Three Essays in Applied Microeconomics:

Essays on How Firm-Level Climate Change Exposure, Firm-Level Political Risk and Debt Financing Affect Corporate Decisions

By

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DEDICATION

To the dearest people in my life: my loving and veracious wife and baby Jahnel for their love, constant support and encouragement.

ABSTRACT

My dissertation investigates the influence of firm-level climate change risk, political risk and debt finance on corporate decisions. It contains three chapters.

Chapter 1 investigates how climate change exposure affects extensive and intensive margins of corporate R&D investment. Using firm-level climate change exposure data, the empirical findings indicate that climate change exposure positively and significantly affects both intensive and extensive margin of corporate R&D investment. I show that carbon intensive firms significantly increase their extensive and intensive margins of corporate R&D in response to an increase in climate changes. As a plausible exogenous shock, I find that after the Paris Agreement and Renewable Portfolio standards adoption, firms increased their corporate intensive margins of R&D. The results are robust with other measures of climate change exposure and with the inclusion of industry and macroeconomic factors. Also, I find that firms in carbon intensive industries engage more in R&D than firms in green industries.

Chapter 2 examines the effects of political risk on firm labor decisions, revealing how firm-level political risk impact wages, employment growth, and labor productivity among U.S. Firms. This study reveals how firm-level political risk affects firm labor decisions. I empirically analyze how firms' labor decisions respond to firm political risk using a sample of 3,131 U.S. firms from 2002 to 2022. My analysis shows that a one standard deviation increase in firm-level political risk is associated with a 9.22 percentage point wage increase. Political risk affects wages significantly when interacted with competition, capital intensity and labor share. Moreover, my findings are consistent using various measures of firm-level political risk and wages. In addition, one standard deviation increase in firm political risk is associated with 8.94 and 30.48 percentage point decreases in employment growth and labor productivity, respectively. My study reveals that the reduction in employment growth and labor productivity is more evident when firm-level political risk is interacted with competition, capital intensity and labor share. My results remain robust after addressing the potential endogeneity issue

using an instrumental variable approach.

Chapter 3 Debt financing is important for financing major investments in the biopharmaceutical industry. Debt financing allows companies to raise funds without giving up ownership or control through indenture of the company. In this study, I analyze the effects of debt financing decisions on profitability in the biopharmaceutical industry. I find that short-term debt, long-term debt and total debt negatively impacts return on assets (ROA) as a firm's profitability measure. A comparison is made between the US and Europe biopharmaceutical firms and the result shows the negative effects of short-term and long-term debt on profitability persist more for US biopharmaceutical firms than Europe firms. Short-term and long-term debt both impact profitability negatively with 10-year lagged R&D intensity and financial distress. Short-term debt's negative impact is stronger in post-Covid-19, indicating increased financial strain. Long-term debt consistently affects profitability negatively, with relative stable effects during the pre- and post-Covid-19.

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Chapter 1

Does Climate Change Exposure Influences the Intensive and Extensive Margins of Corporate R&D Investment?

Abstract

In this paper, I investigate how climate change exposure affects extensive and intensive margins of corporate R&D investment. Using firm-level climate change exposure data, the empirical findings indicate that climate change exposure positively and significantly affects both intensive and extensive margin of corporate R&D investment. I show that carbon intensive firms significantly increase their extensive and intensive margins of corporate R&D in response to an increase in climate changes. Using difference-in-differences (DID) regression analysis, we find that firms in treated States invest significantly more in corporate intensive margins of R&D after the adoption of Renewable Portfolio Standards. The results are robust with other measures of climate change exposure and with the inclusion of industry and macroeconomic factors. Also, I find that firms in carbon intensive industries engage more in R&D than firms in green industries.

1.0 Introduction

Investments in research and development (R&D) by firms play an integral part in determining long-term productivity growth and improving firm value through innovation. Therefore, investing in R&D increases a firm's productive capacity and income-generating potential (Dynan, 2021). R&D helps firms to identify new opportunities, creates innovative products and services, and brings these innovations to market through strategic product launches. The allocation of resources to research and development is categorized into two components: the amount dedicated to R&D spending and the decision to engage in R&D. This differentiation corresponds to the firm-level distinction between the extent of investment (intensive margin) and

the choice to invest or not (extensive margin) in R&D. Climate change can have a significant influence on firms' activities, increase investment uncertainty, and raise financial risks for innovation and R&D. Climate change risks drive firms to increase their capabilities for R&D, as they adapt to environmental challenges, innovate sustainable solutions, and capitalize on emerging opportunities. Therefore, climate-related risks could also increase firms' capacity to engage in R&D and innovation.

Uncertainties within the realm of climate change arise from uncertainties about the the potential physical ramifications of an increase in greenhouse gas concentrations in the atmosphere, coupled with uncertainties surrounding the expenses associated with curtailing emissions of greenhouse gases to decelerate their accumulation in the atmosphere (Risk, 2007). Climate change is a challenging and important global issue with significant implications for many elements of human society, including economic activity. As many firms, especially those in the manufacturing sector, deal with the uncertainties caused by changing climate patterns, its effects on R&D investment are less studied. In this paper, I examine how climate change exposure (CCE) affects the firm's decision to invest in R&D (extensive margin) and the level of R&D spending (intensive margin). This approach provides a more complete understanding of how firms respond to climate change challenges and offers insights into their strategies, resource allocation, and policy interventions.

A large volume of empirical studies provides a relationship between firm and market-level characteristics and firm R&D (Bernstein, 2015; Dong & Gou, 2010; Faleye, Kovacs & Venkateswaran, 2014; Lin, Lin, Song & Li, 2011). However, only few empirical papers have focused on the impact of climate uncertainty on corporate R&D investment (Li, Lin & Lin, 2021; Hoang, 2021). My paper is closely related to the studies of Wang, Wei & Song (2017) which

found that market and policy uncertainties affect R&D investment. The authors measure market uncertainties using the moving standard deviation of current sales revenue and policy uncertainty using political connections and government subsidies. My paper differs from previous studies by focusing on US R&D investment using a firm-level measure of climate change exposure. Prior research in this area analyzes variations in the aggregate measure of climate risk exposure (Global climate risk index, Environmental, Social, and Governance scores, and vulnerability index). I contribute to the existing literature by using a novel measure of climate change exposure that enables me to explore how the variation in firm-level climate change exposure affects corporate investment-related decisions.

This study aims to fill the gap by investigating how climate change exposure impacts R&D margins, specifically how climate-related uncertainties influence organizations' decisions to invest in R&D activities and how much spending is made on R&D investments. Uncertainty including climate change has been shown to have a major impact on R&D investment (Jung & Kwak 2018; Wang, Chen & Huang 2014). According to the strategic growth option theory posited by Abel & Blanchard (1986) and Kulatilaka & Perotti (1998), When there is a strong strategic advantage, more uncertainty can lead to more investment in growth options because it is seen as an opportunity. In line with this this theory, climate change exposure would have a positive relationship with R&D investment when seen as an opportunity but negative effect of climate change exposure on R&D when seen as a threat. Firms gain competitive advantage and improve their future growth when they invest during uncertainty. Investing during periods of high uncertainty could be a valuable opportunity to build trust with stakeholders, sustain a competitive edge, and increase future market value. Studies by Jung & Kwak 2018 and Wang, Chen, & Huang 2014 show that uncertainty has impact on R&D investment. Real options models

(McDonald & Siegel (1986) and Dixit & Pindyck (1994) emphasize that the interaction of capital irreversibility and uncertainty generates option value to delay investment. Because this option's value increases with uncertainty, investment is expected to decrease as uncertainty rises.

To measure climate change exposure, I employ the climate change exposure measure from Saunter, van Lent, Vilkov & Zhang (2023). A major challenge for climate change studies is the difficulty in quantifying firm-level climate change exposures[1]. Sautner et al. (2023) created firm-level climate change exposure data using a machine learning method to create firm-level time-varying metrics of climate change exposures. The measure counts the frequency of specific climate change bigrams in earnings conference call transcripts, then divided by the overall number of bigrams in the transcript.[2] The authors demonstrate that their methods capture firm-level exposures to physical and regulatory shocks caused by climate change. Therefore, firm-level climate change exposure refers to the extent to which a firm or business is vulnerable to the potential risks and opportunities associated with climate change (Cardona, 2012). Climate change exposures of firms are affected by many factors such as climate opportunity (renewable energy, electric vehicles, sustainable agriculture), physical (sea level rises, natural disasters), and regulatory shocks (carbon taxes, cap, and trade markets)[3]. The benefit of using climate change exposure by Sautner et al. (2023) is that it may not always translate into environmental, social and governance (ESG) related activities as other measures (Environmental, Social, and Governance and Corporate Social Responsibility scores). Instead, it can emerge in a variety of

[1] It is difficult to properly quantify firm-level climate change exposure because climate change's effects on firms are very uncertain varies across firms, and there is no consensus on how to estimate firm-level climate change exposure.
2 The authors modified the climate change exposure data so that the topic measures have zero values when climate change exposure is zero. Out of more than 10,000 firms, only 10% of these firms have zero values.
3 The term "exposure" is characterized by the proportion of the dialogue within a transcript dedicated to pertinent subject matter, specifically focusing on climate change opportunities. Bigrams are combination of two words that ensure the topic is relevant to climate change. Some of the keywords captured are "renewable energy," "electric vehicle," "clean energy," "new energy," and "wind power".

outcomes, such as CEO equity incentives (Hossain et al., 2022), corporate social responsibility (Mbanyele & Muchenje, 2022), firm-level total factor productivity (Ren, Zhang, Yan & Gozgor, 2022), cash holdings (Heo, 2021) and leverage (Ginglinger & Moreau, 2022), which standard measures may not fully reflect. In this paper, I examine how climate change exposure affects R&D margins at the firm-level and find that it is essential in explaining how firm investment decisions response to climate change exposure. I use climate change exposure measure identified by Sautner et al. (2020) because the measure exhibits cross-sectional and time-series variations, and they better capture firm-level variations and are more specific than ratings.

To provide empirical evidence on how climate change exposure affects extensive and intensive margins of corporate R&D investment, I use a sample of 2296 U.S firms spanning the period 2002-2022. The baseline result without firm, industry and macroeconomic controls shows a positive relation between climate change exposure and intensive margin of R&D. The coefficients for climate change exposure are positive and statistically significant across all models' specifications. This implies that firms invest in R&D in a period of high climate change exposure. For economic significance, one standard deviation increase in climate change exposure leads to 3.32 percentage point increase in corporate R&D intensive margins. This is a fairly meaningful impact as the average R&D intensive margin is 5.5 percent. After controlling for year, firm, industry, and state fixed effects as well as firm-level, industry and macroeconomic characteristics, my finding shows a positive relationship between climate change exposure and R&D intensive margin. This indicates that firms focus on innovation, which enhances competitiveness, and this improves the ability of these firms to adapt to climate challenges. This increases R&D commitment and fosters long-term sustainability for the firms.

For cross-sectional analysis, I examine whether the relationship between climate change exposure and R&D margins varies across sub-categories of industries. I find a positive and a significant effect between climate change exposure and the amount spent on R&D for carbon intensive and manufacturing firms. The results show that a one standard deviation in the firm-level climate change exposure leads to 25.6 and 8.3 percent increase in R&D for carbon-intensive and manufacturing firms respectively. Also, firm's probability of investing in R&D increases as climate change exposure increases. The result shows that the probability of investing in R&D is 16.56 percent, the decision of a firm to invest in R&D rise with the firm's climate change exposure. The probability of investing in R&D is 24.23 percent for carbon intensive firms as compared 20.16 percent for green firms[4].

I explore the channels through which climate change exposure affects the extensive margin of R&D. The results reveal that firms with an increase in vertical integration, growth opportunities, investment tax credit increases corporate R&D investment when climate change exposures increase. The increase in vertical integration, growth opportunities, and investment tax credits drives higher corporate R&D investment when firms are exposed to climate change. Vertical integration improves supply chain resilience, motivating firms to invest in R&D to adapt to environmental disruptions. Recognizing growth opportunities in climate-related markets encourages R&D investment, as firms seek to develop innovative products or services to capture expanding revenue streams. Investment tax credits reduce the cost of R&D, making it more financially attractive, and enabling firms to allocate resources to innovation, leading to increased R&D investment to address and capitalize on climate change challenges.

[4] Carbon-intensive firms are less environmentally sustainable or climate-friendly. Carbon-intensive firms may face significant climate-related financial, liability, and regulatory risks due to their usage of fossil-fuel energy. Conversely, green firms are those that are position to thrive in a low-carbon world due to reduce carbon emissions.

I conduct an event study using the Paris Agreement period and how climate change exposure influences R&D intensive margins. The result indicates that a positive relationship between climate change exposure and R&D intensive margins when United States join the Paris Accord (2015-2016). However, a negative effect of climate change exposure on R&D when there is an announcement of Paris Accord withdrawal (2017-2020) and the period of rejoin shows a positive effect of climate change exposure on R&D intensive margins.

