7: Risk Exposure Concentration on Debt Maturity Structure (High Managerial Ownership)

	Short-term Debt				Cov. Index	
	≤ 3 yrs		≤ 5 yrs			
	(1)	(2)	(3)	(4)	(5)	(6)
REC	0.01	-0.02	-0.00	-0.02	0.09	0.15
	(0.12)	(-0.29)	(-0.00)	(-0.23)	(0.87)	(1.49)
High CEO Ownership	-0.03		-0.04		0.01	
	(-1.30)		(-1.44)		(0.17)	
High CEO Ownership×REC	0.23*		0.30**		-0.04	
	(1.88)		(2.21)		(-0.21)	
High Exec. Ownership		-0.05*		-0.05*		0.04
		(-1.82)		(-1.80)		(0.96)
High Exec. Ownership×REC		0.31**		0.35***		-0.21
		(2.55)		(2.72)		(-1.15)
Observations	6,962	7,350	7,496	7,911	2,361	2,491
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Firms	1,303	1,331	1,335	1,361	472	482
R-squared	0.14	0.15	0.12	0.12	0.31	0.32

This table reports the OLS regression from estimating equation 2.5. The dependent variable in columns 1-4 is the fraction of debt maturing in 3 (5) years or less, while the dependent variable in columns 5 - 6 is the firm's covenant index. We follow Billett et al., 2007 in constructing the covenant index for each firm at time t. Specifically, an issuer's covenant index during the period is calculated by counting the occurrences of 15 covenant categories in the firm's outstanding public bonds during the calendar year, then dividing the sum by 15. REC is the Herfindahl–Hirschman index of the 44 risk exposures measured at the firm-year level; see section 2.3.1. High CEO Ownership and High Total Exec. Ownership are indicators taking the value of 1 if the percentage ownership (including restricted stocks) is in the top quartile of the industry distribution (Fama-French 49 industry classification), and zero otherwise. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are clustered at the firm level. * p < 0.1, ** p < 0.05, *** p < 0.01. T-statistics in parentheses.

Table 2.8: Risk Exposure Concentration on the Unexplained Portion of Debt Maturity Structure (High Managerial Ownership)

	≤ 3 yrs	≤ 4 yrs	≤ 5 yrs	≤ 3 yrs	≤ 4 yrs	≤ 5 yrs	Cov. Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
REC	0.01	-0.31	-0.33*	-0.04	-0.30	-0.24	0.22**	0.20**
	(0.07)	(-1.56)	(-1.71)	(-0.24)	(-1.58)	(-1.30)	(2.08)	(2.10)
CEO Own.	-0.02	-0.04	-0.06**				0.06***	
	(-0.49)	(-1.13)	(-2.03)				(3.53)	
CEO Own.×REC	0.26	0.32*	0.49***				-0.26***	
	(1.62)	(1.86)	(3.06)				(-3.45)	
Exec. Own.				-0.08**	-0.06*	-0.04		0.06***
				(-2.19)	(-1.75)	(-1.38)		(2.85)
Exec. Own.×REC				0.55***	0.35*	0.33*		-0.24**
				(3.12)	(1.86)	(1.93)		(-2.46)
Observations	6,000	6,232	6,486	6,364	6,611	6,876	2,063	2,186
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.37	0.37	0.44	0.37	0.37	0.43	0.81	0.82

This table reports the estimation results for equation 2.8. The dependent variable in columns 1 and 4 (2 and 5, 3 and 6) is the *unexplained* fraction of debt maturing in 3 (4, 5) years or less, respectively. The dependent variable in columns 7 and 8 is the firm's *unexplained* covenant index. See section 2.6 on the construction of the dependent variable. REC is the Herfindahl–Hirschman index of the 44 risk exposures measured at the firm-year level; see section 2.3.1. CEO Own. (Exec. Own.) is an indicator taking the value of 1 if the percentage ownership, including restricted stocks, is in the top quartile of the industry distribution, and zero otherwise, respectively. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are robust for heteroscedasticity. * p < 0.1, ** p < 0.05, *** p < 0.01. T-statistics in parentheses.

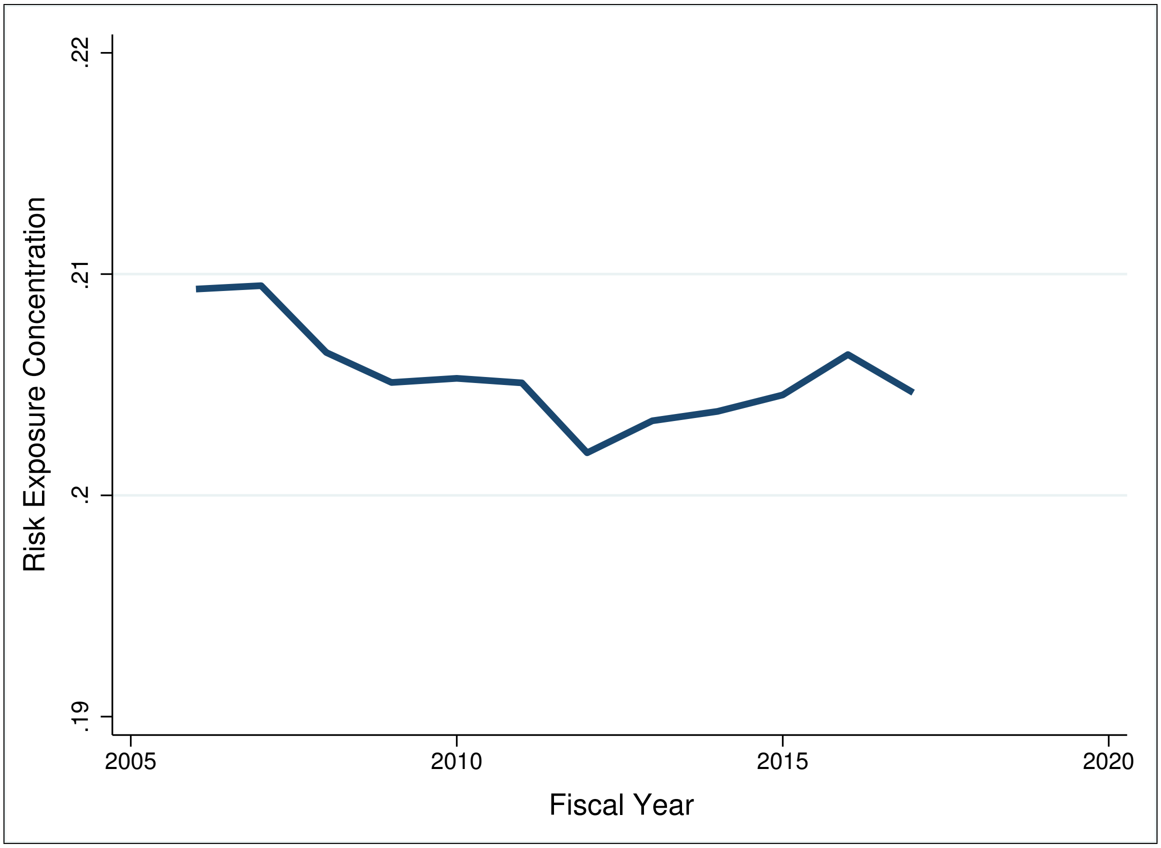

Figure 2.1: Average REC Across Time

This figure plots the time trend for the average risk exposure concentration for all unregulated publicly traded firms between 2006 and 2018. Firms' risk exposure concentration is measured as the Herfindahl index of the firm's exposure to the 44 risk categories. Measures of risk exposure are obtained from the readable text under Item 1 in company 10-K filings, and the categories follow the work of Davis et al., 2021; see section 2.3.1 for further details on measuring exposure levels and appendix A.I on the 44 categories. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample.

CHAPTER 3

CORPORATE PAYOUT AND ECONOMIC POLICY UNCERTAINTY IN THE U.S.[12]

JEL Code : G30; G32

Keywords : Payout Policy, Share Repurchases, Dividends, Economic Policy Uncertainty, Fiscal Policy Uncertainty, Monetary Policy Uncertainty

[12]Author: Eyad Alhudhaif. To be submitted to the Quarterly Journal of Economics.

CHAPTER 3

Corporate Payout and Economic Policy Uncertainty in the U.S.

Abstract

Using a sample of all public firms in the U.S. between 1985 and 2019, I examine whether general economic policy uncertainty, monetary policy uncertainty, and fiscal policy uncertainty have heterogeneous effects on corporate payouts; mainly dividends and open market share repurchases. I find a consistent negative relation between share repurchases and EPU, and the effect seems to be more pronounced under fiscal policy uncertainties as appose to monetary policy uncertainties. Finally, the negative relation is mainly driven by capital constrained firms. Taken together, the findings suggest that withholding funds is more valuable than dispersing cash to investors to mitigate agency costs of free cash flows, at least in the United States. This empirical test relies on the economic policy uncertainty (EPU) index and its subcategories developed by Baker et al., 2016.

3.1 Introduction

Governments often make decisions that affect the environment in which businesses operate. The uncertainty of when, what, and how these policies are implemented can influence corporate decisions, and in some circumstances delay them ; "*In their discussion of their economic forecasts, participants emphasized their considerable uncer-*

tainty about the timing, size, and composition of any future fiscal and other economic policy initiatives... "[1]. Thus, the study of economic policy uncertainty has caught the attentions of academics and policy makers alike. Recent work in the literature investigates the implications of economic policy uncertainty on corporate investment and growth (Baker et al., 2016; Gulen and Ion, 2016), firms' cost of capital and innovation (Xu, 2020), and managerial behavior (Stein and Wang, 2016). Nevertheless, this area of research is still at its early stage.

Using a sample of all public firms in the U.S. between 1985 and 2019, I examine whether general economic policy uncertainty, monetary policy uncertainty, and fiscal policy uncertainty have heterogeneous effects on corporate payouts; mainly dividends and open market share repurchases. This empirical test relies on the economic policy uncertainty (EPU) index developed by Baker et al., 2016. Economic policy uncertainty broadly refers to uncertainties regarding government actions that have direct implication on the economic environment (Attig et al., 2021). Since policy uncertainty is difficult to quantify, Baker et al., 2016 develops an index (EPU Index) based on news articles to capture uncertainties on who, what, and when economic polices are changing. The index contains subcategories that measure the level of uncertainties related to monetary, fiscal, taxation, government spending, and healthcare policies. This paper attempts to find further insight in understanding what specific components of uncertainties trigger changes in corporate payout decisions.

Theoretically, firms' response in payout policy following changes in the level of uncertainty can go either way. On one hand, higher levels of EPU can increase the amount of free cash flows at the firm's balance sheet due to fewer positive NPV

[1]From the minutes of the Federal Open Market Committee meeting in December 2016.

projects available in the market. With such higher information asymmetries during abnormal levels of uncertainty, shareholders may require higher payout levels to reduce management's ability to invest in value-destroying projects. Thus, positive changes in EPU can lead to higher managerial agency costs, which can be mitigated by an increase in corporate payout levels. On the other hand, during periods of elevated uncertainty, the external cost of capital rises (Xu, 2020), implying a greater need for internally generated cash by the firm to fund current and future projects. The trade offs are plausibly affected by the source of the policy uncertainty as well. Monetary policies may have long term effects on prices and accepting long-term NPV projects, while fiscal policy can be seen by the firm as a relatively temporary change in the economic environment. This paper is closely related to Attig et al., 2021. While they examine dividend policies following changes in EPU in an international setting, this paper examines payout policies (Dividends and Share Repurchases) and subcategories of economic policy uncertainties in U.S. based firms. The empirical test may provide further insight on corporate payout policies following periods of high EPU when the overall level of investor protection is high (La Porta et al., 2000). In addition, what specific policy uncertainties governments may need to reduce for an efficient allocation of capital in the market.

After controlling for main corporate payout variables, along with other sources of uncertainties, I find a consistent negative relation between share repurchases and EPU. Economically, a 1 standard deviation change in the EPU index from the sample mean is related to roughly 1.91% decrease in share repurchases or 3.63% in total payout. Further, the effect seems to be more pronounced under fiscal policy uncertainties as appose to monetary policy uncertainties. In addition, I document mild evidence of a negative relation between dividends and monetary policy uncertainty. Finally, the negative relation between payout and EPU is mainly driven by capital constrained firms. Taken together, the findings suggest that withholding funds is more valuable than dispersing cash to investors to mitigate agency costs of free cash flows, at least in the United States.