To assess the causal impact of firm-level climate change exposure on R&D intensive margins, I use an exogenous shock, the Renewable Portfolio Standard (RPS). Analyzing state-level RPS implementation around December 2015, coinciding with the Paris Agreement, reveals firms intensifying R&D investment when I employ difference-in-differences approach. My finding shows that firms in treated States increase their corporate intensive R&D margin after the adoption of State level RPS implementation. The findings indicate that firms pay more attention to climate change exposures after the Paris Agreement and adopting RPS. Also, the estimated coefficients of the interaction terms of climate change exposure x treated firms is positive and significant, indicating that the impacts of firm-level climate change exposure influences R&D in the RPS adopted States.

This paper adds to several lines of research. First, this paper complements the growing studies of how firms respond and adapt to climate change. Prior studies show that climate change exposure influences cash-holding decisions (Heo, 2021), corporate social responsibility (Mbanyele & Muchenje, 2022) and corporate tax avoidance while Ginglinger & Moreau (2022) find a negative relationship between climate change exposure and corporate leverage. My study extends the work of Wang, Wei, and Song (2017), who examine uncertainty at the macro policy

level. However, this study utilizes micro-level data, incorporating a broader range of firms to analyze firm-level climate change data.

Second, this study adds to the growing body of literature on by examining the impacts of climate policies on corporate investment decisions. The evidence from this study provides the mechanism by which climate change exposure can affect firm decisions. Also, firms have to implement policies in the context of climate change is valuable for making informed decisions regarding environmental sustainability and climate adaptation.

Third, this study contributes to the R&D investment literature. Previous studies examine the determinants of firms' R&D focusing on firm fundamentals (Hwang & Lee, 2002; Lai, Lin & Lin, 2015; Shin & Lee, 2022), but the influence of climate change on R&D investment is under study. Therefore, this study contributes to this literature by introducing climate change-related opportunities as an additional influential factor in the contemporary low-carbon landscape, thereby further establishing the link between climate change and R&D investments.

The remainder of the paper is organized as follows. The second section sets out the literature and develops the hypotheses. The third section introduces the empirical method and definition of the variables. Section four presents the empirical results. Section five concludes.

2.0 Literature Review and Hypothesis Development

2.1Theoretical underpinning

Bernanke (1983) was the first to propose using the theory of irreversible choice under uncertainty to explain cyclical investment fluctuations. Others have utilized these models to investigate the relationship between uncertainty and investment (Bloom et al., 2007; Bloom, Draca, & Reenen, 2016; Chen & Funke, 2003). Innovation is a long-term process of experimenting with new technologies and techniques of execution. Uncertainty enhances the

option's value to defer, which is true for R&D investment. Firms under high uncertainty tend to delay investments when they are totally irreversible (Dixit & Pindyck, 1994). Theoretical studies have identified how climate change exposures influence a company's investment decisions.

Real option theory was developed from the works of Myers (1977), McDonald & Siegel (1986), Myers & Majd (1990), and Dixit and Pindyck (1994), has fundamentally influenced both the theoretical and practical aspects of uncertainty- investment decision-making. According to the real options theory, firms tend to reduce their investments when faced with uncertainty. This is because an increase in uncertainty results in a greater value of the firms' option to wait rather than committing to immediate, irreversible, and costly investments (Abel & Eberly, 1996; Abel et al., 1996; Dixit & Pindyck, 1994; Pindyck, 1991). This theory holds significant implications for the relationship between climate change exposure and the extensive and intensive margins of R&D. When firms are confronted with increased climate change-related uncertainty, they invest less according to the real options theory. A growing number of studies examine the impact of uncertainty on investment. According to Czarnitzki & Toole (2007), corporate R&D investment decreases s in response to an increase in market uncertainty. Julio and Yook (2012) use election years to measure for uncertainty and their findings reveal that during election periods, firms experience an average decrease of 4.8 percent in their investment expenditures compared to non-election years. Wang et al. (2014) and Gulen & Ion (2015) adopt the Baker, Bloom, and Davis (BBD) [2016] measure to gauge policy uncertainty, and they find a negative relationship between policy uncertainty and corporate investment. An, Chen, Luo, & Zhang (2016) investigated the impact of political uncertainty on corporate investment and determined that changes in political leadership prompt firms to reduce their corporate investments significantly. Therefore, I hypothesize that

Hypothesis 1a: Climate change exposure significantly reduces the intensive and extensive margin of R&D investment, aligning with the real options theory.

Conversely, the theory of strategic growth options is found in the works of Kulatilaka & Perotti (1998) that suggests that in a situation of strategic competition, uncertainty can serve as an incentive for investing in growth opportunities. When there is a strong strategic advantage, uncertainty leads to higher investment in growth opportunities for firms. Uncertainty creates opportunities for firms. This theory posits that uncertainty can give rise to growth options, and postponing investments may result in competitors seizing the opportunity. As firms take immediate action, it may deter new entrants, leading to an augmentation of market share and profitability, ultimately strengthening the firm's competitive advantage in the future (Kulatilaka & Perotti, 1998). Thus, understanding how firms navigate climate-induced uncertainty and apply these strategic growth option principles is essential for comprehending their R&D decisions in the context of climate change exposure. Empirically, Vo & Le (2017) show that uncertainty boosts a firm's R&D spending when they use an idiosyncratic error of stock returns as a measure of uncertainty. Furthermore, the positive effect of uncertainty on R&D investment is amplified when competition is severe, and a firm's market power is limited. Also, Ross, Fisch, and Varga (2017) reveal that a rise in uncertainty encourages R&D expenditure, and this relationship is positively mitigated by characteristics that increase corporate learning capacity, such as human capital, the scope of businesses' innovation activities, and industry maturity. I expect that climate change exposure improves intensive and extensive margins of R&D base on growth options theory. I hypothesize that

Hypothesis 1b: Climate change exposure increases extensive and intensive margin of R&D investment based on the strategic growth options theory.

The empirical papers on the relationship between uncertainty and R&D investment are mainly based on uncertainty at the macro level. However, this study uses micro-level uncertainty that helps to understand better why and how firms respond to climate change exposures. In cases where there is climate change exposure and discretion regarding investment, the investment opportunity encompasses two choices: a real option and a growth option. These two options share a common feature akin to options in that their value increases as climate change exposure rises.

The moderating influence of firm characteristics: Vertical integration, growth opportunities, and high competition

Vertical integration measures the number of operations carried out within the confines of a firm. Also, vertical integration refers to the ownership of various production and operation links in the supply chain, so interactions between firms are changed to be within the same firm, and resource allocation is controlled by the authority within the organization.

Yuan, Geng, Sun, Cui (2022) analyze the impact of vertical integration on corporate value under uncertainty shock using cross-sectional data during the COVID-19 pandemic outbreak. They observe that there is a significant and positive relationship between vertical integration and the cumulative abnormal return of individual stock during pandemic outbreak.

Vertical integration is a moderating factor in the relationship between climate change and R&D because it provides greater control over supply chains, enhancing adaptability and resilience, and improving coordination throughout the production process. Vertical integration enables firms to make environmentally conscious decisions and develop innovative solutions to address climate change-related challenges effectively. under the shock of uncertainty caused by the COVID-19 pandemic, firms with high vertical integration are less affected by the increased

external transaction costs, so vertical integration could enhance corporate value. Therefore, climate firms with vertical integration are less affected by the increased external transaction costs when exposed to climate-related policy, so vertical integration could enhance R&D. The hypothesis is that

Hypothesis 2: Vertical integration increases the positive and intensifies the relationship between firm-level climate change exposure and intensive margins of R&D investment.

The moderating influence of firm characteristics: growth opportunities

A growing firm might invest more in R&D to sustain and continue its growth. In a period of uncertainty, firms with high growth opportunities invest more in R&D (Li et al., 2022; Atanassov et al., 2017; Van Vo & Le, 2017). Firms with great capacity for growth that face climate change-related concerns may expand R&D to innovate and exploit eco-friendly market demand or cut R&D due to resource allocation and regulatory uncertainties. The decision is influenced by elements such as risk tolerance, financial capability, and perceived trade-offs between short-term and long-term growth objectives in the context of climate change challenges. Therefore, I propose a hypothesis that

Hypothesis 3 Firm-level climate change exposure and growth opportunities have a positive effect on intensive margins of corporate R&D investment.

The moderating role of industry characteristics: Heavy emitter industries

According to Ma, Yuan & Fu (2023), firms that are exposed to climate change opportunities are greatly motivated to expand investment. However, the effect varies significantly between industries. Carbon-intensive industries increase their R&D efforts in response to climate change due to regulatory compliance, reputation management, risk

mitigation, cost reduction, access to new markets, competitive advantage, and long-term viability considerations. However, firms tend to reduce investment or divest when faced with uncertainty until they have acquired more information to enable better-informed decision-making (Hoang, 2021; Hoang & Tran, 2021; Kim & Kung, 2017; Strobel et al., 2018; Xu, 2020). Based on this understanding, I hypothesize that

Hypothesis 4: Intensive and extensive margins of R&D investment increase for carbon-intensive firms as climate change exposures increase.

3.0 Methodology

3.1. Data and Sample

I construct the sample by merging firm-level climate change exposures data with firm-level and industry-specific data with a unique identifier (GVKEY) and the new data created is merged with macroeconomic data. Firm and industry data is obtained from Compustat North America for publicly listed U.S. firms. The firm-level climate change exposures data is obtained from Sautner et al. (2023) and macroeconomic data is sourced from Federal Reserve Economic data (FRED) St. Louis. The sample begins in 2002, since that is where the firm-level climate change exposures data became available. The initial sample contains 30,061 firm-year observations.

I excluded financial firms with Standard Industrial Classification (SIC) codes 6000–6999 and utility firms with SIC codes 49,000–49,999 due to disparities in accounting practices and regulation requirements. Similarly, I exclude firms having negative total assets and sales. Also, I drop year firm observations with missing data for all control variables used in the main models. The final sample is unbalanced panel data including 24923 firm-year observations with 2296 firms from 2002-2022. The graph in figure 1.1 shows an upward trend in climate change

exposure from 2002 to 2022. From 2002-2011, values are stable with minor fluctuations. From 2012-2016, exposure increases, stabilizing around 2014-2016. From 2017-2022, there is a marked rise, reflecting heightened regulatory, stakeholder, and global climate awareness. Also, the graph in figure 1.2 shows how intensive margins of R&D (R&D per sales) change across the various years. The graph in figure 1.3 looks similar to figure 1.2, when R&D is divided by total assets and R&D intensive changes from 2002 to 2022.