The paper is organized as follows. Section 3.2 reviews the related literature. Section 3.3 develops the hypotheses. Section 3.4 describes the data used for this study, section 3.5 examines payout choices and EPU subcategories, section 3.6 conducts additional robustness checks, and section 3.7 concludes.

3.2 Literature Review

One of the classical theories rationing corporate cash disbursements is Jensen's free cash flow hypothesis (Jensen, 1986). That is, managers engage in a payout policy to reduce the excess amount of cash at management's disposal. The argument implies a firm is more likely to take an action if it has experienced reductions in future growth opportunities. Otherwise, the excess cash might be used for value destroying projects or managerial empire building. Payout policy models, the likes of Easterbrook, 1984; Grossman and Hart, 1982, illustrate how the amount of cash returned to shareholders will ultimately lead to reductions in both agency issues and shareholder expropriation.

Methods in distributing the excess cash from the firm involve either the use of dividends or open market share repurchases, as both act as substitutes in reducing agency costs (Grullon and Michaely, 2002). However, managers may prefer one alternative over the other, depending on the cyclical nature of the firm's excess cash flow. A dividend policy is expected by shareholders if the stream of future excess cash flows are increasing, while open market share buybacks are unexpected initiations by managers due to the temporary increase in excess cash funds. Thus, firms with higher variance in their operating cash flows tend to prefer the latter over the former (Grullon and Michaely, 2002). The substitution argument however does not necessarily assume that both alternatives are equally effective in mitigating managerial agency costs. Brav et al., 2005 survey 384 financial executives regarding firm payout policies, and they find, among other things, that a share buyback program is perceived to be less effective at resolving agency conflicts, while a firm's level of corporate governance play a significant role in determining management payout choice. As a result, examining the two methods of payout separately and collectively during periods of elevated agency issues can provide a unique view to managerial view on EPU and fiscal vs. monetary policy uncertainty. That is, whether managers, in their determination of payout policy, perceive the levels of uncertainty to continue in the future, and which uncertainty source matters. Following Miller and Rock, 1985 rationale, in periods of high uncertainty, such as uncertainties in future economic policies, the level of information asymmetry is heighten. As such, an insider manager incurs a higher signaling cost leading to higher levels of dividends than under the full-information optimum.

Uncertainty, specifically economic policy uncertainty, has become an important subject in recent empirical studies due its implications on corporate decisions. The change in uncertainty translates to changes in the minds of consumers, managers, and policy makers about possible future states. For example, uncertainty around fiscal policies may have a negative impact on firms that rely on government spending and uncertainty around monetary policies may have a negative effect on firms that expect future cash flows in the long-term. Bloom, 2014 defines economic uncertainty as a mixture of risk and uncertainty in the stock market, and the country's future economic performance. Thus, uncertainty levels increase during recessions, and decrease during economic booms. Uncertainty is mostly triggered by shocks of bad news, which amplifies recessions further, leading to slow economic growth. In such circumstances, many managers reevaluate their corporate decisions, or withhold these decisions until the uncertainty declines, since these policies may alter the firm's financial and investment choices. Theoretical arguments suggest that managers facing elevated uncertainties are better off postponing the investment decision until these levels return to normal (Dixit et al., 1996; McDonald and Siegel, 1986). Furthermore, managers should postpone irreversible investments since they carry high reversibility costs, and a rise in the level of uncertainty changes the optimal timing of investments due to the real-option feature of investment (Bernanke, 1983).

One of the main challenges in this strain of research is finding an appropriate measure for economic policy uncertainty. An increasingly common proxy used in the literature is the EPU index developed by Baker et al., 2016. The index comprises mainly of the number of articles in the top ten leading newspapers containing keywords such as "Uncertainty", "Economy", and one or more of "Congress, deficit, Federal Reserve, legislation, regulation, White House", then normalized by the total volume of news articles. The authors construct subcategories of the index that adds additional terms to the main index to measure specific economic uncertainties. For example, articles that fulfill the requirements to be categorized in the EPU and also contain the term 'federal reserve' would be included in the monetary policy uncertainty (MPU) sub-index. Baker et al., 2016 find a positive and significant relation between the proposed index and stock price volatility, as well as a negative relation with investment and employment in sectors that are heavily reliant on government policies, such as healthcare and defense, supporting Bernanke, 1983; Dixit et al., 1996; McDonald and Siegel, 1986 conclusions. Gulen and Ion, 2016 document a strong negative relationship between capital investment and the level of uncertainty[2] associated with future policy outcome. The relation is not constant across firms; it is stronger for firms with higher degrees of investment irreversibility and for firms that are more dependent on government spending. These conclusions support other findings in the empirical literature; Jens, 2017. Stein and Wang, 2016 documents a positive relation between earnings management and uncertainty. By observing lower stock price responses to earnings surprises when uncertainty is high, they argue, during periods of high uncertainty, performance is more likely to be attributed to luck rather than skill and effort. Thus, creating an incentive for managers to shift earnings toward lower uncertainty periods.

In addition to corporate investment policy, economic uncertainties commands an equity risk premium as well, due to undiversifiable political risk (Pástor and Veronesi, 2012, 2013), making equity financing more costly during periods of elevated uncertainty. However, similar to any other risk factor, firms' exposure to political risk varies. To some, the cost of equity becomes high enough to turn a subset of positive NPV projects to negative. In addition, economic uncertainty can affect the cost of debt as well through its influence on firms' default risk (Arnott et al., 1994). As Xu, 2020 demonstrates, economic policy uncertainty affects a firm's weighted average cost of capital (WACC), which in turn affects investment policies (Abel and Blanchard, 1986; Gilchrist and Zakrajsek, 2007). Thus, a higher cost of capital may create financing frictions, where firms rely more on internal funds rather than external financing (Kaplan and Zingales, 1995; Myers and Majluf, 1984). Since government expenditure has become very important in recent decades, increasing from 25% of U.S. GDP during the late 30s to almost 40% of GDP in the late 2000s [3], some sectors in the economy rely heavily on government expenditures.

[2] Using the index developed by Baker et al., 2016.

[3] The estimates regarding government expenditures are obtained from the website: https://www.usgovernmentspending.com

Thus, fiscal policy uncertainty may play an even bigger role in corporate payouts, affecting future cash flows for some firms, and thus leading to a higher political risk premium. With the rise in the cost of capital, managers may prefer to raise funds internally over increasing or maintaining their payouts to shareholders.

3.3 Hypothesis Development

In light of the previous findings in the literature, the free cash flow hypothesis described by Jensen, 1986 suggests that excess funds are the main source of agency conflict between managers and shareholders. Since in periods of high economic policy uncertainty, investments decline due to low investment opportunities (Baker et al., 2016; Gulen and Ion, 2016), and excess free cash flows rise, there may be a higher demand from shareholders for cash disbursement, i.e. larger payouts. Furthermore, periods of elevated uncertainty amplify information asymmetry between outsiders and insiders, and thus, as Miller and Rock, 1985 conclude, a higher signaling cost through larger payouts may be required by outside investors. Together, both views suggest a positive association between uncertainty and payouts. On the other hand, during periods of high economic uncertainty, cost of external financing soars due to higher political risk premiums; Pástor and Veronesi, 2012, 2013; Xu, 2020, and therefore, encouraging firms to prefer internally generated funds over external financing when needed. In addition, for firm's that have a higher risk loading on political risk premiums, the preference may be of longer term.

Taking both views into consideration, the direction of the relationship between uncertainty and payout policy can go either way, and an empirical test may provide a useful insight. Thus, in this paper I test the following hypothesis:

Hypothesis 1A : A change in the level of U.S. economic policy uncertainty is associated with a firm's payout policy, and the direction of the association can go either way.

In addition, it is worthwhile to examine whether this relationship is stronger among firms that are capitally constrained, since such type of firms face a stronger rise in the cost of external financing:

Hypothesis 1B : A change in the level of U.S. economic policy uncertainty is associated with a stronger change in a firm's payout policy among capitally constrained firms.

3.4 Sample Construction

The sample comes from several sources. Firm fundamentals are drawn from the annual CRP-Compustat merged dateset. I keep all reports for U.S. public firms between calendar years 1983 - 2019. I then exclude firms operating in the utility and financial sectors (SIC codes 6000-6999 and 4900-4999) since the regulatory restrictions they face may prevent such firms from adjusting their payout policies freely. These filings are then merged with the monthly economic policy uncertainty index developed by Baker et al., 2016[4]. Firm-year observations reporting negative values for dividends, total assets, or total revenue are dropped. The primary payout measures are stock repurchases, dividends, and total payout all scaled by total revenue[5]. That is, prstkc, div, (prstkc+ div) divided by sale, respectively. Alternatively, payouts are scaled by the firm's market value of equity ((csho * prcc_f)+ dlc + dltt + pstkl - txditc). According to Chay and Suh, 2009, cash flow uncertainty plays a significant role in payout policy; higher uncertainty leads to lower payout

[4]The monthly values are available at https//www.policyuncertainty.com.

[5]I report alternative measures of payout using market value of equity as a robustness check.

levels. Following their approach, I proxy for cash flow uncertainty by measuring the standard deviation of the last 12 monthly stock returns. Other standard control variables include firm size (log(at)), Market-to-book ratio, Free cash flow (FCF), Leverage Ratio, ROA, Cash Holdings, Retained Earnings, Equity Ratio, and the natural log of sales growth ($\ln(\frac{sale}{sale_{t-1}} + 1)$).

The variables of interest include measures of economic policy uncertainty (EPU) covering specific areas of policies, mainly monetary and fiscal policies. The categorical EPU index provided by Baker et al., 2016 is based only on news data, and adds additional restrictions on the terms depending on each category. For example, articles that fulfill the requirements to be categorized in the EPU and also contain the term 'federal reserve' would be included in the monetary policy uncertainty (MPU) sub-index. The categories examined in this article includes the main EPU index, Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Tax Policy Uncertainty (TPU), Government Spending Policy Uncertainty (GSU), and Healthcare Policy Uncertainty (HPU). To measure each firm-year's exposure to these sub-categories, I average the past 12 months of the EPU index (and the subcategories separately) leading to the date of the financial statement report.

Finally, I supplement the sample with variables that proxy for other macro-level uncertainties. Following Gulen and Ion, 2016, I use the Michigan Consumer Confidence Index[6] (CCI) to proxy for the overall level of confidence in the economy. To control for political uncertainty, I obtain data on political party votes[7] and estimate the level of political polarization among government representatives in the senate and the house of representatives (Political Polarization). The degree of polariza-

[6]The index measures consumers' level of expectation regarding future economic conditions. The index can be obtained from https://www.sca.isr.umich.edu.

[7]Data is obtained from https://voteview.com/.

tion is estimated using the method proposed by Lewis and Poole, 2004. I average the two polarization indices for each chamber (House of Representatives and the Senate) during each period. Additionally, I control for economic uncertainty using the average analyst dispersion on future GDP forecasts from the Federal Reserve Bank of Philadelphia (GDP Forecast Dispersion). Specifically, I estimate the average dispersion between the 25th and 75th percentile of forecasts for the next 4 quarters during the quarter time t. The final sample includes roughly 120,000 firm-year observations for 7,350 firms between calendar years 1985 and 2019. Table 3.1 reports the summary statistics for the final sample. The virtually all the variables reported follow distributions found in other empirical works in the literature (Chay and Suh, 2009; Cuny and Martin, Gerald S. Puthenpurackal, 2009; Fenn and Liang, 2001; Grullon and Michaely, 2002).

3.4.1 Time Trends

Figures 3.1 and 3.2 depicts the time trend for the cross-sectional mean of the two components of corporate payout and the rolling 12-month average of the EPU index and its subcategories from 1985 to 2019. At first glance, both payout policies seem to have a negative correlation with the EPU and its subcategories. Note, however, that both the index and corporate payouts (especially dividends) follow a cyclical pattern across time. The cyclicality pattern in the EPU index is arguably due to increase news coverage around routine government agency meetings or reports, such as the Federal Reserve report. The cross-sectional average of dividends tend to have consistent spikes around the third quarter of each calendar year. Thus, firms reporting their fiscal year statements during the third quarter tend to have relatively higher dividends than firms reporting their statements during other periods. The main highlight from these figures is that seasonality is an important component in both the EPU index and corporate payouts, and one needs to control for the seasonality effect.