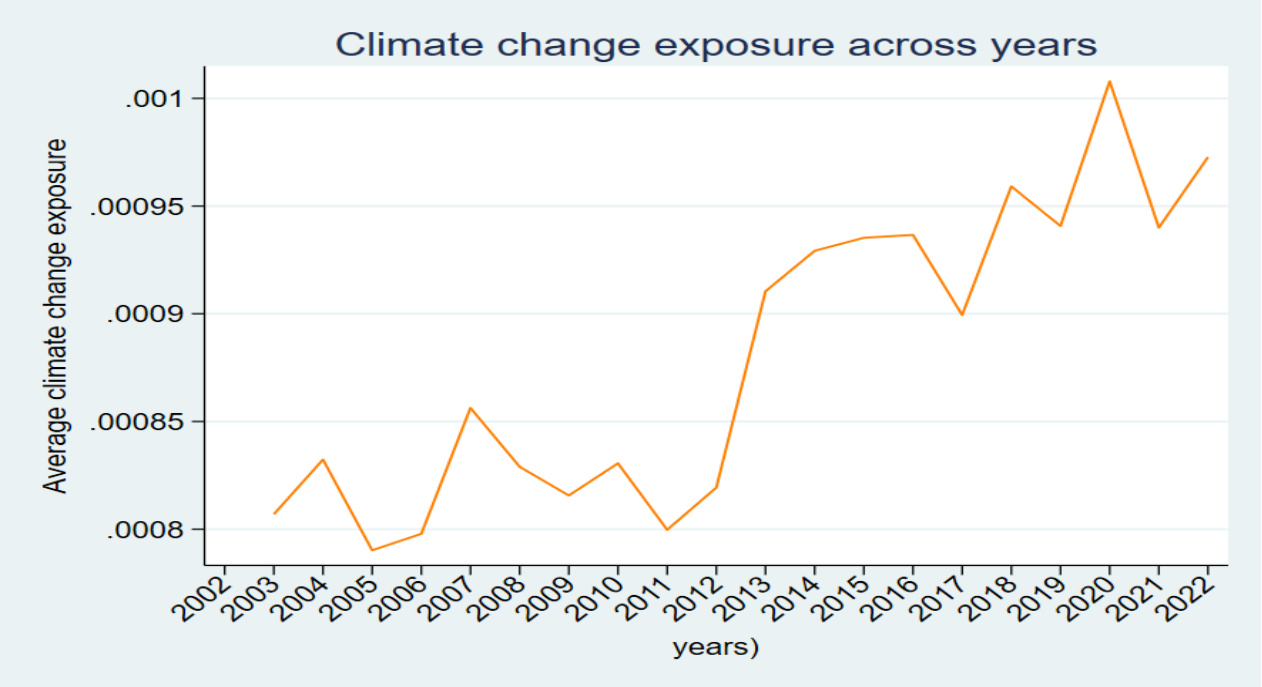

Figure 1.1: A graph showing average climate change exposure from 2002 to 2022

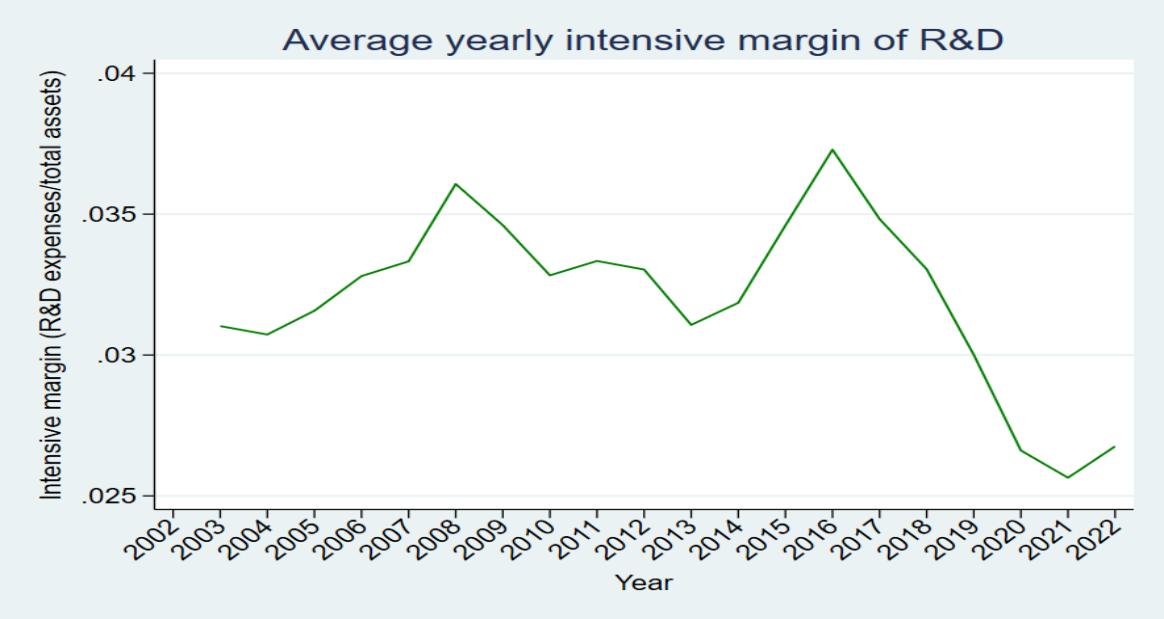

Figure 1.2: A graph showing average intensive margin of R&D (R&D per total assets) from 2002 to 2022

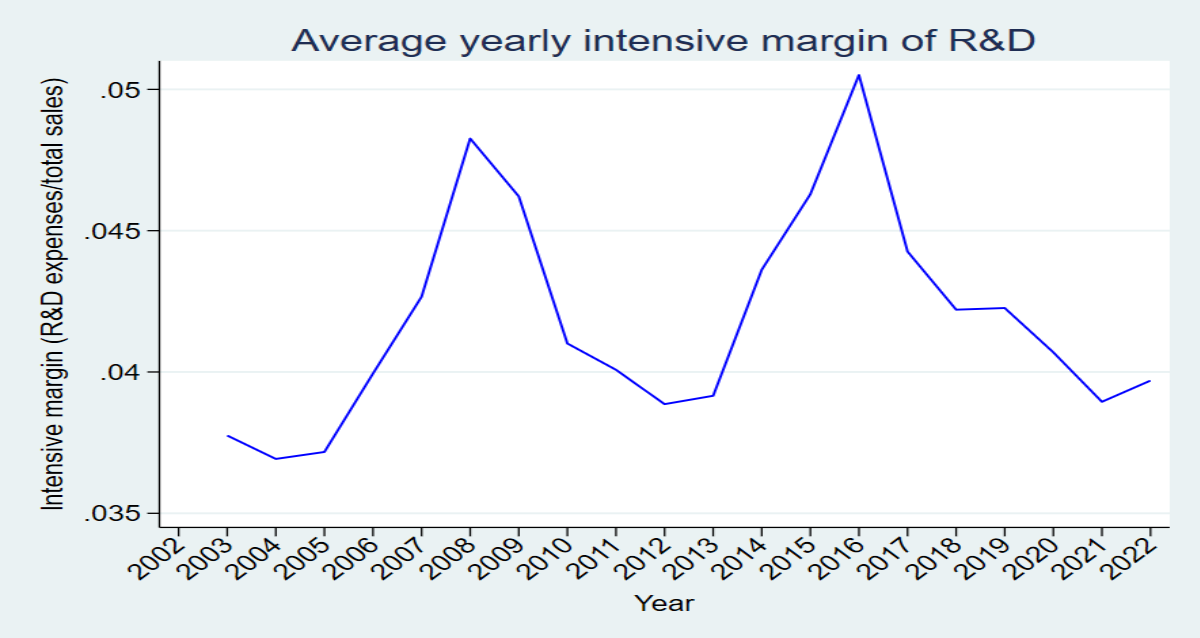

Figure 1.3: A graph showing average intensive margin of R&D (R&D per total sales) from 2002 to 2022

Table 1A shows the number of firms that change with years. 2019 has the highest number of firms while 2022 is the year with lowest number of firms. Table 1B illustrates varying climate

change exposure across industries by 2-digit SIC codes. Manufacturing shows the highest exposure (0.027394), suggesting significant environmental impact. Wholesale has the lowest (0.000193), indicating minimal exposure. Differences across agriculture, metal, construction, retail, and service sectors underscore diverse environmental challenges.

Table 1A: Number of firms over years

Year	Number of firms by year
2002	1070
2003	1795
2004	1724
2005	1621
2006	1530
2007	1419
2008	1349
2009	1293
2010	1229
2011	1164
2012	1113
2013	1083
2014	1125
2015	1173
2016	1197
2017	1169
2018	1122
2019	1,953
2020	1063
2021	978
2022	775

Table 1B: Climate change exposure by Industry (2-digit SIC code)

Major industry base on SIC2	Number of firm-year observations	Climate change exposure
Agriculture production	75	0.000806
Metal	1658	0.003887
construction	501	0.002269
manufacturing	15336	0.027394
wholesale	1118	0.000193
Retail	2181	0.003165
service	4054	0.004034

Table 1C and 1D in show the industry breakdown of carbon-intensive and green industries. Carbon intensive industry are firms with highest concentration of energy use and

carbon emissions while green industry is made up of firms that implemented environmentally friendly policies and practices. Chemicals and allied products have 210 firms, while Oil and gas industry has 106 firms with metal mining having the least number of firms, 9 firms. Industrial machinery and equipment have 642 firms followed by services with 342 firms in the green industry. 380 firms reported missing R&D while 1916 reported positive R&D. Out of 380 firms that reported zero R&D, 336 firms are non-manufacturing firms and 44 are manufacturing firms. Table 1E shows firms with highest climate change exposure over years with ZIX corporation having the highest value (0.044). All control variables are winsorized at the 1st and 99th percentiles to decrease the impact of outliers and data errors on my analysis.[5]

Table 1C: Number of firms in the carbon intensive industry

SIC- 2 Digit industry- Carbon intensive industry	**Number of firms**
Metal Mining	10
Oil and gas extraction	106
Food and kindred products	49
Lumber and wood products	22
Paper and allied products	17
Chemicals and allied products	220
Petroleum and coal products	16
Rubber and miscellaneous plastic products	29
Stone, Clay, Glass, and Concrete Products	17
Primary metal	44
Transportation equipment	33
Railroad transportation	11
Trucking and warehousing	19
Water transportation	11
Transportation by air	21
General Merchandize stores	21
Electric, gas and sanitary services	36

Carbon intensive industries are industries that emit high carbon.

Table 1D: Number of firms in the carbon intensive industry

SIC- 2 Digit industry- green industry	Number of firms
Agriculture production and services	9
Construction	128
Tobacco products	2
Apparel and other textile products	28

[5] Out of the 2296 distinct firms, 682 firms representing about 25 percent fall into carbon intensive industry while the remaining 1614 unique firms fall into the green industries representing 75 percent.

Furniture and fixtures	20
Printing and publishing	42
Leather and leather products	10
Industrial machinery and equipment	622
Transportation and communications	78
Wholesale and retail trade	275
Services	285
Health and legal services	115

Green industries are industries that emit low carbon into the atmosphere.

Table 1E: Firms with highest climate change exposure over years

Year	Firms	climate change exposure
2002	CSX CORP	0.03119
2003	ELXSI CORP	0.03616
2004	ELXSI CORP	0.03063
2005	CSX CORP	0.03064
2006	DAILY JOURNAL CORP	0.03332
2007	DAILY JOURNAL CORP	0.02935
2008	DAILY JOURNAL CORP	0.03140
2009	ELXSI CORP	0.03063
2010	CPAC INC	0.02182
2011	TACTILE SYSTEMS TECHNOLOGY	0.02011
2012	ZIX CORP	0.02933
2013	ZIX CORP	0.03302
2014	CLEARONE INC	0.03966
2015	ZIX CORP	0.04460
2016	LIBERTY EXPEDIA HOLDINGS INC	0.03068
2017	MICRON SOLUTIONS INC	0.03341
2018	LIBERTY EXPEDIA HOLDINGS INC	0.04049
2019	LIBERTY EXPEDIA HOLDINGS INC	0.04333
2020	AMERICAN WOODMARK CORP	0.03420
2021	GOOD TIMES RESTAURANTS INC	0.03268
2022	TACTILE SYSTEMS TECHNOLOGY	0.0159

3.2. Baseline Model Specification

I follow the estimation techniques of Barnerjee & Gupta (2021) to construct control variables and then merge the sample with firm-level climate change measures. I begin my analysis with a fixed effect model for my baseline regression model to examine how climate

change exposures influence intensive margins of R&D. Equation 1 captures how climate change exposures affect intensive margins of R&D after controlling for firm and industry characteristics in equation 1. Furthermore, I lag explanatory variables by one period to prevent problems of simultaneity and reverse causality (Roberts & Whited, 2013; Mairesse & Mohnen, 2010).

$$R\&D_int_{it} = \alpha + \beta_1 CCExposure_{i,t} + \sum \beta_{k,j} X_{k,j,t-1} + \gamma_t + \varpi_i + \phi_j + \varepsilon_{i,t} + \upsilon_{j,t} \quad (1)$$

where i indexes firms, j represents industry and t indexes years. The dependent variable is the intensive margins of R&D, measured as the ratio of R&D expenditure to total assets. The main variable of interest, $CCExposure_{i,t}$ is the firm-level climate change exposure constructed by Sautner et al. (2023). $X_{k,j,t-1}$ is a vector of firm and industry specific control variables, such as firm size, firm age, profitability, leverage, capital investments, dividend dummy, cash holdings, book to market ratio, sales growth, market, Lerner index. γ_t is the time specific and $\varepsilon_{i,t}\ and\ \upsilon_{j,t}$ are the error term. I account for firm and industry fixed effects in the regression model. I include firm fixed effects, which are important because they account for time-invariant firm features that may be unobservable. Robust standard errors are clustered at the firm level to address the issue of heteroscedasticity.

The model specification to investigate how climate change exposure affects extensive margins of R&D is expressed in equation 2 using conditional logit regression. Standard maximum likelihood estimators[6] for binary response panel data models, which use individual heterogeneity as a parameter, are inconsistent when the time dimension (Time) is fixed, and the cross-section size (number) grows. The issue develops as the number of unit-specific unobserved effects accumulates. To identify latent model errors, Chamberlain (1980) suggests using the

[6] The conditional MLE in the unobserved effects logit model relies on the premise of conditional independence (CI), which implies that binary responses are independent over time, given observed variables and unobserved heterogeneity.

conditional logit technique using a logistic distribution. One advantage of this strategy is that it does not specify the distribution of the unobserved effect. I can estimate the partial effects of continuous factors and their impact on the log-odds ratio with consistency. One assumption of using conditional likelihood function is that it is assumed that the fixed effects and explanatory variables are not correlated with error term. I use the conditional logit propose by McFadden because all covariates vary by choice among firms. Then McFadden proposed the conditional logit model in this form

$$\Pr\ (R\&D_ext_i = j|X_{i0} \dots X_{ik}) = \frac{\exp\ (X_{ij}'\mathcal{B})}{\sum_{i=0}^{j} \exp\ (X_{ij}'\mathcal{B})}, \quad (2)$$

j = 0, ..., j. The parameter vector β is common for all choices, whereas the covariates vary by choice.

where i indexes' firms. The dependent variable is the extensive margin and is a dummy variable. Dummy variable of equals to 1 equal if the firm reported positive R&D expense in the corresponding year and 0 otherwise. The main variable of interest, $CCExposure_{i,t}$ is the firm-level climate change exposure constructed by Sautner et al. (2023). For the purpose of this study, I reported the marginal effects and the standard errors.