3.5 Empirical Analysis

3.5.1 Corporate Payout and Economic Policy Uncertainty

To examine the effects of economic policy uncertainty on corporate payout, I start with the baseline panel OLS estimation taking the form:

$$Payout_{i,t} = \alpha_i + \beta Log(Uncer.)_{i,t-1} + \gamma' X_{t-1} + \delta' Y_{t-1} + \kappa_j + \nu_z + \epsilon_{i,t} \tag{3.1}$$

Where $Payout_{i,t}$ is firm i's payout ratio multiplied by 100 for fiscal year t. X_{t-1} is a vector of control variables commonly used in the payout literature (Chay and Suh, 2009; Cuny and Martin, Gerald S. Puthenpurackal, 2009; Fenn and Liang, 2001; Grullon and Michaely, 2002) lagged by one period. Y_{t-1} is a vector of macro-level uncertainties, mainly the GDP Forecast Dispersion level and the Consumer Confidence Index. α_i is a firm fixed effect, κ_j is an industry fixed effect, and ν_z is a quarter fixed effect for firm i's report date since payouts tend to have a seasonal component; see figures 3.1 and 3.2. The coefficient of interest is β, which estimates the effect of EPU (or its subcategories) on corporate payout.

Table 3.2 reports the results using the main EPU index when estimating dividends, share repurchases, and total payout. Most of the control variables have their expected signs across the different specifications. The coefficient of interest is negative and statistically significant for share repurchases and total payout, while the estimation model for dividends in column 3 suggests no significant relation. In economic terms, a 1 standard deviation change (27.36) in the EPU index from the sample mean (97.59) is related to roughly 1.91% decrease in share repurchases or 3.63% in total payout. The results in column 3 contrasts the findings documented by Attig et al., 2021. Two potential factors may explain why the results could be different when using the U.S. sample. First, the overall level of managerial agency costs in the U.S. are relatively lower compared to the rest of the world due to the relatively higher levels of investor protection, and thus, dividend effectiveness in mitigating agency costs is higher (La Porta et al., 2000). As such, the net benefit of preserving internally generated cash during periods of economic uncertainty outweighs the increased agency costs of free cash flow. Second, the different taxation rates between capital appreciation and income during the sample period may have an influence on the effect of EPU on payout policy in general.

Table 3.3 reports the results using the subcategories of the EPU index. Panels B through E suggests that the negative effect of EPU on share repurchases comes primarily from fiscal policy uncertainties (i.e., taxation and government spending), while dividends respond negatively mainly from monetary policy uncertainties. Share repurchases is a managerial discretion choice, and thus, there is no commitment from managers on the level of payout compared to dividends. The results from table 3.3 suggests that firms withhold funds used for share repurchases when fiscal policy uncertainty arises as appose to monetary policy uncertainties. Perhaps view fiscal uncertainties to be temporary while monetary policy uncertainties have a lasting effect on firm fundamentals, such as the cost of capital (Pástor and Veronesi, 2012, 2013). Table 3.4 replicates table 3.3 while using the market value of equity as the denominator instead of total sales. Consistent with the previous estimates, share repurchases remains negative and statistically significant at the 1% level. Taken together, increases in economic policy uncertainty leads to lower share repurchases, and the effect is more pronounced with uncertainties related to fiscal policy compared to monetary ones.

3.5.2 The Capital Constraints Channel

Results from the previous section suggest that internally generated funds become more valuable during periods of elevated EPU. If such a relation exists, then the effect of EPU and its subcategories on corporate payout should be more pronounced among firms that have higher barriers accessing external capital markets. Thus, in this section I test whether the effect of EPU is larger among firms that have relatively high capital constraints. Following Hadlock and Pierce, 2010, I first estimate a capital constraint score (SA Index) for each firm-year calculated as $(-0.737 \times Size) + (0.043 \times Size^2) - (0.04 \times Age))$. Size is the natural log of total assets adjusted to 2004 dollars and capped at \$4.5 billion. Age is the number of years the firm is in the Compustat universe with non missing equity price if the IPO date is missing. Otherwise, age is the number of years since the IPO year, and capped at 37. A firm is categorized to be capitally constrained if the SA index is lower than the yearly median[8]. I then re-estimate equation 3.1 on the two subsamples. Tables 3.5 and 3.6 report the results for all three payout policies using the EPU subcategories. The results are consistent with the increase value of internally generated funds following heightened episodes of fiscal policy uncertainty. Interestingly, higher levels of monetary policy uncertainty lead unconstrained firms to increase share buybacks and constrained firms to decrease dividends.

[8]Using the yearly mean yields similar results.

3.6 Robustness

3.6.1 Endogeneity

Uncertainty levels in economic policy can be the result of other factors in the economy that also affect corporate payouts. To alleviate endogeneity concerns from my analysis, I estimate a 2 Stage Least Squares regression. The first stage estimates the level of EPU due to exogenous changes in the political environment, and the second stage estimates firm payouts using the predicted value from the first stage. Exogenous changes in the political environment are proxied by the level of political polarization. Specifically, The degree of polarization is measured using the method proposed by Lewis and Poole, 2004. I average the two polarization indices for each chamber (House of Representatives and the Senate) during each period. Thus, the following regressions are estimated:

$$\begin{aligned} Log(Index)_{i,t} = \alpha_i + \gamma^{'} X_{t-1} + \delta^{'} Y_{t-1} \\ + \kappa_j + \nu_z + \epsilon_{i,t} \end{aligned} \tag{3.2}$$

and the second stage takes the form:

$$\begin{aligned} Payout_{i,t,j,z} = \alpha_i + \beta \widehat{Log(Index)}_{i,t} \\ + \gamma^{'} X_{t-1} + \delta^{'} Y_{t-1} \\ + \kappa_j + \nu_z + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

Table 3.7 report the results for the second stage regressions. The effect of EPU on payout policy is negative and more pronounced across the three different payout methods.

3.7 Concluding Remarks

Investors' confidence in being able to predict future economic policy changes are essential to maintain growth and flow of capital to the firm, especially fiscal policy. In this paper, I find evidence of a negative effect of economic policy uncertainty on corporate payouts. The effect is more pronounced on share buybacks, and capitally constrained firms. The results suggest that uncertainties related to future government spending may have a negative effect by creating capital frictions, and thus, firms that have potential growth are restricted to only internally generated cash flows. Future tests examining the relation between changes in uncertainties and cash levels on balance sheet may provide an additional insight to how payout policy decisions are made with relation to cash levels at the firm, and therefore, add a deeper understanding of corporate behavior during episodes of fiscal and monetary uncertainties.

Tables and Figures

Table 3.1: Descriptive Statistics

	SD	Mean	Min	Median	Max	N
Payout Variables:						
DIV_SALE	0.03	0.01	0.00	0.00	0.19	153,091
REPUR_SALE	0.05	0.02	0.00	0.00	0.31	143,749
TOTAL_PAY_SALE	0.07	0.03	0.00	0.00	0.42	143,749
DIV_MVE	0.02	0.01	0.00	0.00	0.11	152,933
REPUR_MVE	0.03	0.01	0.00	0.00	0.22	143,535
TOTAL_PAY_MVE	0.05	0.02	0.00	0.00	0.27	143,535
EPU & EPU Sub-indices:						
Log(EPU)	0.29	4.54	4.03	4.53	4.99	134,915
Log(MPU)	0.35	4.47	3.68	4.53	5.13	134,915
Log(FPU)	0.43	4.52	3.73	4.58	5.31	134,915
Log(TPU)	0.41	4.53	3.70	4.50	5.35	134,915
Log(GSU)	0.64	4.42	3.04	4.44	5.50	134,915
Log(HPU)	0.53	4.57	3.63	4.60	5.67	134,915
Firm Chrs.:						
ROA	0.22	-0.03	-1.23	0.03	0.25	137,690
FCF	0.21	0.00	-1.03	0.05	0.33	136,090
LEV	0.21	0.27	0.00	0.24	0.97	118,976
Market-to-Book	1.59	1.66	0.27	1.13	10.03	132,736
CASH	0.20	0.17	0.00	0.09	0.88	136,895
RET_EARN	3.95	-0.74	-27.81	0.34	1.83	130,989
EQUITY_RATIO	0.22	0.52	0.04	0.51	0.94	132,384
SGR	0.21	0.76	0.25	0.74	1.88	137,695
SIZE	2.26	5.29	0.78	5.15	10.87	137,349
$\sigma(RETURNS)$	0.10	0.17	0.04	0.14	0.58	107,908
Measures of Uncertainty:						
CCI	11.60	87.80	62.32	90.79	108.16	153,639
Political Polarization	0.07	0.71	0.59	0.72	0.85	153,639
GDP Forecast Dispersion	0.57	1.42	0.77	1.28	3.43	153,639

This table reports the descriptive statistics for the final sample used to examine corporate payouts following changes in economic policy uncertainty.DIV_SALE is dividends over total sales (dvc/sale). REPUR_SALE is total share buybacks during the fiscal year over total sales (prstkc / sale). TOTAL_PAY_SALE is the sum of DIV_SALE and REPUR_SALE. DIV_MVE is dividends over the market value of equity (dvc/mve), where mve is the sum of ((csho * prcc_f)+ dlc + dltt+ pstkl - txditc). REPUR_MVE is total share buybacks during the fiscal year over market value of equity (prstkc / mve). TOTAL_PAY_MVE is the sum of DIV_MVE and REPUR_MVE. Log(EPU) is the natural log of the firm's exposure to the EPU index, measured as the 12-month average of the monthly EPU index leading to the date of the financial report. The EPU index and its subcategories (Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Tax Policy Uncertainty (TPU), Government Spending Policy Uncertainty (GSU), and Healthcare Policy Uncertainty (HPU)) are developed by Baker et al., 2016. Size is Ln(at). ROA is (ib / at). FCF is the firm's free cash flow estimate ((oibdp - capx) / at). RET_EARN is the level of retained earnings over common equity (re/ceq). LEV is book leverage ((dlc + dltt) at). CASH is (che /at). EQUITY_RATIO is (ceq/at). SGR is the log of sales growth (Log(sale/ $sale_{t-1}$)). $\sigma(RETURNS)$ is the standard deviation of the firm's monthly returns using the last 12 months. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile.

Table 3.2: Corporate Payout and EPU

	Total Payout		Dividends	Share Repurchases
	(1)	(2)	(3)	(4)
Log(EPU)	-1.01***	-0.67***	-0.07	-0.53***
	(-14.77)	(-5.20)	(-1.61)	(-5.33)
ROA		1.17***	0.24**	0.60***
		(4.12)	(2.57)	(2.83)
FCF		0.69**	0.29**	0.61***
		(2.14)	(2.43)	(2.64)
LEV		-1.47***	-0.46***	-1.12***
		(-3.20)	(-2.87)	(-3.23)
Market-to-Book		0.11***	0.03*	0.09***
		(3.06)	(1.96)	(3.19)
CASH		3.33***	0.64***	2.18***
		(8.66)	(5.30)	(7.47)
RET_EARN		-0.06***	-0.02***	-0.04***
		(-5.31)	(-6.24)	(-4.51)
EQUITY_RATIO		1.59***	0.37**	0.86**
		(3.45)	(2.38)	(2.55)
SGR		-1.30***	-0.25***	-0.88***
		(-8.86)	(-7.25)	(-7.93)
SIZE		0.91***	0.16***	0.72***
		(15.11)	(7.65)	(15.80)
$\sigma(RETURNS)$		-2.07***	-0.69***	-1.22***
		(-6.17)	(-6.50)	(-4.84)
CCI		-0.00	-0.01***	0.01**
		(-0.01)	(-4.54)	(2.55)
GDP Forecast Dispersion		0.17**	-0.10***	0.25***
		(2.06)	(-2.94)	(3.99)
Constant	7.80***	0.63	1.09***	-0.63
	(23.95)	(0.63)	(3.10)	(-0.84)
Observations	125372	59776	64422	59776
Firm, Ind. & Quarter FE		Yes	Yes	Yes
No. Firms	14,131	7,350	7,666	7,350
R-squared	0.00	0.37	0.56	0.29

This table reports the Panel OLS regression results from estimating equation 3.1. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by total sales. Log(EPU) is the natural log of the 12-monthly average of the EPU index leading to the date of the financial report. The EPU index is developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are clustered at the firm level. * p < 0.1, ** p < 0.05, *** p < 0.01. T-statistics in parentheses.