3.3.Measurements of variables

To test the hypotheses regarding how climate change exposure affects intensive margins of R&D investment, I use intensive and extensive margins of R&D as the dependent variables. The intensive margin of R&D is how much to invest in R&D in the business. The intensive margin of R&D is defined as the total expenditure in R&D over the number of firms engaged in R&D activities. Using Compustat data, one concern pertains to potential selectivity issues arising from firms with zero R&D investment. Moreover, a zero R&D ratio in a specific year for some firms may be due to substantial past or planned future investments. Hence, a zero value does not signify a significant behavioral difference regarding innovation. There are 4178 missing firm

observations for R&D and 7699 firm observations with zero R&D. I follow the R&D investment literature (Banerjee & Gupta 2021; Sunder et al., 2017; Wang, Wei & Song, 2017; Lin et al. 2011; Czarnitzki & Toole, 2008) and set the missing R&D expenses to zero. Following previous literature Yeh et al., 2010 and Hoang, 2021, I construct intensive margins of R&D as positive values of R&D expenditure divided by total sales. Analyzing intensive margins helps understand how much emphasis and investment are given to R&D spending. Other alternative measures are R&D expenditure (R&D divided by assets, R&D divided by number of employees and average R&D) were used in the robustness tests.

An extensive margin is the increase in R&D expenditure captured by the number of firms that begin doing R&D. Also, the extensive margin is the firm's decision to invest or not. This is based on firms that reported positive R&D and firms that report zero R&D and having missing R&D. I constructed the extensive margin, dependent variable, as a dummy variable, and it is set to 1 if the firm reported a positive R&D spend in a given year and 0 otherwise[7].

The main variable of interest is firm-level climate change. I utilize data developed by Saunter et al. (2020) to assess the extent of climate change exposure at the firm level[8]. These researchers create dynamic indicators of climate change exposure by analyzing earnings conference call transcripts. They employ a machine learning algorithm to generate sets of climate change-related word pairs (referred to as "bigrams") and gauge the frequency of these bigrams in the transcripts, normalized by the total number of bigrams. Essentially, this measurement reflects the presence of climate change-related events or disruptions specific to each firm. In their study, they demonstrate how these climate exposure measures effectively capture firm-level

[7] A limitation to this study comparing firms with missing R&D versus those with zero or positive R&D might be challenging due to non-random selection.
[8] The COMPUSTAT data is a long panel which contains a large set of firms from various industries. This helps to examine firm-level heterogeneity and allows to exploit individual fixed effects.

vulnerabilities associated with both the physical and regulatory impacts of climate change. This measure captures the market's assessment of the exposure of a firm to numerous upside and downside climate change aspects, including physical dangers, regulatory actions, and technology opportunities.

Following previous research (Barnerjee & Gupta (2021), I control for firm factors that have been shown to impact R&D margins significantly. Firm size is the natural logarithm of the book value of total assets. Firm age is the difference between the year under investigation and the year when the company's data became available in Compustat and CRSP datasets. As a result, firm age proxies experience, and R&D activities may benefit or be detrimental from organizational ageing. Market-to-book is the ratio is the ratio of asset market value to asset book value. The market to book ratio is included because, if a firm is innovative, higher earnings are directed towards R&D investments. Capital investment is corporate capital expenditure divided by total asset book value. Cash holding (cash hold) is measured as cash scaled by the value of total assets. Total debt is the sum of long-term debt and debt in current liabilities scaled by total assets. I include total debt to capture how the capital structure of the firm and its internal financing decisions affect R&D margins. Industry Sale growth (sales growth) is the percentage of sales (sale) growth from the previous year to the current year by 2-digit industry. A dividend dummy indicates 1 if firms pay dividends to common shareholders and 0 if they do not. Profitability (ROA) is pretax income scaled by total assets. I lag explanatory variables by one period to avoid simultaneity and reverse causality problems (see Mairesse and Mohnen, 2010). The variable descriptions are found in Appendix A.

4.0 Discussion of Results

The summary statistics are presented in Table 1. I measure the intensive margin of R&D investment as R&D expenditure scaled by total assets. On average, firms spend about $167.27 million on R&D. Firms spend. The mean of intensive margin of R&D is 3.2 percent with a standard deviation of 6.67 percent. The average value of the intensive margin of R&D is significantly higher than its median value. This implies that many firms spend less (or nothing) on R&D and there is a significant variance in the measure of climate change exposures. On average, firms spend 5.5 percent of their total assets on R&D investment. Firm-level climate change exposure has a mean of 0.0009 (0.9 percent) and a standard deviation of 0.0023 (0.23 percent). The values for the climate change exposure values are slightly lower than those in Sautner et al. (2023), who examined data from 10,673 companies in 34 nations. The correlation matrix in Table 2 provides early evidence that the intensive margin of R&D investment is positively correlated with firm-level climate change.

This gives early support for the hypothesis of strategic growth option theory. Firm size and age are negatively correlated with the intensive margin of corporate R&D. The result is that larger and older firms tend to invest less in R&D. Larger and older firms may invest less in R&D due to a preference for stability, profitability from existing products, potential difficulties in adjusting to innovative changes and other industry conditions.

Table 2: Summary Statistics

The summary statistics for the variables in this paper are shown in table 2. I present the mean, standard deviation, and the various percentile distributions. Financial firms (SIC 6000-6999) and utility firms (SIC 4900- 4999) were excluded from the analysis. I winsorize all continuous variables between the 1% and 99% percentiles. The sample data includes public firms in United States obtained from Compustat from 2002 to 2022. The Appendix contains a detailed set of variable definitions.

	N	Mean	Std. Dev.	p25	P50	p75	p99
Panel A: Variable of interest							
Dependent variables							
Positive R&D (millions of dollars)	24923	167.277	936.8362	0	0.43	25.985	4566
R&D intensive margin (R&D/ total assets)	24923	0.055	0.4714	0	0.0025	0.0415	0.4215
R&D intensive margin (R&D/ total sales)	24923	0.0322	0.0667	0	0.0026	0.036	0.2869
R&D extensive (1=engage and 0 otherwise)	24923	0.8554	0.3517	0	1	1	1
Climate related variables	24923						
Climate change exposure	24923	0.0009	0.0023	0.0001	0.0003	0.0007	0.0117
Opportunity exposure	24923	0.0002	0.0010	0	0	0.0001	0.0047
Regulatory exposure	24923	0.0001	0.0002	0	0	0	0.0009
Physical exposure	24923	0.0003	0.0001	0	0	0	0.0003
Firm-specific variables	24923						
Firm size	24923	6.6805	2.2495	5.0854	6.7523	8.2318	11.7389
Firm age	24923	30.9538	9.9642	15	20	37	70
Total debt	24923	0.1661	0.1618	0.0324	0.1273	0.2466	0.6846
Cash holding	24923	0.1188	0.1262	0.0305	0.0784	0.1619	0.6032
Dividend dummy	24923	0.4578	0.4982	0	0	1	1
Profitability	24923	0.0968	0.2126	0.0633	0.1137	0.1655	0.3776
Tobin Q	24923	1.6473	1.6233	0.8357	1.2081	1.8934	7.926
Book to market ratio	24923	0.0008	0.1581	0	0	0.0001	0.0003
Capital investment	24923	0.2199	0.2336	0.1116	0.1766	0.278	0.7864
Industry Controls	24923						
Industry sales growth	24923	0.2802	14.0722	-0.0256	0.0603	0.1627	1.2956
Lerner index (Market power)	24923	0.0506	2.0989	0.0515	0.113	0.191	0.5987
Panel B: Macroeconomic Controls							
Inflation	21	2.43333	1.73590	1.6	2.1	3.2	8
Interest Rate	21	1.38524	1.67559	0.12	0.54	2.16	5.24
Real GDP	21	9.72044	0.11426	9.64077	9.69892	9.81522	9.91257
Global Fin. Crisis (2007-2009)	21	0.14286	0.35857	0	0	0	1

Table 3: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) R&D intensive	1.000										
(2) Climate change exposure	0.012	1.000									
(4) Firm size	-0.160	-0.044	0.021	1.000							
(5) Firm age	-0.146	-0.035	0.033	0.140	1.000						
(6) Total debt	-0.127	-0.001	-0.050	0.210	0.083	1.000					
(7) cash holding	0.390	0.040	-0.008	-0.279	-0.193	-0.339	1.000				
(8) Profitability	-0.344	-0.033	-0.006	0.295	0.114	-0.023	-0.215	1.000			
(9) Tobin Q	0.214	0.025	-0.013	-0.081	-0.209	-0.269	0.272	-0.202	1.000		
(10) Book to market ratio	0.002	0.002	-0.002	-0.001	-0.006	-0.026	0.001	-0.002	0.005	1.000	
(11) Market power	-0.266	0.000	-0.006	0.090	0.030	0.021	-0.111	0.378	-0.138	0.000	1.000

This table reports correlation analysis. Definitions of variables are found in Appendix. The sample period is 2002 – 2022.

4.1. Main Regression Results

Table 4 presents the regression results where the dependent variable is the intensive margin of R&D (R&D divided by total assets). In column (1), I conduct univariate regression without adding any control variables, the coefficient is significantly positive at a 1% significant level. For economic significance, one standard deviation increase in climate change exposure leads to a 3.32 percent increase in the intensive margin of corporate R&D investment[9]. In column 2, the estimated coefficient is positive and statistically significant at 5%. The economic effect is that one standard deviation increase in climate change exposure increases the intensive margin of R&D by 1.50 percent when I include firm-level characteristics with year and firm-fixed effects. This result is consistent with hypothesis 1b that suggests that climate change exposure increases intensive margin of R&D investment based on the strategic growth options theory (Vo & Le, 2017; Ross, Fisch & Varga, 2017). In column 3, I use the industry-intensive margin of R&D as the dependent variable. The effect of climate change exposure on firms' intensive margin of R&D investment is significantly positive at a 5% significance level. The positive effect of climate change exposure increases more on the industry-intensive margin of R&D when industry

[9] I compute the estimated economic effect by multiplying the climate change exposure coefficient (0.9641) by the standard deviation of climate change exposure (0.0023) and dividing it by the mean of the R&D intensive (0.055).

and year-fixed effects are accounted for. This means that the economic significance is relatively large. In column 4, which has the full model and the key baseline regression, the estimated coefficient for climate change exposure is negative and statistically significant at 5%. The economic interpretation is that one standard deviation increase in climate change exposure leads to a 5.15 percent increase in the intensive margin of R&D investment. The finding shows that firms exposed to climate change leads to an increase in intensive R&D margins.

The positive coefficient for cash holding suggests that firms with higher cash reserves tend to invest more in R&D. This suggests that financial flexibility enables firms to devote resources to innovation. Profitability exhibits a negative relationship with an intensive margin of R&D. This indicates that more profitable firms may allocate fewer resources to R&D spending. I examine the effects of climate change exposure on the intensive margin of corporate R&D investment.

Table 4: Firm-level climate change exposure and R&D intensive margins.
This table presents fixed effects estimate of the effects of climate change exposure (CCE) on corporate R&D intensive margins using R&D/total sale as the dependent variable. Model 1 reports estimate using the CCE measure of climate change without any controls. Model 2 reports the estimates of how CCE affects R&D intensive margins after controlling for year, and firm fixed effect. Model 3 result shows how CCE affects R&D intensive margins at the industry level (2-digit SIC industry) when year effects industry fixed effects and firm-level characteristics are included. Column (4) and model 4 includes year, firm, industry effects as well as firm, industry, and macroeconomic controls. Appendix A presents variable definitions. Standard errors are clustered at the firm level. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3) Industry	(4)
	R&D	R&D	R&D	R&D
climate change expo	0.9641***	0.436**	30.5018***	1.4942**
	(0.2295)	(0.1741)	(7.6231)	(0.5939)
Firm size		0.005***	0.9358***	0.0078***
		(0.0006)	(0.0183)	(0.0011)
Total debt		-0.0661***	-1.755***	-0.057***
		(0.0053)	(0.2209)	(0.0148)
Firm age		-0.0005***	0.0027*	-0.0008***
		(0.0001)	(0.0014)	(0.0001)
Cash holding		0.2019***	0.8884***	0.2925***
		(0.0189)	(0.1756)	(0.0497)
Dividend dummy		-0.0259***	-0.4106***	-0.0386***
		(0.0015)	(0.0278)	(0.0024)
Profitability		-0.1332***	-0.537***	0.1774***

		(0.034)	(0.1203)	(0.0594)
Tobin Q		0.0093***	0.0131	0.0044
		(0.0023)	(0.0173)	(0.0048)
Book to market ratio		-0.0005*	-0.1816***	0.0012***
		(0.0003)	(0.0414)	(0.0004)
Capital investment		0.0065	0.4249	-0.0181
		(0.0045)	(0.2934)	(0.0215)
Sale growth			-0.0092***	-3.61e-06
			(0.0029)	(0.0002)
Lerner			0.0004	-0.1845***
			(0.0035)	(0.0221)
Inflation				0.0011
				(0.0007)
Federal interest rate				0.0026***
				(0.0005)
Global Financial Crisis				0.0167***
				(0.0039)
Global financial crisis				-0.0182
				(0.0135)
Constant	0.037***	0.0182***	-5.7392***	0.1727
	(0.0002)	(0.0065)	(0.3276)	(0.1248)
Observations	24923	24923	11650	24923
R-squared	0.0016	0.2252	0.7128	0.6596
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes
Industry Effects	No	No	Yes	Yes

Potential Mechanism

The interaction effects of how climate change exposure affects intensive margin of R&D

Climate change exposure affects the intensive margin of R&D through various channels. In this section, I discuss the potential economic channels through which climate change exposure increases the intensive margin of corporate R&D, including vertical integration and growth opportunities in Table 5. The estimated coefficient in model 1 is 1.7882, which is statistically significant at 1%. This shows that the interaction between Climate Change exposure and vertical integration significantly increases intensive R&D margins. The estimated coefficient is positive and statistically significant at 5%. This supports hypothesis 2 which suggests that vertical integration and climate change exposure have a positive relationship on intensive margins of

R&D investment. This supports the view that vertically integrated firms are better positioned to leverage their internal capabilities to respond climate change policies and its effect on intensive margin of R&D investment. Also, in model 2, the interaction term has a coefficient of 0.4809, and is positive and statistically significant at 5%. This suggests that the effect of climate change exposure on intensive margin of R&D is enhanced by growth opportunities. This supports hypothesis 3 which indicates that the effect of climate change exposure on intensive margin of R&D is influenced by the level of growth opportunities.