Table 3.3: Corporate Payout and EPU Sub-categories (Scaled by total sales)

	Total Pay	Div.	Shr. Repur.
Log(MPU)	-0.09	-0.19***	0.06
	(-1.13)	(-6.51)	(1.02)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.37	0.56	0.29
		Panel (B)	
Log(FPU)	-0.45***	-0.02	-0.39***
	(-5.32)	(-0.55)	(-6.00)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.37	0.56	0.29
		Panel (C)	
Log(TPU)	-0.49***	-0.04	-0.41***
	(-5.99)	(-1.32)	(-6.45)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.37	0.56	0.29
		Panel (D)	
Log(GSU)	-0.27***	0.01	-0.25***
	(-4.61)	(0.44)	(-5.68)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.37	0.56	0.29
		Panel (E)	
Log(HPU)	-0.83***	-0.08***	-0.68***
	(-10.43)	(-2.93)	(-11.03)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.37	0.56	0.29

This table reports the Panel OLS regression results from estimating equation 3.1. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by total sales. Log(EPU) is the natural log of the firm's exposure to the EPU index, measured as the 12-month average of the monthly EPU index leading to the date of the financial report. The EPU index and its subcategories (Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Tax Policy Uncertainty (TPU), Government Spending Policy Uncertainty (GSU), and Healthcare Policy Uncertainty (HPU)) are developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 3.4: Corporate Payout and EPU Sub-categories (Scaled by equity)

	Total Pay	Div.	Shr. Repur.
Log(MPU)	0.37***	-0.02	0.34***
	(6.03)	(-1.01)	(6.85)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.22	0.50	0.16

		Panel (B)	
Log(FPU)	-0.28***	0.02	-0.28***
	(-4.86)	(1.05)	(-6.08)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.22	0.50	0.16

		Panel (C)	
Log(TPU)	-0.31***	0.01	-0.30***
	(-5.41)	(0.38)	(-6.51)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.22	0.50	0.16

		Panel (D)	
Log(GSU)	-0.20***	0.01	-0.19***
	(-4.94)	(0.75)	(-5.93)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.22	0.50	0.16

		Panel (E)	
Log(HPU)	-0.60***	-0.07***	-0.47***
	(-10.75)	(-3.81)	(-10.66)
Controls	Yes	Yes	Yes
Firm, Industry, and Quarter FE	Yes	Yes	Yes
R-squared	0.22	0.50	0.16

This table reports the Panel OLS regression results from estimating equation 3.1. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by the market value of equity. Log(EPU) is the natural log of the firm's exposure to the EPU index, measured as the 12-month average of the monthly EPU index leading to the date of the financial report. The EPU index and its subcategories (Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Tax Policy Uncertainty (TPU), Government Spending Policy Uncertainty (GSU), and Healthcare Policy Uncertainty (HPU)) are developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 3.5: Corporate Payout and EPU (By Level of Capital Constraints)

	Low Capital Constraints			High Capital Constraints		
	Total	Div.	Shr. Repr.	Total	Div.	Shr. Repr.
Log(EPU)	0.23	0.05	0.10	-1.59***	-0.14*	-1.28***
	(1.54)	(1.19)	(0.89)	(-7.34)	(-1.65)	(-7.65)
Observations	27126	29803	27126	23645	25325	23645
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Firms	4,220	4,479	4,220	3,055	3,189	3,055
R-squared	0.31	0.44	0.26	0.46	0.63	0.37

This table reports the Panel OLS regression results from estimating equation 3.1 using subsamples based on the firm's capital constraint score (SA) developed by Hadlock and Pierce, 2010. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by total sales. Log(EPU) is the natural log of the 12-monthly average of the EPU index leading to the date of the financial report. The EPU index is developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

Table 3.6: Corporate Payout and EPU (By Level of Capital Constraints)

	Low Capital Constraints			High Capital Constraints		
	Total	Div.	Shr. Repr.	Total	Div.	Shr. Repr.
Log(MPU)	0.34***	-0.05	0.32***	-0.31**	-0.25***	-0.11
	(3.31)	(-1.48)	(3.92)	(-2.37)	(-4.76)	(-1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.44	0.26	0.45	0.63	0.37
			Panel (B)			
Log(FPU)	0.06	0.06**	-0.06	-1.23***	-0.12**	-0.98***
	(0.62)	(2.05)	(-0.73)	(-8.39)	(-2.20)	(-8.60)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.44	0.26	0.46	0.63	0.37
			Panel (C)			
Log(TPU)	0.04	0.06*	-0.07	-1.22***	-0.13**	-0.97***
	(0.41)	(1.85)	(-0.88)	(-8.50)	(-2.41)	(-8.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.44	0.26	0.46	0.63	0.37
			Panel (D)			
Log(GSU)	0.07	0.05**	-0.03	-0.84***	-0.08*	-0.67***
	(1.01)	(2.42)	(-0.53)	(-8.24)	(-1.90)	(-8.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.44	0.26	0.46	0.63	0.37
			Panel (E)			
Log(HPU)	-0.24***	0.04	-0.29***	-1.33***	-0.10*	-1.10***
	(-2.71)	(1.33)	(-4.18)	(-9.77)	(-1.93)	(-10.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.31	0.44	0.26	0.46	0.63	0.37

This table reports the Panel OLS regression results from estimating equation 3.1 using subsamples based on the firm's capital constraint score (SA) developed by Hadlock and Pierce, 2010. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by total sales. The EPU index and its subcategories are developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1st and 99th percentile. Error terms are clustered at the firm level. * p < 0.1, ** p < 0.05, *** p < 0.01. T-statistics in parentheses.

Table 3.7: Corporate Payout and EPU (S2LS)

	(1) Total Payout	(2) Dividends	(3) Share Repurchases
Log(EPU)	-13.07***	-9.47***	-4.85*
	(-3.50)	(-4.47)	(-1.94)
Observations	59378	63992	59378
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
No. Firms	7,312	7,631	7,312

This table reports the second stage regression estimates using equations 3.2 and 3.3. Dependent variables are corporate payouts (Total, dividends, and share repurchases) scaled by total sales. Log(EPU) is the natural log of the firm's exposure to the EPU index, measured as the 12-month average of the monthly EPU index leading to the date of the financial report. The EPU index and its subcategories (Monetary Policy Uncertainty (MPU), Fiscal Policy Uncertainty (FPU), Tax Policy Uncertainty (TPU), Government Spending Policy Uncertainty (GSU), and Healthcare Policy Uncertainty (HPU)) are developed by Baker et al., 2016. See section 3.4 for further details on all variable definitions. All independent variables are lagged one period. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentile. Error terms are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics in parentheses.

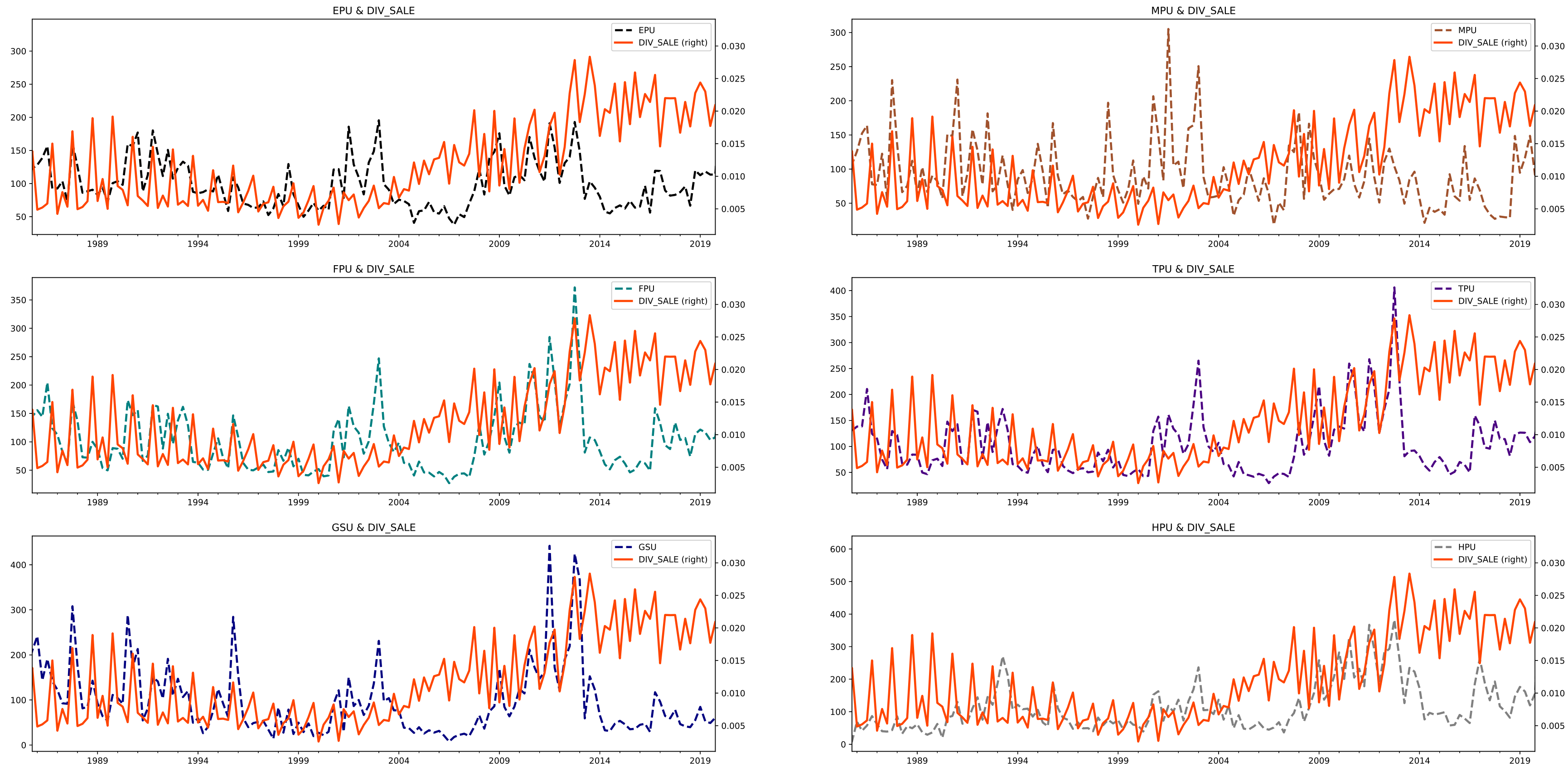

Figure 3.1: Cross-sectional Average Dividend Payout and Economic Policy Uncertainty (1985-2019)

This figure presents the time trend for the cross-sectional average of dividend payout (divided by total revenue) for a given quarter and the various subcategories of the Economic Policy Uncertainty Index (EPU). EPU and its subcategories are obtained from Baker et al., 2016. Dividend payout ratio is measured as total dividends declared for the fiscal year over total sales (DVC / SALE). The data covers the period from January 1985 to the end of November 2019.

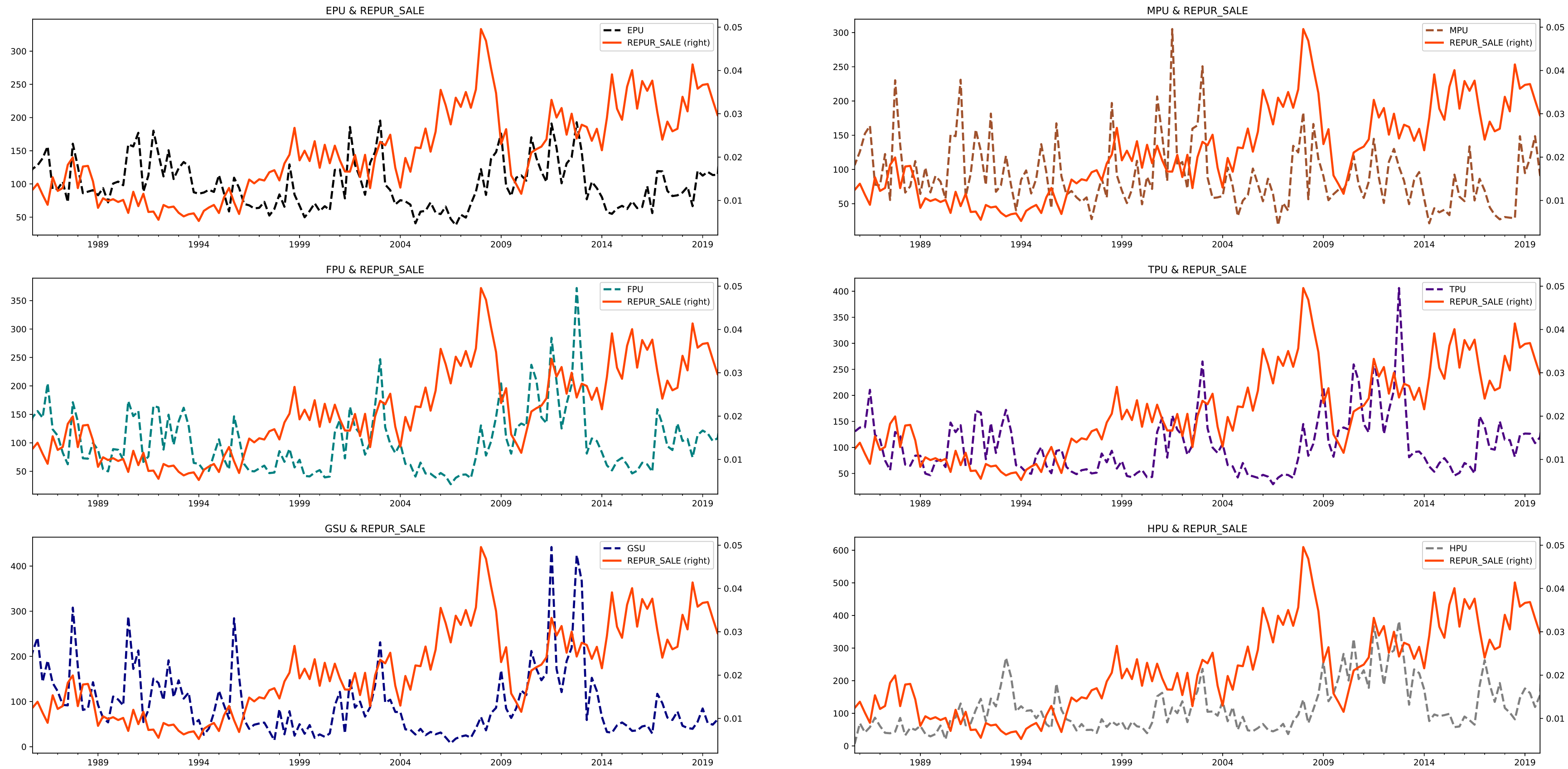

Figure 3.2: Cross-sectional Average Share Repurchases and Economic Policy Uncertainty (1985-2019)

This figure presents the time trend for the cross-sectional average of share repurchases for a given quarter and the various subcategories of the Economic Policy Uncertainty Index (EPU). EPU and its subcategories are obtained from Baker et al., 2016. Share buyback ratio is measured as the total shares repurchased for the fiscal year over total sales (PRSTK / SALE). The data covers the period from January 1985 to the end of November 2019.

Bibliography

Abel, A. B., & Blanchard, O. J. (1986). Investment and Sales: Some Empirical Evidence. *National Bureau of Economic Research*.

Adam, T., & Goyal, V. K. (2008). The investment opportunity set and its proxy variables. *Journal of Financial Research*, *31*(1), 41–63. https://doi.org/10.1111/j.1475-6803.2008.00231.x

Admati, A. R., Demarzo, P. M., Hellwig, M. F., & Pfleiderer, P. (2018). The Leverage Ratchet Effect. *Journal of Finance*, *73*(1), 145–198. https://doi.org/10.1111/jofi.12588

Arnott, R., Greenwald, B., & Stiglitz, J. E. (1994). Information and Economic Efficiency. *Information Economics and Policy*, *6*(1), 77–82.

Attig, N., El Ghoul, S., Guedhami, O., & Zheng, X. (2021). Dividends and economic policy uncertainty: International evidence. *Journal of Corporate Finance*, *66*(March 2019), 101785. https://doi.org/10.1016/j.jcorpfin.2020.101785

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.3386/w21633

Barclay, M. J., & Smith, C. W. (1995). The Maturity Structure of Corporate Debt. *The Journal of Finance*, *50*(2), 609–631.

Barnea, A., Haugen, R. A., & Senbet, L. W. (1980). A Rationale for Debt Maturity Structure and Call Provisions in the Agency Theoretic Framework. *The Journal of Finance*, *35*(5), 1223–1234.

Barrero, J. M., Bloom, N., & Davis, S. J. (2021). *Why Working From Home Will Stick*. https://doi.org/http://dx.doi.org/10.2139/ssrn.3741644

Bartlett, R., & Partnoy, F. (2020). The Misuse of Tobin ' s Q. *Vanderbilt Law Review*, *73*(2), 353–424.

Becker, B., Campello, M., Thell, V., & Yan, D. (2018). Debt Overhang and the Life Cycle of Callable Bonds. *SSRN Electronic Journal*, (December). https://doi.org/10.2139/ssrn.3302502

Bens, D. A., Berger, P. G., & Monahan, S. J. (2011). Discretionary disclosure in financial reporting: An examination comparing internal firm data to externally reported segment data. *Accounting Review*, *86*(2), 417–449. https://doi.org/10.2308/accr.00000019

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks. *Journal of Financial Economics*, *76*(2), 237–269. https://doi.org/10.1016/j.jfineco.2004.06.003

Berger, P. G., & Hann, R. N. (2007). Segment profitability and the proprietary and agency costs of disclosure. *Accounting Review*, *82*(4), 869–906. https://doi.org/10.2308/accr.2007.82.4.869

Berger, P. G., & Ofek, E. (1995). Diversification's Effect on Firm Value. *Journal of Financial Economics*, *37*(1), 39–65. https://doi.org/10.1016/0304-405X(94)00798-6

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, *98*(1), 85–106.

Bick, A., Blandin, A., & Mertens, K. (2021). Work From Home Before and After the COVID-19 Outbreak. *Working Paper*.

Billett, M. T., King, T. H. D., & Mauer, D. C. (2007). Growth opportunities and the choice of leverage, debt maturity, and covenants. *The Journal of Finance*, *62*(2), 697–730. https://doi.org/10.1111/j.1540-6261.2007.01221.x

Blei, D. M., Mcauliffe, J. D., & Mar, M. L. (2010). Supervised Topic Models, 1–22.

Bloom, N. (2014). Fluctuations in Uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–176. https://doi.org/10.1257/jep.28.2.153

Bloom, N., Davis, S. J., & Zhestkova, Y. (2021). COVID-19 Shifted Patent Applications toward Technologies that Support Working from Home. *Working Paper*.

Brav, A., Graham, J. R., Harvey, C. R., & Michaely, R. (2005). Payout Policy in the 21st Century. *Journal of Financial Economics*, *77*(3), 483–527. https://doi.org/10.1016/j.jfineco.2004.07.004

Brown, S., & Powers, E. (2020). The life cycle of make-whole call provisions. *Journal of Corporate Finance*, *65*(October), 101772. https://doi.org/10.1016/j.jcorpfin.2020.101772

Chava, S., & Roberts, M. R. (2008). How Does Financing Impact Investment? The Role of Debt Covenants. *The Journal of Finance*, *63*(5), 2085–2121. https://doi.org/10.1111/j.1540-6261.2008.01391.x

Chay, J.-B., & Suh, J. (2009). Payout Policy and Cash-flow Uncertainty. *Journal of Financial Economics*, *93*(1), 88–107.

Chen, H., Xu, Y., & Yang, J. (2021). Systematic risk, debt maturity, and the term structure of credit spreads. *Journal of Financial Economics*, *139*(3), 770–799. https://doi.org/10.1016/j.jfineco.2020.09.002

Childs, P. D., Mauer, D. C., & Ott, S. H. (2005). Interactions of corporate financing and investment decisions: The effects of agency conflicts. *Journal of Financial Economics*, *76*(3), 667–690. https://doi.org/10.1016/j.jfineco.2004.06.012

Choi, J., Hackbarth, D., & Zechner, J. (2018). Corporate debt maturity profiles. *Journal of Financial Economics*, *130*(3), 484–502. https://doi.org/10.1016/j.jfineco.2018.07.009

Choi, J., Hackbarth, D., & Zechner, J. (2020). *Granularity of Corporate Debt*. https://doi.org/10.1017/S0022109020000149

Coles, J. L., Daniel, N. D., & Naveen, L. (2008). Boards: Does One Size Fit All? *Journal of Financial Economics*, *87*(2), 329–356. https://doi.org/10.1016/j.jfineco.2006.08.008

Cuny, C. J., & Martin, Gerald S. Puthenpurackal, J. J. (2009). Stock Options and Total Payout. *Journal of Financial and Quantitative Analysis*, *44*(2), 391–410.

Custódio, C., Ferreira, M. A., & Laureano, L. (2013). Why are US firms using more short-term debt? *Journal of Financial Economics*, *108*, 182–212. https://doi.org/10.1016/j.jfineco.2012.10.009

Datta, S., Doan, T., & Toscano, F. (2021). Top executive gender, board gender diversity, and financing decisions: Evidence from debt structure choice. *Journal of Banking and Finance*, *125*, 106070. https://doi.org/10.1016/j.jbankfin.2021.106070

Datta, S., Iskandar-Datta, M., & Raman, K. (2005). Managerial stock ownership and the maturity structure of corporate debt. *The Journal of Finance*, *60*(5), 2333–2350. https://doi.org/10.1111/j.1540-6261.2005.00800.x

Davis, S. J., Hansen, S., & Seminario-Amez, C. (2021). Firm-level Risk Exposures and Stock Returns in The Wake of COVID-19. *Working Paper*. https://doi.org/10.3386/w27867

Diamond, D. W. (1991). Debt Maturity Structure and Liquidity Risk. *The Quarterly Journal of Economics*, *106*(3), 709–737.

Diamond, D. W., & He, Z. (2014). A Theory of Debt Maturity : The Long and Short of Debt Overhang. *The Journal of Finance*, *69*(2), 719–762.

Dixit, A. K., Pindyck, R. S., & Davis, G. A. (1996). Investment Under Uncertainty. *Resources Policy*, *22*(3), 217.

Easterbrook, F. H. (1984). Two Agency-cost Explanations of Dividends. *American Economic Review*, *74*(4), 650. https://doi.org/10.2307/1805130

Ewens, M., Peters, R., & Wang, S. (2021). *Measuring Intangible Capital with Market Prices*. https://doi.org/10.31235/osf.io/kvp2f

Fenn, G. W., & Liang, N. (2001). Corporate Payout Policy and Managerial Stock Incentives. *Journal of Financial Economics*, *60*(1), 45–72.

Flannery, M. J. (1986). Asymmetric Information and Risky Debt Maturity Choice. *The Journal of Finance*, *41*(1), 19–37. https://doi.org/https://doi.org/10.1111/j.1540-6261.1986.tb04489.x

Franco, F., Urcan, O., & Vasvari, F. P. (2016). Corporate diversification and the cost of debt: The role of segment disclosures. *Accounting Review*, *91*(4), 1139–1165. https://doi.org/10.2308/accr-51325

Gilchrist, S., & Zakrajsek, E. (2007). Investment and the Cost of Capital: New Evidence from the Corporate Bond Market. *National Bureau of Economic Research*.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, *118*(1), 107–155. https://doi.org/10.1162/00335530360535162

Grossman, S., & Hart, O. (1982). Corporate Financial Structure and Managerial Incentives. *The Economics of Information and Uncertainty*, 107–140.

Grullon, G., & Michaely, R. (2002). Dividends , Share Repurchases , and the Substitution Hypothesis. *The Journal of Finance*, *57*(4), 1649–1684.

Gulen, H., & Ion, M. (2016). Policy Uncertainty and Corporate Investment. *Review of Financial Studies*, *29*(3), 523–564. https://doi.org/10.1093/rfs/hhv050

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, *23*(5), 1909–1940. https://doi.org/10.1093/rfs/hhq009

Harford, J., Klasa, S., & Maxwell, W. F. (2014). Refinancing Risk and Cash Holdings. *The Journal of Finance*, *69*(3), 975–1012.

Jens, C. E. (2017). Political Uncertainty and Investment: Causal Evidence from US Gubernatorial Elections. *Journal of Financial Economics*, *124*(3), 563–579.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *American Economic Review*, *76*(2), 323–329. https://doi.org/10.2139/ssrn.99580

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/https://doi.org/10.1016/0304-405X(76)90026-X

Johnson, S. A. (2003). Debt Maturity and the Effects of Growth Opportunities and Liquidity Risk on Leverage. *Review of Financial Studies*, *16*(1), 209–236. https://doi.org/10.1093/rfs/16.1.0209

Kaplan, S. N., & Zingales, L. (1995). Do financing constraints explain why investment is correlated with cash flow? *National Bureau of Economic Research*.