Table 5: Channels through which Firm-level climate change exposure and R&D intensive margins

This table presents fixed effects estimate of the effects of climate change exposure (CCE) on intensive margins of corporate R&D using R&D/total sale as the dependent variable. This examines the potential channels through which climate change exposure affects intensive margin of corporate R&D. Appendix A presents variable definitions. The sample comprises 2296 firms in the COMPUSTAT data from 2002- 2022, excluding financial firms (SIC 6000-6999) and utility firms (SIC 4900-4999). Standard errors are clustered at the firm level. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) R&D	(2) R&D
Climate Change exposure	0.7913***	0.4902**
	(0.1976)	(0.2371)
Vertical integration	0.0373***	
	(0.0075)	
CC exposure x integration	1.7882***	
	(0.3057)	
Growth opportunities		0.0087***
		(0.0032)
CC exposure x growth		0.4809**
		(0.2447)
Firm size	-0.0013***	-0.0011***
	(0.0003)	(0.0002)
Firm age	-0.0033***	-0.0054***
	(0.0008)	(0.0004)
Total debt	-0.0001***	-0.0002***
	(0.0001)	(0.0001)
Cash holding	0.108***	0.1197***
	(0.0076)	(0.0084)
Dividend dummy	-0.0109***	-0.0096***
	(0.001)	(0.0005)
Profitability	-0.0668***	-0.0425***
	(0.0194)	(0.0125)
Tobin Q	0.0052***	-0.0021
	(0.0009)	(0.0032)
Book to market ratio	-0.0011***	-0.0007***

	(0.0002)	(0.0002)
Capital investment	0.0119**	0.0077**
	(0.0049)	(0.0035)
Constant	0.2562***	0.2362***
	(0.0388)	(0.0272)
Observations	24923	21238
R-squared	0.3021	0.2405
Year Effects	Yes	Yes
Firm Effects	Yes	Yes
Industry Effects	Yes	Yes
Other Controls	Yes	Yes

I carry out a sub-sample analysis between carbon intensive firms and green firms as well as manufacturing and non-manufacturing firms. The result shows that climate change exposure increases the intensive margin of corporate R&D investment more for firms in the carbon-intensive industries than firms in the green industries. I carry out a sub-sample analysis between manufacturing and non-manufacturing firms. Also, this suggests that manufacturing firms facing higher climate change tend to invest significantly more in intensive margin of R&D as compared to non-manufacturing firms. The findings align with hypothesis 4 which states that intensive margins of R&D investment increase for carbon-intensive and manufacturing firms as climate change exposures increase.

Table 6: Firm-level climate change exposure and R&D intensive margins across industry.
This table presents fixed effects estimate of the effects of climate change exposure (CCE) on corporate R&D intensive margins using R&D/total sale as the dependent variable. Model 1 and 2 reports the estimates of how CCE affects R&D intensive margins among carbon intensity firms (firms that emits high carbons) and green firms after controlling for year, firm, industry effects as well as firm, industry and macroeconomic. Columns (3-4) show estimates among manufacturing and non-manufacturing firms when year, firm, industry effects as well as firm, industry and macroeconomic controls are included. Appendix A presents variable definitions. The sample comprises 2296 firms in the COMPUSTAT data from 2002- 2022. Standard errors are clustered at the firm level. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1) Carbon intensity firms	(2) Green firms	(3) Manufacturing firms	(4) Non-manufacturing firms
Dependent: Intensive margin				
climate change expo	7.4232**	0.5531*	2.4082**	0.8735
	(3.5261)	(0.2400)	(1.3103)	(0.1973)
Firm size	0.0128***	0.0066***	0.0111***	0.0042***
	(0.0023)	(0.0010)	(0.0018)	(0.0006)
Total debt	-0.0484	-0.0772***	-0.0585**	-0.0464***

	(0.0644)	(0.0110)	(0.0269)	(0.0062)
Firm age	-0.0015***	-0.0007***	-0.0007**	-0.0012***
	(0.0005)	(0.0003)	(0.0003)	(0.0002)
Cashholding	0.6327***	0.1724***	0.3955***	0.1378***
	(0.1449)	(0.0400)	(0.0824)	(0.0164)
Dividend dummy	-0.0545***	-0.0306***	-0.0573***	-0.0197***
	(0.0072)	(0.0035)	(0.0032)	(0.0014)
Profitability	0.2652**	0.0946	0.1987**	0.0259
	(0.1068)	(0.0794)	(0.0811)	(0.0477)
Tobin Q	-0.0100	0.009***	0.0008	0.0078***
	(0.0194)	(0.003)	(0.0077)	(0.0011)
Book to market ratio	-0.0003	0.0007	0.0022*	0.0008**
	(0.0170)	(0.0009)	(0.0013)	(0.0004)
Capital investment	0.0156	-0.0358	0.0118	-0.0056
	(0.0190)	(0.0364)	(0.0192)	(0.0245)
Sale growth	0.0002	-0.0004	-0.0047	-0.0001
	(0.0001)	(0.0005)	(0.006)	(0.0001)
Lerner	-0.1988***	-0.1819***	-0.1884***	-0.0772*
	(0.0499)	(0.0212)	(0.0213)	(0.0427)
Inflation	0.0021	0.0007	0.0001	0.0019***
	(0.0015)	(0.0008)	(0.0007)	(0.0006)
Federal interest rate	0.0028***	0.0026***	0.0044***	-0.0001
	(0.0010)	(0.0006)	(0.0010)	(0.0003)
Global Financial Crisis	0.0478***	0.0032*	0.0227***	0.0034**
	(0.0150)	(0.0019)	(0.0075)	(0.0015)
Real GDP	-0.0626***	-0.0082	-0.0275*	0.0012
	(0.0195)	(0.0163)	(0.0162)	(0.0121)
Constant	0.5708***	0.0988	0.2483*	0.0079
	(0.1662)	(0.1570)	(0.1421)	(0.1198)
Observations	6535	18388	14335	10588
R-Squared	0.3697	0.7846	0.6746	0.3750
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes

Climate change exposure and extensive margin of R&D

I examine the effects of climate change exposure on extensive margin of R&D. Without any controls, the result in Table 7 shows that climate change exposure affects extensive margin of R&D positively. The probability of engaging in R&D is 16.56 percent, statistically significant at 5% in column 1. In column 3, the extensive margin of R&D increases by 16.11 percent when firm and macroeconomic controls are included.

Table 7: Firm-level climate change exposure and R&D extensive margins.

This table reports the regression results estimating Equation (1). All the variables are defined in Appendix A. I estimate conditional logistic regressions when the R&D measure is a binary variable. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(3)
Dependent: R&D Extensive	Marginal Effects	Marginal Effects
climate change expo	0.16557***	0.1611*
	(0.1049)	(0.1038)
Firm size		0.0297***
		(0.0011)
Total debt		0.0267***
		(0.0148)
Firm age		0.0293***
		(0.0219)
Cash holding		0.0345***
		(0.0497)
Dividend dummy		0.0087*
		(0.0024)
Profitability		0.0263***
		(0.0018)
Tobin Q		0.0036**
		(0.0018)
Book to market ratio		0.0064
		(0.0167)
Capital investment		-0.0181
		(0.0215)
Sale growth		0.0293
		(0.0002)
Lerner		0.0025**
		(0.0010)
Inflation		0.0015
		(0.0051)
Federal interest rate		0.0091
		(0.0074)
Global Financial Crisis		0.0019
		(0.0039)
Real GDP		0.0288
		(0.0454)
Observations	24923	24923
Pseudo R-Squared	0.0001	0.0187
Year Effects	Yes	Yes
Firm Effects	No	Yes
Industry Effects	No	Yes

I further test whether the extensive margin of R&D effect is stronger for carbon-intensive firms when climate change exposure increases. The result shows that the extensive margin of

R&D increases by 24.23 percent for firms in carbon-intensive industries when climate change exposure increases as compared to green firms' 10.16 percent. This finding supports the interpretation that climate change exposure improves firms' incentives to engage in R&D and this is consistent with the strategic growth option theory.

Table 8: Firm-level climate change exposure and R&D extensive margins.
This table presents regression results on a subsample of firms in carbon intensive and green industry. high corrupt and low corrupt states. The dependent variable is extensive margin of R&D (R&D measure is a binary). All the firm controls from the baseline model are included in the regression. All the firm variables are winsorized at 1% and these are defined in Appendix 1. Standard errors are clustered at firm level. *, **, *** indicates statistical significance at the 10%, 5% and 1% level, respectively.

	Carbon intensive firms	Green firms	Manufacturing firms	Non-manu facturing firms
Dependent: R&D Extensive	Marginal Effects	Marginal Effects	Marginal Effects	Marginal Effects
climate change expo	0.2423**	0.1016*	0.3486**	0.4141
	(0.0230)	(0.1239)	(0.674)	(0.3735)
Firm size	0.0043**	0.0157***	0.0294***	0.0194***
	(0.0017)	(0.0020)	(0.0023)	(0.0012)
Total debt	0.0179	0.1142***	0.0899**	0.0378***
	(0.0231)	(0.0210)	(0.0284)	(0.0106)
Firm age	0.0007**	0.0013***	0.0015***	0.0010***
	(0.0003)	(0.0003)	(0.0004)	(0.0002)
Cash holding	0.1063***	0.2840***	0.4422***	0.0339***
	(0.0259)	(0.0387)	(0.0442)	(0.0101)
Dividend dummy	0.0132**	0.0164**	0.0397***	0.0217***
	(0.0078)	(0.0066)	(0.0099)	(0.0042)
Profitability	0.0297**	0.2428***	0.5746***	0.0163**
	(0.0127)	(0.0351)	(0.0500)	(0.0060)
Tobin Q	0.0089**	0.0008	0.0086**	0.0005
	(0.0028)	(0.0022)	(0.0039)	(0.0006)
Book to market ratio	0.0097	0.0059	0.1818	0.0313
	(0.0828)	(0.0177)	(0.1584)	(0.0217)
Capital investment	0.0205	0.1215***	0.4603***	0.0019
	(0.0206)	(0.0225)	(0.0313)	(0.0058)
Sale growth	0.0003	0.0011***	0.0022***	0.0001
	(0.0009)	(0.0003)	(0.0004)	(0.003)
Lerner	0.0056	0.0040***	0.1906**	0.001
	(0.0041)	(0.0012)	(0.0240)	(0.002)
Observations	6,530	18,373	14,322	10,581
Pseudo R-Squared	0.0263	0.0282	0.1977	0.0548
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	Yes	Yes
Industry Effects	No	No	Yes	Yes
Other controls	No	No	Yes	Yes

Event Study base of different time events of Paris Agreement

I use the different time events for Paris Agreement to estimate different treatment effects depending on intensive margin of R&D. The Paris Agreement is a climate change adaptation and mitigation accord inside the United Nations Framework Convention on Climate Change (UNFCCC). The Paris Agreement is a legally enforceable international climate change treaty design by United Nations. It was adopted by 198 parties on 12 December 2015 and went into effect on November 4, 2016. Its goal is to keep global warming below 2 degrees Celsius, preferably 1.5 degrees Celsius, compared to pre-industrial levels. As a result, I purposefully chose this shock with a large worldwide impact to make comparisons across time. The Paris Agreement raises climate change regulatory exposure and may push firms with high climate change risk or those in climate-sensitive industries to spend more on environmentally friendly initiatives.

I conduct an event study using treatment effects at different time periods from when the program was received: 1= during the adoption of Paris Accord (2015-2016), 2 = announcement of withdrawal from the Paris Accord (2017-2020) and 3=rejoining the Paris Accord. The main aim of this test is to show that firms' intensive margin of R&D is influenced by climate change exposure under different time periods of Paris Agreement. I estimate the following regression model to examine the impact s climate change exposures on the intensive margin of corporate R&D:

$$R\&D_int_{it} = \alpha + \beta_1 CCExposure_{i,t} + \beta_2 time_{Paris\ Agreement_t} + \beta_3 CCExposure_{i,t} * time_{Paris\ Agreement_t} + \sum \beta_{k,j} X_{k,j,t-1} + \delta_t + \varpi_i + \varepsilon_{i,t} \quad (3)$$

where i and t index firm and year, respectively. The dependent variable *CSR* represents the corporate social responsibility score of firm i at time t. The key explanatory variable is the interaction term $CCExposure \times time_{Paris\ Agreement_t}$. The $time_{Paris\ Agreement_t}$ is a dummy

variable that equals 1= during the adoption of Paris Accord (2015-2016), 2 = announcement of withdrawal from the Paris Accord (2017-2020) and 3=rejoining the Paris Accord. *CC Exposure* is the firm-level climate change risk index in year t. $X_{k,j,t-1}$ are the firm-level, industry, and macroeconomic control variables. The interaction term's coefficient, β_3, captures the influence of the Paris Agreement on firms' amount spend on R&D in those years.

The interaction term coefficient is positive and statistically significant at the 5% level when US join the Paris Accord. This shows that the positive impact of climate change exposure on intensive margin of R&D increase during the Paris Accord adoption period. Also, the negative interaction effect (-1.4382 and -1.6443 in model 1 and 2) suggests that climate change exposure had a negative impact on intensive margin of R&D during the withdrawal period. Uncertainty about future laws and incentives may have led firms to limit their R&D investments in climate-related technologies, preferring to wait for more stable policy signals. In model 1 and 2, the estimated coefficients (1.2855 and 2.8295 in model 1 and 2) are positive and statistically significant at the 5% level. This shows a strong positive interaction effect, indicating that the rejoining of the Paris Accord significantly enhanced the positive impact of climate change exposure on intensive margin of R&D.

Table 9: Firm-level climate change exposure and intensive margin of R&D.
This table reports the regression results estimating Equation (3). All the variables are defined in Appendix A. I estimate the fixed regressions for the effects of different time periods of Paris Accord on intensive R&D measure. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

	Model 1	Model 2
climate change exposure	2.4876**	2.3717**
	(1.0788)	(0.9881)
Events:		
Paris Accord adoption (2015-2016)	0.0107***	0.0118***
	(0.0009)	(0.0027)
Paris Accord withdrawal (2017-2020)	-0.0022	-0.0230
	(0.0009)	(0.0047)
Rejoin (2021-present)	0.0017**	0.0624**

	(0.0018)	(0.0079)
Paris Accord adoption x CC exposure	2.3115**	2.0439**
	(1.1504)	(1.0722)
Paris Accord withdrawal x CC exposure	-1.4382*	-1.6443*
	(1.0900)	(0.9468)
Paris Accord withdrawal x CC exposure	1.2855**	2.8295**
	(1.2025)	(1.1935)
Firm size		0.0039***
		(0.0011)
Total debt		-0.0281***
		(0.0023)
Firm age		- 0.0007***
		(0.0001)
Cash holding		0.2922***
		(0.0488)
Dividend dummy		-0.0314***
		(0.0027)
Profitability		0.1664**
		(0.0566)
Tobin Q		0.0052
		(0.0047)
Book to market ratio		-0.0005
		(0.0008)
Capital investment		-0.0116
		(0.0220)
Sale growth		0.0001
		(0.0002)
Observations	24,923	24,923
R-Squared	0.001	0.6619
Year Effects	Yes	Yes
Firm Effects	No	Yes
Industry Effects	No	Yes
Controls	No	Yes

Quasi-natural experiment base on Renewable Portfolio Standard (RPS)

To identify the causal effect of climate change exposure on the intensive margin of R&D, I focus on the Renewable Portfolio Standard and use a Difference-in-Differences (DiD) research design to examine the impacts of this policy on the intensive margin of corporate R&D.

Renewable Portfolio Standard

The United States through Members of Congress have varied perspectives on climate change, propose measures like carbon pricing, clean energy standards, and GHG-abating

technology funding. Some resolutions oppose multisector carbon pricing for economic reasons. Votes on comprehensive climate policy are rare, but enacted laws include renewable energy tax incentives and carbon capture efforts (Congressional Research Service report, 2019). Renewable portfolio standards (RPS) are one of these policies, which require that a particular percentage of a state's power supply be generated from renewable sources, have been a major exception. The first RPS was enacted in Iowa in 1991, and others have since followed suit. I concentrate on the impact of RPS, which is extensively employed as substantive state-level climate policy (Rabe, 2006). RPS requires electricity retailers to supply a particular percentage of renewable energy to increase renewable energy supply (Lee, 2020). RPS regulations were enacted in 29 states and the District of Columbia as of 2015, accounting for 62% of total electricity generation[10].

However, 18 States continue to adopt RPS after 2015. So, they are the treatment group, and the treatment period of interest is 2015 and beyond as shown in figure 1.4 and Table 10A.

States that continue to make regular and significant revisions after 2015

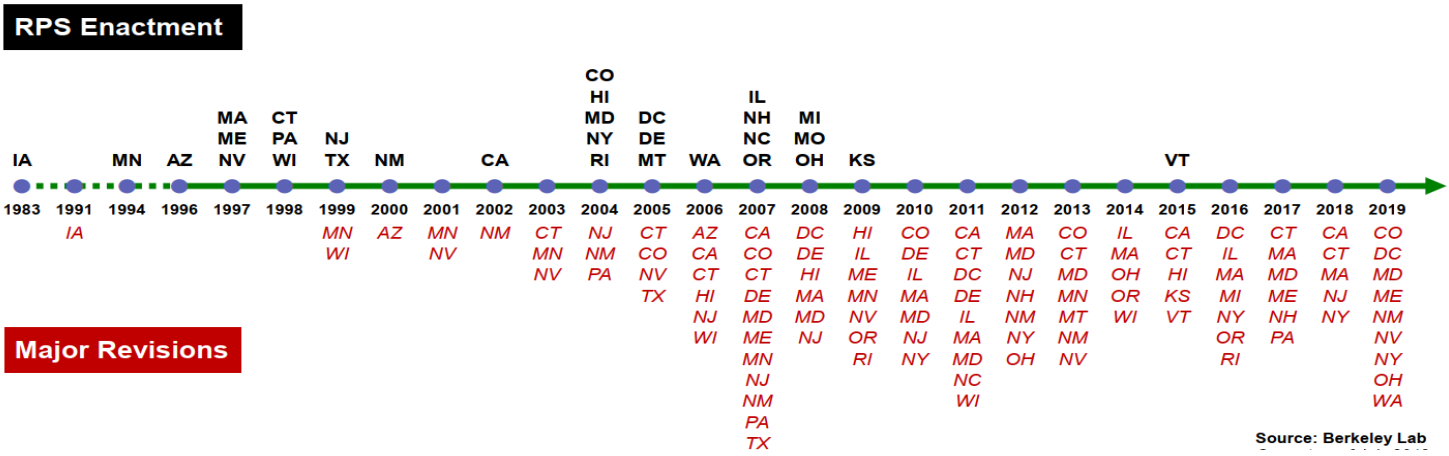

Figure 1.4: States that continue to make regular and significant revisions after 2015

Source: Berkeley Lab, 2019

[10] Renewable Portfolio Standards (RPS) demand that utilities sell a certain amount of their electricity from renewable sources. States established these requirements to diversify their energy resources, foster domestic energy generation, and promote economic development.

Table 10 A: States that adopted and not adopted RPS after the Paris Agreement

Treated States	Control States
Illinois	Alabama
Massachusetts	Alaska
Michigan	Arizona
New York	Arkansas
Oregon	Delaware
Rhode Island	Florida
Connecticut	Georgia
Maryland	Hawaii
Maine	Idaho
New Hampshire	Indiana
Pennsylvania	Iowa
California	Kansas
New Jersey	Kentucky
Colorado	Louisiana
New Mexico	Minnesota
Nevada	Mississippi
Ohio	Missouri
Washington	Montana
	Nebraska
	North Carolina
	North Dakota
	Oklahoma
	South Carolina
	South Dakota
	Tennessee
	Texas
	Utah
	Vermont
	Virginia
	West Virginia
	Wisconsin
	Wyoming

I use differences in differences research design base on States that adopt RPS programs (Treated States) and the non-adoption States (Control States). I control for other covariates that could influence changes in intensive margin of R&D. I use differences in differences research

design base on States that adopt RPS programs (Treatment States) and the non-adoption States (Control States).

$$R\&D_int_i = \alpha + \beta_1 Post_year_i + \beta_2 RPS\ State_i + \beta_3 Post_year_i * RPS\ State_i + \sum \beta_{k,j} X_{k,j,t-1} + \delta_t + \varpi_i + \varepsilon_{i,t} \quad (4)$$

where i and t index firm and year, respectively. The dependent variable $\&D_int$ represents the intensive margin of R&D of firm i at time t. $Post_year_{i,t}$ is treatment period of interest is 2015 and beyond. $RPS\ State$ is a dummy variable that equals 1 for a firm in the State adopting RPS after 2016 (defined as treatment firms) and zero for non-adopting States (control firms). The key explanatory variable is the interaction term $Post_year_i * RPS\ State_i$. *CCExposure* is the firm-level climate change risk index in year t. $X_{k,j,t-1}$ are the firm-level, industry and macroeconomic control variables. The interaction term's coefficient, β_3, captures the influence of the RPS on firms' amount spend on R&D in those years. I expect a positive and statistically significant coefficient of the interaction term between climate change exposure and the Paris Agreement. Before running the analysis, I tested for the parallel trend assumption.

Parallel Trend Assumption

I demonstrate and confirm the parallel trends assumption in figure 1.5, which posits that the pre-intervention trends in the outcome variable are consistent between the treatment and control groups. This assumption necessitates that, in the absence of the policy intervention, the difference in the outcome variable remains constant between the treatment group and the control group. In Figure 5, the intensive margin of R&D of both groups displays similar trends. This shows that the parallel trends assumption is satisfied.

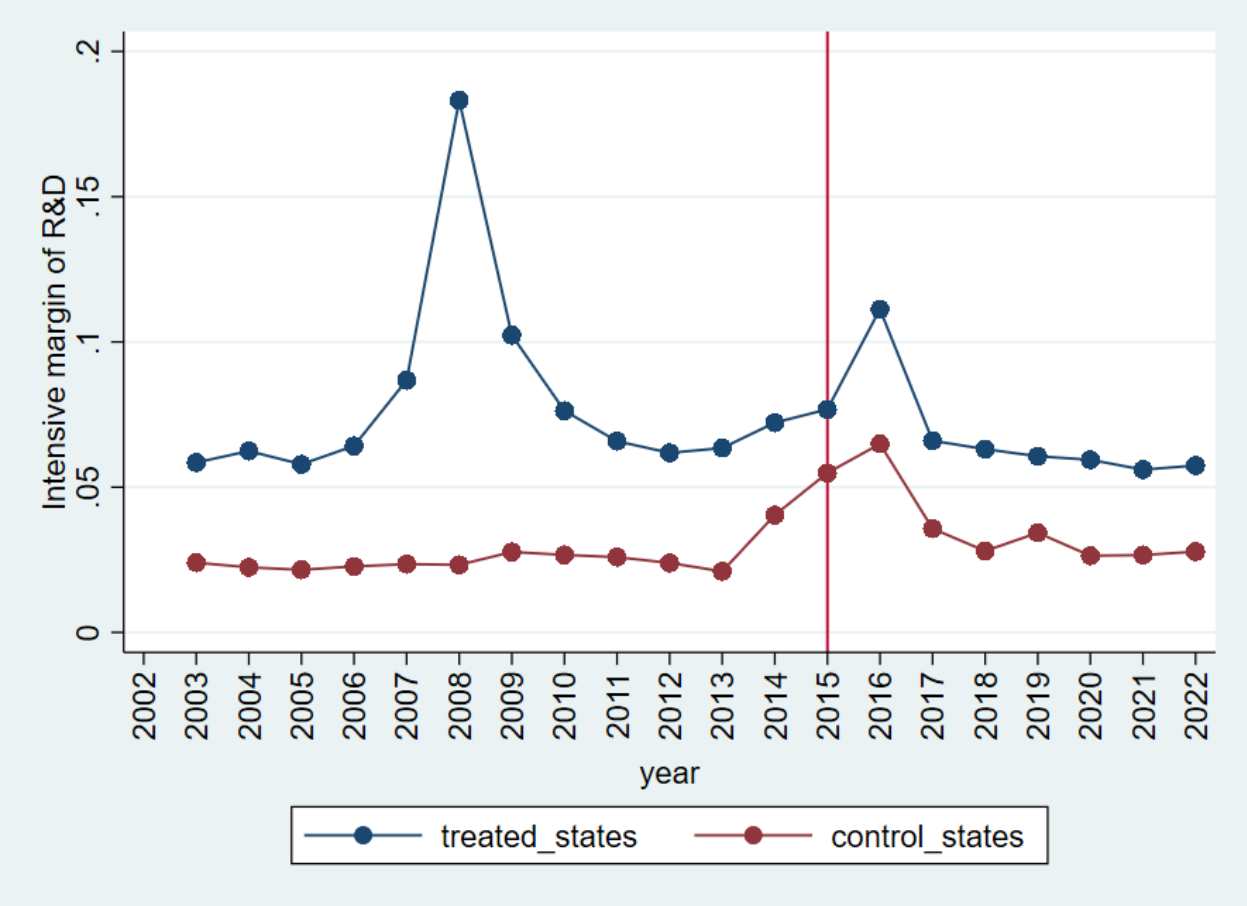

Figure 1.5: Trend of intensive margin of R&D between the "Treated States" vs "Control States"

In Table 10B, I conduct a preliminary analysis of the treatment effects of the outcome variable (intensive margin of R&D). I computed average intensive margin of R&D for pre-policy and post-policy periods. Applying the difference-in-difference, my result shows positive effect and a statistically significant increase in intensive margin of R&D by 0.023. The analysis of the treatment effects of other covariates is in Table 10C.