Khanna, T., & Palepu, K. (2000). The Future of Business Groups in Emerging Markets : Long-Run Evidence from Chile. *The Academy of Management Journal*, *43*(3), 268–285. https://doi.org/https://www.jstor.org/stable/1556395

Kolasinski, A. C. (2009). Subsidiary debt, capital structure and internal capital markets. *Journal of Financial Economics*, *94*(2), 327–343. https://doi.org/10.1016/j.jfineco.2008.12.005

La Porta, R., Lopez-De-Silanes, F., Shleifer, A., & Vishny, R. W. (2000). Agency Problems and Dividend Policies around the World. *The Journal of Finance*, *55*(1), 1–33. https://doi.org/10.1111/0022-1082.00199

Lamont, O. (1997). Cash flow and investment: Evidence from internal capital markets. *The Journal of Finance*, *52*(1), 83–109. https://doi.org/10.1111/j.1540-6261.1997.tb03809.x

Leland, H. E. (1994). Corporate Debt Value, Bond Covenants, and Optimal Capital Structure. *The Journal of Finance*, *49*(4), 1213–1252. https://doi.org/https://doi.org/10.1111/j.1540-6261.1994.tb02452.x

Lewis, J. B., & Poole, K. T. (2004). Measuring Bias and Uncertainty in Ideal Point Estimates via the Parametric Bootstrap. *Political Analysis*, *12*(2), 105–127. https://doi.org/10.1093/pan/mph015

Loughran, T., & Mcdonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Loughran, T., & Mcdonald, B. (2014). Measuring readability in financial disclosures. *Journal of Finance*, *69*(4), 1643–1671. https://doi.org/10.1111/jofi.12162

McDonald, R., & Siegel, D. (1986). The Value of Waiting to Invest. *The Quarterly Journal of Economics*, *101*(4), 707–727.

Miller, M. H., & Rock, K. (1985). Dividend Policy Under Asymmetric Information. *The Journal of Finance*, *40*(4), 1031–1051. https://doi.org/10.1111/j.1540-6261.1985.tb02362.x

Myers, S. C. (1977). Determinants of Corporate Borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/https://doi.org/10.1016/0304-405X(77)90015-0

Myers, S. C., & Majluf, N. S. (1984). Corporate Financing and Investment Decisions when Firms have Information that Investors do not have. *Journal of Financial Economics*, *13*(2), 187–221. https://doi.org/https://doi.org/10.1016/0304-405X(84)90023-0

Nagarajan, N. J., & Sridhar, S. S. (1996). Corporate responses to segment disclosure requirements. *Journal of Accounting and Economics*, *21*(2), 253–275. https://doi.org/10.1016/0165-4101(95)00419-X

Nini, G., Smith, D. C., & Sufi, A. (2009). Creditor control rights and firm investment policy. *Journal of Financial Economics*, *92*(3), 400–420. https://doi.org/10.1016/j.jfineco.2008.04.008

Olibe, K. O., Rezaee, Z., Flagg, J., & Ott, R. (2019). Corporate diversification, debt maturity structures and firm value: The role of geographic segment data. *Quarterly Review of Economics and Finance*, *74*, 206–219. https://doi.org/10.1016/j.qref.2019.01.011

Opler, T., Pinkowitz, L., Stulz, R. M., & Williamson, R. (1999). The Determinants and Implications of Corporate Cash Holdings. *Journal of Financial Economics*, *52*(1), 3–46. https://doi.org/https://doi.org/10.1016/S0304-405X(99)00003-3

Pástor, Ľ., & Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. *Journal of Finance*, *67*(4), 1219–1264. https://doi.org/10.1111/j.1540-6261.2012.01746.x

Pástor, Ľ., & Veronesi, P. (2013). Political Uncertainty and Risk Premia. *Journal of Financial Economics*, *110*(3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007

Peters, R. H., & Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, *123*(2), 251–272. https://doi.org/10.1016/j.jfineco.2016.03.011

Press, E., & Beneish, M. (1993). Costs of technical violation of accounting-based debt covenants. *Accounting review: A quarterly journal of the American Accounting Association*, *68*(2), 233–257.

Rajan, R. G., Servaes, H., & Zingales, L. (2000). The Cost of Diversity : The Diversification Discount and Inefficient Investment. *The Journal of Finance*, *55*(1).

Servaes, H. (1996). The Value of Diversification During the Conglomerate Merger Wave. *The Journal of Finance*, *51*(4), 1201–1225. https://doi.org/https://doi-org.pallas2.tcl.sc.edu/10.1111/j.1540-6261.1996.tb04067.x

Smith, C. W., & Warner, J. B. (1979). On financial contracting. An analysis of bond covenants. *Journal of Financial Economics*, *7*(2), 117–161. https://doi.org/10.1016/0304-405X(79)90011-4

Stein, L. C. D., & Wang, C. C. Y. (2016). Economic Uncertainty and Earnings Management. *Harvard Business School Working Paper*, 44. http://www.hbs.edu/faculty/Publication%20Files/16-103%7B%5C_%7D867157e3-f869-4c72-95be-b93ac3a37b2f.pdf

Stohs, M. H., & Mauer, D. C. (1996). The Determinants of Corporate Debt Maturity Structure. *The Journal of Business*, *69*(3), 279–312.

Taddy, M. (2013). Multinomial Inverse Regression for Text Analysis. *Journal of the American Statistical Association*, *108*(503), 755–770.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, *62*(3), 1139–1168. https://doi.org/10.1111/j.1540-6261.2007.01232.x

Titman, S., & Tsyplakov, S. (2007). A dynamic model of optimal capital structure. *Review of Finance*, *11*(3), 401–451. https://doi.org/10.1093/rof/rfm017

Wernerfelt, B., & Montgomery, C. A. (1988). Tobin's Q and the Importance of Focus in Firm Performance. *The American Economic Review*, *78*(1), 246–250. https://doi.org/https://www.jstor.org/stable/1814713

Xu, Z. (2020). Economic policy uncertainty, cost of capital, and corporate innovation. *Journal of Banking and Finance*, *111*, 105698. https://doi.org/10.1016/j.jbankfin.2019.105698

Yermack, D. (1996). Higher Market Valuation of Companies with a Small Board of Directors. *Journal of Financial Economics*, *40*(2), 185–211. https://doi.org/10.1016/0304-405X(95)00844-5

APPENDIX A

Supplemental Information

A.I Risk Factors & Exposures

Risk factors, and their associated terms, are obtained from Davis et al., 2021. They are copied from the appendix of their paper and listed here for reference:

1. Advertizing: ['advertisers', 'advertiser', 'audience', 'audiences', 'advertising', 'advertising revenue', 'digital media', 'marketers', 'advertising expenditures']

2. Alternative Energy: ['biodiesel', 'ethanol', 'fuels', 'corn', 'biomass', 'diesel', 'biofuels', 'alternative fuel', 'alternative energy sources', 'renewable']

3. Card Payments: ['card', 'cards', 'credit card', 'visa', 'mastercard', 'debit', 'merchant', 'merchants', 'credit cards', 'cardholder', 'card issuers', 'card transactions', 'cardholders', 'atm', 'american express', 'electronic payment', 'interchange', 'payment services', 'pos', 'check', 'gift', 'interchange fees', 'pci', 'atms', 'point of sale']

4. Clearing Houses: ['clearing house', 'clearing', 'futures']

5. Commercial Property: ['hotels', 'hotel properties', 'hotel', 'properties', 'resorts', 'retail properties', 'property', 'such properties', 'shopping centers', 'commercial property', 'rooms', 'new properties', 'land parcels', 'such property', 'real properties', 'other properties', 'suites', 'management companies']

6. Display Technology: ['display', 'displays', 'format', 'digital', 'signage', 'displayed', 'screens', 'navigation', 'ads', 'interactive', 'radar', 'video', 'film', 'multimedia', 'cameras', 'films']

7. Financial Management: ['unrealized loss position', 'unrealized losses', 'fixed maturity securities', 'unrealized loss', 'fixed maturity', 'unrealized', 'investment portfolio', 'otti', 'fixed income

securities', 'temporary impairments', 'loss position', 'market value', 'fair value', 'decline in value', 'portfolio']

8. Foreign Exchange: ['yen', 'canadian dollar', 'british pound sterling', 'rupee', 'dollar value']

9. Franchising: ['franchisees', 'franchisee', 'franchise', 'franchisors', 'franchised', 'franchise agreements', 'landlords', 'lessees', 'franchisor', 'franchise agreement', 'tenants', 'franchising', 'anchor tenants']

10. Gambling: ['gaming', 'casino', 'slot', 'horse', 'native']

11. Gold & Silver: ['gold', 'silver']

12. Healthcare Providers: ['surgeons', 'hospitals', 'dentists', 'dental', 'clinics', 'pathology']

13. Insurance: ['reinsurance', 'reinsurers', 'reinsurance agreements', 'reinsurance', 'arrangements', 'ceded', 'reinsurance contracts', 'reinsured', 'reinsurer', 'commercial insurance', 'catastrophe', 'insurers', 'insurance policies', 'mortgage insurance', 'coverages', 'insurer', 'captive', 'insurance policy', 'insureds', 'cost of reinsurance', 'casualty', 'statutory surplus', 'insurance company', 'insurance operations']

14. Mortgages: ['mortgage', 'residential mortgage', 'mortgages', 'mortgage loan', 'commercial mortgage', 'certain mortgage', 'mortgage loans', 'other mortgage', 'residential mortgage loan', 'rmbs', 'loan', 'cmbs', 'mbs', 'abs', 'federal home loan mortgage corporation', 'ginnie mae', 'mortgage lending', 'federal national mortgage association', 'commercial mortgage loan', 'mortgage financing', 'other loans', 'subprime', 'securitized', 'first mortgage', 'such loans', 'first lien', 'agency securities', 'mortgage origination', 'securitization', 'mortgage market', 'originations', 'loan sales', 'origination', 'securitizations', 'asset', 'borrowers', 'mortgage banking', 'servicer', 'gse', 'backed', 'mortgaged', 'mortgage industry', 'federal housing administration', 'fha']

15. REITs: ['reit', 'ric', 'reits', 'reit status', 'reit qualification', 'taxable reit subsidiary', 'taxable reit subsidiaries', 'trss', 'gross income test', 'trs', 'bdc', 'reit income', 'internal revenue', 'income test', 'reit distribution', 'partnership', 'income tests', 'taxable years', 'qualify', 'asset tests', 'hedge accounting treatment', 'gross income tests', 'gross income', 'reit gross income', 'investment company', 'income tax', 'distribution requirement', 'taxable year', 'spin']

16. Residential Construction: ['homebuilding', 'residential construction', 'land development', 'housing']

17. Restaurants: [‘restaurants’, ‘restaurant’]

18. Traditional Retail: [‘retail’, ‘outlet’, ‘retail sales’, ‘retailers’, ‘specialty stores’, ‘convenience stores’, ‘automotive’, ‘department stores’, ‘retail business’, ‘retailer’, ‘furniture’, ‘beauty’, ‘retail outlets’, ‘retail operations’, ‘other retailers’, ‘new vehicle’, ‘shopping center’, ‘branded’, ‘club’, ‘casual’, ‘establishments’, ‘cosmetics’, ‘building products’, ‘upscale’, ‘retail space’, ‘recreational’]

19. Workforce: [‘workforces’, ’labor force’]

20. Aircraft & Airlines: [‘aircraft’, ‘commercial aircraft’, ‘boeing’, ‘flight’, ‘airlines’, ‘faa’, ‘jet’, ‘flights’, ‘fly’, ‘passenger’]

21. Travel: [‘travel’, ‘air travel’, ‘business travel’, ‘travelers’, ‘tourism’, ‘airline’, ‘vacation’, ‘airline industry’, ‘destinations’, ‘traveling’, ‘traffic’]

22. Communications: [‘satellite’, ‘satellites’, ‘cable’, ‘band’, ‘broadband’, ‘frequencies’, ‘cable television’, ‘signals’, ‘gateway’, ‘carriage’, ‘wireless broadband’, ‘wireline’, ‘gps’, ‘microwave’, ‘data communications’, ‘programming’, ‘station’, ‘spectrum’, ‘broadcasters’, ‘fcc’, ‘transmitter’, ‘voip’]