Table 10B: Preliminary analysis of treatment effects

	Treatment Group	Control Group	Treatment Effect
Post	0.079	0.025	0.054
Pre	0.070	0.039	0.031
DID Estimator	0.009	-0.014	**0.023**** **(0.013)**

value in parenthesis is standard error for treatment effects.

Table 10C: Analysis of Treatment Effects

Variable(s)	Mean Control	Mean Treated	Diff.	P-value
climate change expo	0.001	0.002	0.001	0.018**
Firm size	6.445	6.338	-0.107	0.002***
Total debt	1.206	1.099	-0.107	0.000***
Firm age	31.366	31.29	-0.077	0.588
Cash holding	0.099	0.134	0.035	0.000***
Dividend dummy	0.471	0.418	-0.053	0.000***
Profitability	0.113	0.09	-0.023	0.000***
Tobin Q	1.45	1.593	0.143	0.000***
Book to market ratio	0.004	-0.001	-0.004	0.142
Capital investment	0.22	0.236	0.016	0.000***
Sale growth	0.387	0.177	-0.21	0.356
Lerner	0.089	-0.007	-0.096	0.012**
Inflation	2.392	2.397	0.005	0.787
Global financial crisis	0.246	0.248	0.002	0.762
Real GDP	9.649	9.648	-0.001	0.341

***, ** and * indicate mean difference-in-differences between treatment and control groups and statistically significant at the 1%, 5% and 10% levels, respectively

The estimated difference-in-differences of 2.22 percent suggests that the intensive margin of R&D in the states that were especially affected by the RPS program after 2015 increase as compared to the non-adopting States without other covariates. However, when other covariates were included in the model as shown in column 2 of Table 11, The interaction term "RPS Treated x Post period" shows a positive and statistically significant impact at 10%, suggesting that the Renewable Portfolio Standards (RPS) policy effectively increase intensive margin of R&D for adopting States than non-adopting States.

Table 11: Difference-in-difference after RPS Implementation

	(1) R&D	(2) R&D
RPS Treated	0.0539***	0.0234***
	(0.0103)	(0.0083)
RPS Treated x Post period	0.0222**	0.0294*
	(0.0103)	(0.0161)
Post period	0.0136**	-0.0109

	(0.0057)	(0.0069)
climate change exposure		0.4974
		(0.4584)
Firm size		0.0036*
		(0.0019)
Cash holding		0.3224***
		(0.0717)
Profitability		-0.3873***
		(0.1485)
Tobin Q		0.0268
		(0.019)
Book to market ratio		-0.0012*
		(0.0006)
Capital investment		0.0074
		(0.0229)
Inflation		0.0046***
		(0.0012)
Federal interest rate		0.0021
		(0.0014)
Global Financial Crisis		0.0323***
		(0.0068)
Real GDP		-0.0061**
		(0.0027)
Observations	24923	24903
R-squared	0.0039	0.0669
Year Effects	Yes	Yes
Firm Effects	No	Yes
Industry Effects	No	No

Table 12 provides insights into the effect of Renewable Portfolio Standards (RPS) treated States and post year periods on intensive margin of R&D, considering climate change exposure as a moderating factor. In column 1, the interaction term "Post period x CC exposure" is positive and statistically significant at 10%, suggesting that the post-policy period further enhances the impact of climate change exposure on intensive margin of R&D corporate investment. Furthermore, in column 2, the interaction term "RPS Treated x CC exposure" is positive and significant, implying that RPS treatment combined with climate change exposure leads to increased intensive margin of R&D corporate investment.

Table 12: Interaction of post-period and treated effects and climate change exposure on R&D intensive margin

	(1) R&D	(2) R&D
climate change exposure	2.3189**	1.3615***
	(1.0724)	(0.3866)
Post period x CC exposure	2.1003*	
	(1.1087)	
Post period	0.0153	
	(0.0098)	
RPS treated		0.0154**
		(0.0073)
RPS treated x CC exposure		0.0141
		(0.9118)
Firm size	0.0037***	0.0037***
	(0.0012)	(0.0012)
Total debt	-0.027***	-0.0271***
	(0.0022)	(0.0022)
Firm age	-0.0006***	-0.0006***
	(0.0002)	(0.0001)
Cash holding	0.2567***	0.2559***
	(0.0484)	(0.0482)
Dividend dummy	-0.025***	-0.025***
	(0.003)	(0.003)
Profitability	0.1686***	0.1683***
	(0.0565)	(0.0565)
Tobin Q	0.0027	0.0027
	(0.0048)	(0.0048)
Book to market ratio	-0.00004	-0.0002
	(0.0005)	(0.0004)
Capital investment	-0.0132	-0.0136
	(0.0222)	(0.022)
Sale growth	0.0001	0.0001
	(0.0002)	(0.0002)
Lerner	-0.185***	-0.185***
	(0.0219)	(0.0219)
Constant	0.5128	-0.012
	(0.3562)	(0.1661)
Observations	24922	24922
R-squared	0.6652	0.6651
Year Effects	Yes	Yes
Firm Effects	Yes	Yes
Industry Effects	Yes	Yes
Controls	Yes	Yes

Robustness tests

I conduct several robustness checks. I re-estimate the basic regressions (Table 13) using different measures of intensive margin of R&D by applying the Generalized method of moments (GMM). To account for the impact of lagged R&D investment on current investment (Bloom, 2007), I include two lags of the dependent variables into the model and use a dynamic panel generalized method of moments (GMM) estimator to address endogeneity concerns (Wintoki, Linck, & Netter, 2012). In column 1, I measure intensive margins of R&D using R&D per total assets. The finding shows that the coefficient of climate change exposure is positive and statistically significant at 5%. Also, the coefficient of climate change is positive and statistically significant at 5% when R&D is divided employment. And climate change exposure influence R&D intensive margins positively and statistically significant at 1% when average R&D as the measure for intensive margin of R&D. Overall, I reconfirm my findings using alternative dependent variables of intensive margin of R&D.

Table 13: Results of 2-way system GMM models

VARIABLES	(1) RD/Assets	(2) RD/Emp	(3) Average R&D
$(\mathrm{RD/assets})_{t-1}$	0.4853***		
	(0.0038)		
$(\mathrm{RD/assets})_{t-2}$	-0.0161***		
	(0.0030)		
$(\mathrm{RD/Emp})_{t-1}$		0.5005***	
		(0.0005)	
$(\mathrm{RD/Emp})_{t-2}$		0.0656***	
		(0.0004)	
$(\mathrm{Avg_RD})_{t-1}$			1.1504***
			(0.0001)
$(\mathrm{Avg_RD})_{t-2}$			-0.0551***
			(0.0001)
Climate change exposure	0.0918**	7.3446**	7.1110***
	(0.0489)	(5.2854)	(33.1411)
Firm size	-0.0165***	4.8272***	2.8397***
	(0.0006)	(1.3749)	(0.3195)
Firm age	-0.0003***	-3.9659***	-1.4249***
	(0.0001)	(4.8554)	(0.0822)
Total debt	-0.0060***	-6.5721	-6.7488***

	(0.0023)	(2.9744)	(1.0881)
Cash holding	-0.0161***	6.8635***	-15.9940***
	(0.0019)	(0.2672)	(0.7556)
Dividend dummy	0.0021***	1.7150***	4.8482***
	(0.0005)	(1.5708)	(0.1713)
Profitability	-0.0518***	-8.6208***	-8.6894***
	(0.0026)	(3.1284)	(1.0516)
Tobin Q	-0.0001	-5.6941***	5.6620***
	(0.0002)	(6.7396)	(0.1554)
Book to market ratio	0.0006	-1.3002	-0.4221
	(0.0005)	(0.2328)	(0.9794)
Capital investment	0.0033**	8.5106**	-0.0460
	(0.0014)	(0.0380)	(0.7615)
Salegrowth	0.0003***	3.2552***	-0.3494***
	(0.0000)	(1.7578)	(0.0447)
Market power	-0.0015***	-8.9753***	0.2501***
	(0.0001)	(4.0280)	(0.0739)
Constant	-0.2905***	-8.5299***	-6.4038***
	(0.0307)	(5.2267)	(1.1739)
Observations	20,205	19,779	20,204
Number of firms	2,018	1,998	2,018
Observation	20205	19779	20204
AR (1)	-4.476	-2.377	-2.219
AR (2)	0.334	0.154	0.547
Sargan	319.7	688.2	1015
Controls	Yes	Yes	Yes

Similarly, I use different measures for climate change exposure including opportunities exposure, regulation exposure, and physical exposure. The estimated coefficients of the different measures of climate change exposure influence intensive margins of R&D positively and statistically significant at 1%. Compared with the baseline results, the effect of a one standard deviation increases in the climate change opportunity exposure increase intensive margin of R&D by 0.01 percent. Also, the economic interpretation of climate change regulatory exposure on intensive margin of R&D shows that one standard deviation increase in regulatory exposure leads to a 0.0068 percent increase in intensive margin of R&D. Furthermore, one standard deviation increase in climate change physical exposure leads to 0.004 percent increase in intensive margin of R&D. The results remain consistent with the baseline findings that climate change exposure causes firms to increase their intensive margin of R&D as shown in Table 14.

Table 14: Different measures of climate change exposures on the intensive margin of R&D using GMM models

VARIABLES	(1) Opportunity exposure	(2) Regulatory exposure	(3) Physical exposure
$(\text{RD/total asset})_{t-1}$	0.4670***	0.5421***	0.2135***
	(0.0043)	(0.0013)	(0.0115)
$(\text{RD/total asset})_{t-2}$	0.0077**	0.1398***	0.3556***
	(0.0031)	(0.0007)	(0.0110)
CC Opportunity exposure	0.007***		
	(0.0001)		
CC Regulatory exposure		0.023***	
		(0.0000)	
CC Physical exposure			0.028***
			(0.0004)
Firm size	-0.0130***	-0.0266***	0.0074***
	(0.0005)	(0.0000)	(0.0009)
Firm age	-0.0019***	-0.0027***	0.0013***
	(0.0002)	(0.0000)	(0.0003)
Total debt	-0.0121***	-0.0082***	-0.0166**
	(0.0028)	(0.0005)	(0.0067)
Cash holding	-0.0517***	-0.0552***	-0.0660***
	(0.0011)	(0.0002)	(0.0062)
Dividend dummy	0.0050***	0.0002	-0.0036
	(0.0010)	(0.0003)	(0.0023)
Profitability	-0.0690***	-0.0219***	-0.1274***
	(0.0018)	(0.0003)	(0.0074)
Tobin Q	0.0011***	-0.0032***	0.0060***
	(0.0001)	(0.0000)	(0.0002)
Book to market ratio	-0.0240**	2.0550***	0.0155
	(0.0105)	(0.3849)	(0.0803)
Capital investment	-0.0006*	-0.0137***	-0.0097***
	(0.0003)	(0.0001)	(0.0025)
Constant	0.0755	-1.3086***	-0.9648***
	(0.0485)	(0.0154)	(0.1051)
Observations	7,397	2,150	1,129
Number of firms	1,666	885	626
Observations	7397	2150	1129
AR (1)	-2.402	-1.392	-1.001
AR (2)	1.240	-1.661	0.830
Sargan	325.5	195.9	84.86
Controls	Yes	Yes	Yes

5.0 Conclusion

In this paper, I analyze the impact of climate change exposure on firms' intensive and extensive margin of corporate R&D investment. To measure the firm-level climate change

exposures, I employ firm-level climate change exposure data developed Sautner et al. (2020). I show that firms increase their intensive and extensive margin of R&D in response to increases in climate change exposures. The measure describes firm-level exposures to opportunity, physical and regulatory shocks caused by climate change. My findings are robust to the use of different climate change exposures and intensive margin of R&D measurements. I identify the causal effect of intensive margin of R&D in response to climate change exposure. Furthermore, I find that this impact is more pronounced for firms in carbon intensive sectors, firms with vertical integration, and firms with more growth opportunity. Using the difference-in-difference (DiD) approach, I show that intensive margin of R&D increase for firms in the treated States that implement Renewable Standard Portfolio. These findings have important consequences for climate policy and give a strong basis for continuous efforts to enhance the firm's understanding about climate change. Overall, my findings indicate that climate risk has recently become a significant component in understanding firm R&D investment.