23. Traditional Media: [‘newspapers’, ‘newspaper’, ‘television’, ‘circulation’, ‘movie’, ‘outlets’, ‘publications’, ‘radio’, ‘other media’, ‘print’, ‘advertising revenues’, ‘news’, ‘publishing’, ‘tv’, ‘broadcast’, ‘entertainment’, ‘pages’, ‘los angeles’, ‘stations’, ‘hd’]

24. Energy Infrastructure: [‘pipelines’, ‘pipeline systems’, ‘pipeline’, ‘gathering systems’, ‘pipeline system’, ‘processing plants’, ‘storage tanks’, ‘processing facilities’, ‘terminals’, ‘storage facilities’, ‘gathering’, ‘refineries’, ‘gas pipeline’, ‘terminal’, ‘downstream’, ‘transmission facilities’, ‘gas processing’, ‘common carrier’, ‘gas gathering’, ‘fractionation’, ‘refinery’, ‘ferc’, ‘wells’, ‘transmission system’, ‘midstream’, ‘generation facilities’]

25. Oil & Gas: [‘oil’, ‘ngls’, ‘ngl’, ‘oils’, ‘liquids’, ‘natural gas’, ‘petroleum’, ‘hydrocarbon’, ‘hydrocarbons’, ‘marcellus shale’, ‘exploration’]

26. Drug Trials: [‘preclinical’, ‘nonclinical’, ‘preclinical studies’, ‘preclinical testing’, ‘preclinical development’, ‘clinical testing’, ‘clinical studies’, ‘clinical’, ‘clinical development programs’, ‘clinical trials’, ‘trials’, ‘toxicology’, ‘validation’, ‘clinical development’, ‘clinical data’, ‘development programs’, ‘confirmatory’, ‘trial results’, ‘clinical research’, ‘drug development’, ‘research and development’, ‘research programs’, ‘vivo’, ‘research’, ‘clinical trial’, ‘stage clinical

trials', 'investigator', 'clinical study', 'drug candidates', 'clinical trial results', 'vitro', 'efficacy', 'product candidates', 'progress', 'commercialization activities', 'commercial use', 'collaborative', 'drug candidate', 'submission', 'antibody', 'compounds', 'inconclusive', 'investigational']

27. E-commerce: ['ecommerce', 'e commerce', 'online', 'electronic commerce', 'direct marketing', 'payment processing', 'amazon', 'network', 'pc', 'pcs', 'website', 'online services']

28. Electronic Components & Devices: ['optics', 'optical', 'sensor', 'ray', 'filter', 'graphics', 'high performance', 'coating', 'electronic components', 'electronics', 'sensors', 'magnetic', 'chips', 'substrates', 'laser', 'micro', 'memory', 'analog', 'photovoltaic', 'fiber', 'coatings', 'thin', 'composites', 'logic', 'flash', 'chip', 'polymer', 'handheld', 'fibers', 'serial', 'surfaces', 'ir', 'lighting', 'industrial applications', 'boxes', 'glass', 'portable', 'cables', 'electrical', 'transformers', 'appliances', 'audio', 'printers', 'intel', 'tech', 'assemblies', 'biomedical', 'appliance', 'data storage', 'drives', 'valve', 'valves', 'peripheral', 'consumables', 'stack', 'industrial', 'hvac', 'matrix', 'power systems', 'wired', 'modular', 'phones', 'libraries', 'chamber', 'embedded', 'catalyst', 'reagents', 'batteries', 'plumbing', 'furnaces', 'bio', 'radiation', 'finishing', 'graphic']

29. Food: ['wheat', 'grains', 'sugar', 'fruit', 'milk', 'grain', 'coffee', 'dairy', 'protein', 'proteins', 'sodium', 'powder', 'wine', 'packaging materials', 'crops', 'foods', 'fresh', 'agricultural products', 'synthetic', 'additives', 'enzymes', 'salt', 'ingredients', 'specialty', 'additive', 'organic', 'ingredient']

30. Foreign Countries: ['china', 'india', 'taiwan', 'chinese', 'south africa', 'asia', 'russia', 'beijing', 'shanghai', 'hong kong', 'asia pacic region', 'united arab emirates', 'countries', 'the philippines', 'korea', 'chinas', 'mexico', 'western europe', 'egypt', 'switzerland', 'overseas', 'latin america', 'unitedstates', 'united kingdom', 'europe', 'belgium', 'asian', 'germany', 'singapore', 'france', 'ukraine', 'indonesia', 'norway', 'finland', 'asia pacific', 'japan', 'certain countries', 'iceland', 'japanese', 'sweden', 'operations in mexico', 'operations in china', 'north america', 'peru', 'korean', 'australia', 'dubai', 'world', 'european', 'thailand', 'european union', 'industrialized', 'other countries', 'russian' , 'england', 'many countries', 'worldwide', 'foreign countries', 'central bank', 'globally', 'german', 'chinese government']

31. Health Insurance: ['medicare', 'medicaid', 'cms', 'payers', 'prescription drug', 'partd', 'health plans', 'physician', 'payors', 'reimbursement', 'health insurance', 'health care', 'healthcare', 'third party payers', 'hospital', 'health plan', 'payment system', 'hhs', 'payer', 'clinical laboratory', 'third party payors', 'reimbursement levels', 'department of health and human services',

'payor', 'subsidy', 'prescription drugs', 'ppaca', 'mma', 'care organizations', 'coding', 'federal government', 'patients', 'private insurers', 'care programs', 'reimbursement policies']

32. Investment Funds: ['investment funds', 'private equity funds', 'hedge funds', 'private equity fund', 'investment managers', 'private equity', 'limited partnerships', 'separate accounts', 'pooled', 'advisers', 'investment management', 'other investment', 'clo', 'investment advisers', 'asset managers']

33. Manufacturing: ['manufacturing', 'manufacture', 'product manufacturing', 'manufacturing process', 'manufacturing operations', 'manufacturing processes', 'manufacturing activities', 'production processes', 'manufacturing capabilities', 'commercial manufacturing', 'manufacturing facilities', 'production process', 'third party manufacturing', 'manufacturing equipment', 'assembly', 'wafer fabrication', 'contract manufacturers', 'third party manufacturers', 'contract manufacturing', 'product development', 'manufacturing capacity', 'commercial supply', 'manufacture of products', 'technical', 'new manufacturing', 'manufacturing facility', 'product components', 'production facilities', 'process technology', 'manufacturing services', 'commercial scale', 'contract manufacturer', 'volume production', 'finished products', 'manufacturers']

34. Metal Products: ['steel', 'aluminum', 'metal', 'copper', 'titanium', 'metals', 'stainless', 'pulp', 'plastics', 'resin', 'scrap', 'rubber', 'iron', 'rolled', 'raw materials', 'mill', 'mills', 'fabricated', 'raw material', 'diamond', 'hot']

35. Power Generation: ['coal', 'electricity', 'ash', 'coke', 'steam', 'sand', 'power plants', 'power plant', 'electric power', 'energy sources', 'electric generating', 'water', 'tons']

36. Raw Metals & Minerals: ['tantalum', 'tin', 'tungsten', 'conflict minerals', 'democratic republic of congo', 'minerals', 'zinc', 'precious metals', 'such minerals', 'oxide', 'platinum']

37. Semiconductors: ['semiconductor', 'semiconductors', 'silicon', 'semiconductor manufacturing', 'ic', 'semiconductor industry', 'semiconductor products', 'network equipment', 'consumer electronics', 'oems', 'technology industry', 'wafers', 'original equipment manufacturers', 'capital equipment', 'technology companies']

38. Video Games: ['games', 'game', 'titles', 'players', 'app', 'consoles', 'movies', 'android', 'windows', 'player', 'mobile devices', 'streaming', 'facebook', 'studios', 'smartphones', 'music', 'handsets', 'smartphone', 'handset', 'console', 'subscribers', 'mobile phones']

39. Web-Based Services: ['cloud', 'saas', 'cloud computing', 'web', 'hosted', 'server', 'internet', 'premise', 'virtual', 'data center', 'networking', 'messaging', 'browser', 'mobility', 'wireless networks', 'hosting', 'subscription', 'network security', 'wireless', 'telephony', 'data centers', 'centric', 'bandwidth']

40. Banking: ['bank', 'banks', 'bank subsidiary', 'state bank', 'savings bank', 'financial institution', 'bank subsidiaries', 'national bank', 'bank holding company', 'institution', 'subsidiary bank', 'financial institutions', 'the corporation', 'ots', 'institutions', 'depository institution', 'national banks', 'bank holding companies', 'savings banks', 'banking', 'prudential', 'fhlb', 'banking institutions', 'savings institutions', 'community banks', 'financials', 'financial companies', 'depository', 'federal home loan bank', 'extensions of credit', 'bank regulators', 'chartered', 'wells fargo bank', 'federal bank', 'wells fargo', 'bhc act', 'bhca', 'corporations', 'bank of america', 'holding companies']

41. Deposits: ['fdic', 'fdics', 'deposit insurance', 'occ', 'insured institutions', 'frb', 'dif', 'insured depository institutions', 'special assessment', 'restoration plan', 'comptroller of the currency', 'assessment rate', 'assessment rates', 'reserve ratio', 'insurance assessments', 'federal banking regulators', 'federal banking agencies', 'loss sharing', 'loss share', 'federal banking agency']

42. Shipping Containers: ['vessels', 'vessel', 'cargo', 'rigs', 'tank', 'fleets', 'drilling rigs', 'containers', 'trailers', 'engines', 'tractors']

43. Transportation: ['freight', 'trucking', 'shipping', 'delivery services', 'ocean', 'carriers', 'shipping costs', 'other transportation', 'shipments', 'railroads', 'haul', 'fuel costs', 'railroad', 'inbound', 'transportation industry', 'ports', 'fuel surcharges', 'carrier', 'container', 'port', 'transit']

44. Software Services: ['solutions', 'solution', 'software solutions', 'technology solutions', 'platform', 'technology platform', 'communications services', 'service offerings', 'platforms', 'intelligent', 'analytics', 'tools', 'technologies', 'product offerings', 'edge', 'technology platforms', 'capabilities', 'modules', 'architectures', 'business solutions', 'functionality', 'devices', 'crm', 'innovative products', 'connectivity', 'new solutions', 'suite of products', 'automation', 'ecosystem', 'network services', 'new technologies', 'new services', 'module', 'management products', 'enterprise', 'functionalities', 'product line', 'next generation', 'scalability', 'professional services', 'applications', 'agile', 'new features', 'management system', 'new technology', 'testing services', 'service delivery', 'electronic devices', 'wireless carriers', 'business model', 'enabled',

‘seamless’, ‘enterprise customers’, ‘technical services’, ‘support services’, ‘new applications’, ‘new business models’, ‘integrated’, ‘lte’, ‘range of services’, ‘health information technology’, ‘diagnostic tests’, ‘enhanced products’, ‘additional services’, ‘technical support services’]

45. Software & Hardware Products = [‘software’, ‘software products’, ‘software applications’, ‘hardware’, ‘software systems’, ‘operating system’, ‘third party software’, ‘proprietary software’, ‘interfaces’, ‘interface’, ‘it infrastructure’, ‘architecture’, ‘other technology’, ‘computer hardware’, ‘operating systems’, ‘computer’, ‘software vendors’, ‘third party technology’, ‘hardware products’, ‘servers’, ‘new software’, ‘software development’, ‘proprietary technology’, ‘digital content’, ‘it systems’, ‘algorithms’, ‘data management’, ‘customization’, ‘analytic’, ‘open source’, ‘malware’, ‘information systems’, ‘technology infrastructure’, ‘firewalls’, ‘open source software’, ‘such technologies’, ‘bugs’, ‘communications systems’, ‘integrations’, ‘open source code’, ‘computers’, ‘compatibility’, ‘information management’, ‘proprietary’, ‘algorithm’, ‘source code’, ‘technology systems’, ‘internal systems’, ‘customized’, ‘provisioning’, ‘computer systems’, ‘encryption’, ‘optimized’, ‘business processes’, ‘proprietary technologies’, ‘undetected errors’]

A.II Supplemental Information for Chapter 1

The following list declares all the variables, and their respective definitions, used in the article "The Asymmetry Between Growth Opportunities and Debt Maturity Structure":

1. **EDGAR:**

   $R.E._{i,j}$: Firm i's risk exposure to risk factor j is measured as the total number of terms associated with the risk factor j captured in "Item 1" of the 10-K report divided by the total number of terms captured for all the 44 risk factors

   Total R.E.$_{Pos.}$: The total exposure to the following eight growth-increasing risk factors (Web Services, Software Services, Semiconductors, Alternative Energy, Drug Trials, Residential Construction, Display Technology, and E-Commerce). Specifically, Total R.E.$_{Pos.,i,t} = \sum_{j=1}^{j=8} R.E._{i,t,j}$ for firm i at time t

   Total R.E.$_{Neg.}$: The total exposure to the following eight growth-reducing risk factors (REITs, Oil and Gas, Healthcare Providers, Travel, Healthcare Insurance, Shipping Containers, Metal Products, and Foreign Countries). Specifically, Total R.E.$_{Neg.,i,t} = \sum_{j=1}^{j=8} R.E._{i,t,j}$ for firm i at time t

   Delaware Incorp. : An indicator taking the value of 1 if the filing firm's head quarter is in the state of Delaware

2. **Compustat:** Variables are obtained from annual and quarterly data. Note that variable names for quarterly variables are mostly equal to annual variable names listed here + the letter Q at the end.

   Market-to-Book : $\frac{(CSHOQ \times PRCCQ)+DLCQ+DLTTQ+PSTKQ-TXDITCQ}{ATQ}$. The value of this variable is considered missing if $CSHOQ < 0$ (Negative Total Shares Outstanding) or $PRCCCQ < 1$ (Penny Stocks)

Market-to-Book *(Alt.)* : $\frac{ATQ+(CSHOQ \times PRCCQ)-SEQQ-TXDITCQ}{ATQ}$. An alternative measure for the Market-to-Book. The value of this variable is considered missing if $CSHOQ < 0$ (Negative Total Shares Outstanding) or $PRCCCQ < 1$ (Penny Stocks) or $SEQQ < 0$ (Negative Book Value of Equity)

Q^{tot} : Following Peters and Taylor, 2017, Total q is measured as:

$$Q_{i,t}^{tot} = \frac{V_{i,t}}{K_{i,t}^{phy} + K_{i,t}^{int}} \tag{A.1}$$

Where firm i's Total q at time t is the total market value of the firm divided by the sum of its replacement cost of capital; physical capital K^{phy} (Property, Pant, and Equipment) and intangible capital K^{int}. Intangible capital includes externally obtained capital (Goodwill from the balance sheet) and internally generated capital of knowledge and organization. Thus,

$$K^{int} = INTANQ + Knowledge + Organization \tag{A.2}$$

$INTANQ$ is treated as zero if missing. Knowledge is measured as:

$$G_{i,t} = (1 - \theta_{R\&D})G_{i,t-1} + XRDQ \tag{A.3}$$

$XRDQ$ is treated as zero if missing, and the depreciation rate $\theta_{R\&D}$ varies by industry. The rates are obtained from Ewens et al., 2021. Organization is measured as:

$$G_{i,t} = (1 - \theta_{SG\&A})G_{i,t-1} + \gamma \times \text{SG\&A} \tag{A.4}$$

Because SG&A may include R&D expense, I follow the authors' who develop the measure by adding the following condition: If $XRDQ$ is larger than $XSGAQ$ but less than $COGSQ$, SG&A = $XSGAQ$. Otherwise, SG&A = $XSGAQ - XRDQ - RDIPQ$. SG&A is treated as zero if $XSGAQ$ is missing. The depreciation rate $\theta_{SG\&A}$ varies by industry. The rates are obtained from Ewens et al., 2021. Lastly, since the sample of this study starts in 2018, the initial capital $G_{i,2015}$ for both knowledge and organization capital are obtained from WRDS, and firm measures of Q^{tot} for the years 2017-2019 are randomly verified using data provided by one of the authors (Ryan Peters)

$\ln(Assets)$: The natural log of AT

$\ln(Asstes)^2$: The natural log of AT squared

Leverage : $\frac{DLC+DLTT}{AT}$

Profitability : $\frac{EBITDA}{AT_{t-1}}$

$\sigma(Profitability)$: The standard deviation of profitability using the past 4 consecutive years and the current period. The minimum number of years required to measure this variable is 3

ROA : $\frac{NIQ}{ATQ}$

Capital Expenditures : $\frac{CAPXY}{ATQ}$

R&D/Sales : $\frac{XRDQ}{REVTQ}$, if missing, the variable takes a value of 0

R&D Dummy : An indicator taking a value of 1 if the variable $XRDQ$ is missing

Asset Maturity : Following Billett et al., 2007, Johnson, 2003, and Chen et al., 2021, asset maturity is measured as the value weighted average for the maturities of current assets and property, plant and equipment. More specifically, $\frac{ACT}{AT} \times \frac{ACT}{COGS} + \frac{PPENT}{AT} \times \frac{PPENT}{DP}$

COVID-19 Shock : An indicator taking the value of 1 if the date of the filing is after 3/1/2020

Placebo Shock : An indicator taking the value of 1 if the year of the filing is 2019

Public Debt ≤ 3 yrs : $\frac{DD1+DD2+DD3}{DLC+DLTT}$, this variable is considered missing if either DLC or $DLTT$ is missing or the value is outside the interval (0,1)

Public Debt ≤ 5 yrs : $\frac{DD1+DD2+DD3+DD4+DD5}{DLC+DLTT}$, this variable is considered missing if either DLC or $DLTT$ is missing or the value is outside the interval (0,1)

Public Debt > 5 yrs : $1 - \frac{DD1+DD2+DD3+DD4+DD5}{DLC+DLTT}$, this variable is considered missing if either DLC or $DLTT$ is missing or the value is outside the interval (0,1)

Cash : $\frac{CH}{AT}$

Tangible Assets : $\frac{PPENT}{AT_{t-1}}$

3. **FISD:**

$\ln(\overline{Maturity_w})$: The natural log of the issuer's weighted average maturity for its bond portfolio during the period. Weights are based on the balances of each outstanding bond

GRAN : Granularity of corporate public debt is a proxy for the firm's maturity concentration. It is measured following the approach of Choi et al., 2018. Specifically, $GRAN = \frac{1}{HERF_j}$ where $HERF_j = \sum_i w_i^2$. The term w_i is the fraction of amount outstanding that is maturing in each maturity bucket i

Covenant Index : Following the work of Billett et al., 2007, an issuer's covenant index during the period is calculated by counting the occurrences of 15 covenant categories (see Billett et al., 2007) in any of the issuer's outstanding bonds during the period, then dividing the sum by 15.

Maturing Bond$_{2020}$: An indicator taking the value of 1 if an issuer has a bond maturing in 2020 in its portfolio. The indicator is measured after filtering for any early retirements or defaults using the FISD 2019 historical library

Maturing Bond$_{2019}$: An indicator taking the value of 1 if an issuer has a bond maturing in 2019 in its portfolio. The indicator is measured after filtering for any early retirements or defaults using the FISD 2018 historical library

Call Exercise : An indicator taking the value of 1 if an issuer exercised a call option on any of its outstanding bonds that are callable during the period, and 0 otherwise.

A.II.1 Alternative Proxy for the Growth Shock

The following two tables replicate tables 1.5 and 1.6 when I measure Total R.E. as the sum of the top *five* risk factors from figure 1.3 instead of *eight*.

Table A.1: Regression of Debt Maturity Structure on Growth Opportunities (Growth-inducing Factors)

	≤ 3 yrs		≤ 5 yrs	> 5 yrs	High Cash$_{t-1}$	Low Cash$_{t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Total R.E.$_{Pos.}$	0.05*	0.06	0.15***	-0.15***	0.11*	0.00
	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)
Shock×Total R.E.$_{Pos.}$	-0.13***	-0.12***	-0.14***	0.14***	-0.10	-0.15***
	(0.03)	(0.04)	(0.05)	(0.05)	(0.07)	(0.05)
Leverage		-0.09***	0.17***	-0.17***	-0.06	-0.11***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Asset Maturity		-0.00	-0.00	0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Assets)		-0.11***	0.04**	-0.04**	-0.12***	-0.10***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
ln(Assets)^2		0.01***	-0.01***	0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ(Profitability)		-0.07	-0.13**	0.13**	-0.06	-0.07
		(0.05)	(0.06)	(0.06)	(0.07)	(0.06)
Constant	0.34***	0.84***	0.46***	0.54***	0.85***	0.82***
	(0.01)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
Observations	8,390	4,805	4,394	4,394	2,092	2,640
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	3,183	2,219	2,061	2,061	1,208	1,403
R-squared	0.04	0.12	0.08	0.08	0.14	0.10

This table reports estimation results for regressing debt maturity structure choice on firm's total level of exposure to five *growth-inducing* risk factors (Total R.E.$_{Pos.}$) around the COVID-19 health pandemic shock. The regression model estimates equation 1.5. Columns 1 and 2 use the fraction of short-term debt maturing in 3 years or less as the dependent variable. Column 3 uses the fraction of short-term debt maturing in 5 years or less while column 4 uses the fraction of debt maturing after 5 years as the dependent variable. Columns 5 and 6 replicates the estimation for column 2 when using subsamples of cash levels at period $t-1$. High Cash$_{t-1}$ = 1 if the firm's cash to asset ratio is higher than its industry median while Low Cash$_{t-1}$ = 1 if it is lower than the median. Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The five risk factors are (Web Services, Software Services, Semiconductors, Alternative Energy, and Drug Trials). *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All independent variables, except (*Shock*), are lagged one period. Detailed descriptions of all the variables used in this table are available in appendix A.II. Industry classifications follows the Fama-French 49 method. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the Fama-French 49 industry level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Table A.2: Regression of Debt Maturity Structure on Growth Opportunities (Growth-reducing Factors)

	$\leq$ 3 yrs		$\leq$ 5 yrs	> 5 yrs	High Cash$_{t-1}$	Low Cash$_{t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Total R.E.$_{Neg.}$	0.10**	0.19***	0.24***	-0.24***	0.29***	0.14**
	(0.044)	(0.05)	(0.06)	(0.06)	(0.08)	(0.06)
Shock×Total R.E.$_{Neg.}$	-0.12**	-0.08	-0.07	0.07	-0.10	-0.08
	(0.05)	(0.06)	(0.06)	(0.06)	(0.09)	(0.07)
Leverage		-0.09***	0.17***	-0.17***	-0.06	-0.11***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Asset Maturity		-0.00*	-0.00*	0.00*	-0.00*	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Assets)		-0.11***	0.04**	-0.04**	-0.12***	-0.11***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
ln(Assets)^2		0.01***	-0.01***	0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ(Profitability)		-0.07	-0.12**	0.12**	-0.06	-0.08
		(0.05)	(0.06)	(0.06)	(0.07)	(0.06)
Constant	0.33***	0.84***	0.47***	0.53***	0.86***	0.82***
	(0.01)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
Observations	8,390	4,805	4,394	4,394	2,092	2,640
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	3,183	2,219	2,061	2,061	1,208	1,403
R-squared	0.03	0.12	0.08	0.08	0.14	0.10

This table reports estimation results for regressing debt maturity structure choice on firm's total level of exposure to five *growth-reducing* risk factors (Total R.E.$_{Neg.}$) around the COVID-19 health pandemic shock. The regression model estimates equation 1.5. Columns 1 and 2 use the fraction of short-term debt maturing in 3 years or less as the dependent variable. Column 3 uses the fraction of short-term debt maturing in 5 years or less while column 4 uses the fraction of debt maturing after 5 years as the dependent variable. Columns 5 and 6 replicates the estimation for column 2 when using subsamples of cash levels at period $t-1$. High Cash$_{t-1}$ = 1 if the firm's cash to asset ratio is higher than its industry median while Low Cash$_{t-1}$ = 1 if it is lower than the median. Firm-level risk exposures are constructed using the factors found by Davis et al., 2021. The five risk factors are (REITs, Oil and Gas, Healthcare Providers, Travel, and Healthcare Insurance). *Shock* takes the value of 1 if the time period is after June 1st, 2020, and 0 otherwise. Companies with SIC codes (6000-6999, 4900-4999) are excluded from the sample. All independent variables, except (*Shock*), are lagged one period. Detailed descriptions of all the variables used in this table are available in appendix A.II. Industry classifications follows the Fama-French 49 method. All continuos variables are winsorized at the 1st and 99th percentile. Standard errors are clustered at the Fama-French 49 industry level. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.