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Appendix

Variable Definitions

Variable	Definition	Source
Climate change exposure	The relative frequency of climate change-related bigrams in earnings conference call transcripts. The authors count the number of such bigrams and divide by the total number of bigrams found in the transcripts. Other measures climate change physical exposure, climate change regulatory exposure and climate change opportunities exposure.	Saunter, van Lent, Vilkov, and Zhang (2023)
Climate Change Risk	The frequency with which bigrams connected to climate change are stated simultaneously with the phrase's "risk" or "uncertainty" (or synonyms thereof) in one sentence in earnings conference call transcripts. The number of such bigrams is counted and divided by the total number of bigrams in the transcripts.	Saunter et al. (2023)
R&D intensive margin (R&D)	Positive R&D expenditures (xrd) divided by total sale (sale). Other measures are R&D expenditure divided by employee; R&D expenditure divided by total assets.	Compustat
R&D extensive margin	Equals 1 if a firm reported zero or positive R&D expenditure and 0 otherwise including reporting blank R&D.	Compustat
Paris Agreement (after 2016)	Dummy variable with a value of 1 in the years following the 2015 signing of the Paris Agreement and 0 otherwise.	Author's calculation
State adoption RPS	Dummy variable equals 1 if a firm is in a State implementing the Renewable Portfolio Standard and 0 otherwise.	Author's calculation
Firm size	Natural logarithm of total assets (at).	Compustat
Firm age	Age is computed as one plus the current year under investigation minus the firm's year of birth.	Compustat
Total debt	The ratio of the firm's long- and short-term debt (dltt+dlc) divided to the total assets (at).	Compustat
Cash holding	Cash and short-term investments (che) divided by total assets (at).	Compustat
Dividend dummy	Dummy variable equals 1 if firm pays positive dividend (dvpsx_f) and 0 otherwise.	Compustat

Profitability	Return on assets is the ratio of the firm's earnings before interest, taxes, depreciation, and amortization (ebitda) to the book value of total assets (at).	Compustat
Tobin Q	measure as total asset (at) less book value of equity plus market value of equity divided by total asset. Book value of equity is calculated as total asset (at) less total liability (lt) and liquidation value of preferred stock (pstkl) plus deferred taxes and investment tax credit (txditc), and market value of equity (prcc_f x csho_f).	Compustat
Book to market (BTM) ratio	The book to market ratio is the book value of common equity (ceq) to the firm's market value of equity (csho_f x prcc_f).	Compustat
Capital investment	The ratio of capital expenditure (capx) to total assets (at).	Compustat
Industry Sales growth	Sales growth is the percentage growth in sales from the end of the previous year to the end of the current year based on 2-digit industry code.	Compustat
Market power	The ratio of net operating profits (sale minus cost of goods sold minus selling, general and administrative expense) to the total sale (sale). Measures the market power.	Compustat
Carbon intensive industries	Equals 1 for firms that emit high carbon and 0 otherwise	Author's calculation
Green industries	Equals 1 for firms that emit low carbon and 0 otherwise	Author's calculation
Inflation Rate	The consumer price index measures inflation as the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services over year. (FPCPITOTLZGUSA)	FRED St. Louis
Interest Rate	The federal funds rate is the overnight interest rate at which depository institutions trade federal funds (balances maintained at Federal Reserve Banks). The federal funds rate is the primary interest rate in the United States' financial industry. (FEDFUNDS).	FRED St. Louis
Real GDP	The real GDP is the inflation-adjusted worth of goods and services produced by labor and property in the United States.	FRED St. Louis
Global Fin. Crisis (2007-2009)	Equals 1 for years 2007-2009 representing global financial crisis and 0 otherwise	Author's calculation

Chapter 2

Firm-level Political Risk and Responsiveness of Firm Labor Decisions: Evidence from U.S. Firms

Abstract

This study reveals how firm-level political risk affects firm labor decisions. I empirically analyze how firms' labor decisions respond to firm political risk using a sample of 3,131 U.S. firms from 2002 to 2022. My analysis shows that a one standard deviation increase in firm-level political risk is associated with a 9.22 percentage point wage increase. Political risk affects wages significantly when interacted with competition, capital intensity and labor share. Moreover, my findings are consistent using various measures of firm-level political risk and wages. In addition, one standard deviation increase in firm political risk is associated with 8.94 and 30.48 percentage point decreases in employment growth and labor productivity, respectively. My study reveals that the reduction in employment growth and labor productivity is more evident when firm-level political risk is interacted with competition, capital intensity and labor share. My results remain robust after addressing the potential endogeneity issue using an instrumental variable approach.

1.0 Introduction

Firms face uncertainty from various sources, including market conditions, technological advancements, competitive environment, financing availability, and government policies. Politicians and regulatory bodies regularly make decisions that alter the firms' operating environment. The business environment is significantly impacted by political system risks, particularly those pertaining to trade, regulation, taxation, economic policy, budgets, and rule

enforcement. Some events have shed important light on the risks associated with political systems and their effects on capital expenditures, wage growth, employment, and firm investments. Examples of these events include the US Federal Government's repeated shutdowns, the US-China trade war, and the United Kingdom's decision to exit from the European Union (Rouine, 2022). Evidence from the literature highlights that corporate behavior and decision-making are significantly impacted by the political system (Julio and Yook, 2012; Pástor and Veronesi, 2013; Gulen and Ion, 2016). The risk associated with political systems has attracted growing attention from politicians, business leaders, and researchers. Thus, it is essential to understand the effect that political risks may have on a firm's labor decisions. This study extends this line of research by investigating the effect of firm-level political risk on firm labor decisions in the United States.

Political risk refers to potential financial, market, or personnel losses resulting from political actions or disruptions. Political risk, defined as uncertainty associated with political activity (Watts and Zimmerman, 1990), is becoming more prevalent due to societal polarization (Gad et al., 2023).[11] According to Kobrin (1979), political risk can be defined as a single event, such as presidential elections, or as limits imposed on the economic environment, such as regulatory activities. Robock (1971) distinguishes between macro-political risk, which affects the entire market, and micro-political risk, which affects narrow economic fields or individual businesses. Therefore, uncertainty applies to all levels of study at macro- and micro-level. Political risk significantly impacts decision-making in globalized business environments (Wang, 2013), affecting labor decisions such as hiring, layoffs, wage adjustments, pensions, and workforce composition. So, managing and understanding risk within the business environment is critical for sustaining firm growth and long-term success. In this paper, I empirically investigate the effect of

[11] In this study, the words "political risk," "political uncertainty," and "political shock" are used interchangeably.

firm-level political risk on corporate labor decisions in the United States. Exploring political risk's impact on labor-related strategies in organizations enhances understanding of labor decision-making in politically uncertain environments, contributing to existing literature.

Most existing literature focuses on the relationship between economic and political uncertainty and firms' decisions at the aggregate and macroeconomic levels (Bloom, 2007; Jura, Ludvigson &Ng, 2015). Prior research shows that political risk influences firms' financial, investment, and dividend decisions (Jens, 2017; Julio & Yook, 2012; Bonaime et al., 2018; Colak et al., 2017). However, a few papers show that financial reporting quality (Jung et al., 2014), stock price informativeness (Ben-Nasr & Alshwer, 2016), CEO-director ties (Khedmati et al., 2020), and institutional ownership (Ghaly et al., 2020) all have an impact on corporate employment decisions. There is less research on how firm-level political shocks affect corporate labor decisions, especially labor productivity at the micro-level. Thus, a better understanding of this relationship can help bridge the gap between the firm-level literature on uncertainty which looks at how firms respond to changes in political shocks.

Quantifying the effects of political risk has frequently proven challenging due to a lack of firm-level data on the extent of exposure to political risk, as well as data on the kind of political issues about which firms are most concerned. Political uncertainty is difficult due to all the risks it might present. For instance, different studies measure political risk or policy uncertainty related to national or gubernatorial elections. Several studies employ timing around national elections or specific political events to assess policy uncertainty and risk (Bachman, 1992; Pantzlis, Stangeland, & Turtle, 2000; Fowler, 2006; Białkowski, Gottschalk, & Wisniewski, 2008; Floros, 2008; Pástor & Veronesi, 2016). Other authors measure political risk using event studies to account for periods of protests. Jens (2017) examines the impact of political uncertainty on investment.

The author measures political uncertainty using a dummy variable equal to one when a U.S. gubernatorial election takes place in a certain state and year between 1984 and 2008. Howell (2011) measures political risk by constructing an index using twelve main risk factors and nineteen sub-components, weighted based on their impact. Other studies use measures alternative methods for measuring political risk. Howell created the International Country Risk Guide (ICRG) to assess political instability. The political risk rating aims to analyze the political stability of nations covered by ICRG on a comparable basis.

I employ a firm-level political risk index developed by Hassan et al. (2019) to examine how labor decisions respond to firm-level political risk due to the absence of direct measure of political risk. Hassan et al. (2019) used a unique technique based on the textual analysis of a firm's quarterly earnings conference calls. Their technique measures the proportion of conversations between stakeholders and business management that focuses on the risks related to political issues and politics in general. Previous studies have typically relied on aggregate measures of political uncertainty, using indices like the Economic Policy Uncertainty (EPU) and the Geopolitical Risk Index (GRI), or focusing on significant political events, such as presidential election periods. However, these aggregate measures are insufficient in capturing the variations in firm-level exposure to political risk (Hassan et al., 2019; Ahmad et al., 2023). I contribute to the existing literature by using a new measure of political risk that enables us to explore how the variation in firm-level political risk can affect labor decisions (wages, employment growth and labor productivity). Firms face different political risks depending on their industry structure, operational location, supplier, and customer bases. However, aggregate measures of political uncertainty cannot capture this variation appropriately.

Using a sample of 24,574 firm-year observations of 3,131 unique U.S. firms covering the period from 2002-2022, I establish that wages are positively linked with firm political risk. This positive link has economic significance: a one standard deviation rise in firm political risk corresponds to a 9.22 percentage wage increase. An increase of one standard deviation of firm political risk leads to an 8.94 percentage points decrease in employment growth and a 30.48 percentage point decrease in labor productivity. These results are consistent after controlling for year, industry, and firm-level characteristics. Thus, the relationship between firm-level political risk, wages, employment growth, and labor productivity is not dependent on a particular set of controls. The positive relationship between firm-level political risk and wages holds for the various forms of political risk.

I study and analyze three possible interactions by which political risk can influence labor decisions. First, I show that an increase in firm-level political risk with an increase in competition, capital intensity and labor share increase wages. Conversely, competition, capital intensity and labor share decrease labor productivity as firm-level political risk increases.

I present further evidence to support the association between firm political risk and corporate labor decisions. I employ the Partisan Conflict Index (PCI) instrumental variable (IV) per previous research (Gulen & Ion, 2016; Aisen & Veiga, 2011). Using two-stage least squares, I confirm that firm-level political risk increases wages but reduces employment growth and labor productivity after removing exogenous components from our variable of interest. Next, I focus on the mechanisms by which firm-level political risk affects labor decisions. The results show that competition and firm-level political risk increase wages, capital intensity increases labor productivity, and increased labor share decreases labor productivity.

This study adds to the body of literature in various ways. First, I contribute to the growing literature on the link between political risk and corporate labor decisions. I demonstrate how labor indicators such as wages (employment growth and labor productivity) increase (falls) as firm-level risk increases. This study provides empirical evidence that uncertainty produced by the political risk has important effect on firm labor decisions. Consequences. The implication of this finding for policy makers and regulators is that they should pay particular attention to the uncertainty that influences labor outcomes at firm level. Also, while previous microeconomic research has primarily focused on either employment or wages (Hassan et al., 2019), this paper extends the literature by examining how labor productivity responds to increased political risk. The findings show that labor productivity decreases as firm-level political risk increases.

Finally, this contributes to the literature by bridging the gap between corporate finance and labor markets relationship. The economics literature has made significant advances in describing the dynamics of labor markets. While that literature examines labor markets at the individual, sector, or economy levels, it has focused less on identifying firm-level mechanisms underlying these interactions firm heterogeneity. Hence, understanding how firms' labor decisions respond to risk is an essential determinant of firms' labor decisions.

The paper proceeds: Section 2 presents a literature review and hypothesis development. I discuss methodology in section 3, I lay out our empirical results in Section 4, and Section 5 concludes the paper.

2.0 Literature Review and Hypothesis Development

A significant and growing literature studies the relationship between firm-level political risk and corporate decisions. The effects of uncertainty have often been addressed from a macroeconomic perspective (Bloom, 2009; Bachman, Elstner & Sims, 2014; Baker et al., 2016).

One weakness is the assumption that political risk remains constant during non-political events. El Ghoul et al. (2018) proposes an alternative measurement to capture the dynamics of political uncertainty. Baker et al. (2016) established the aggregated Economic Policy Uncertainty (EPU) index, a well-recognized indicator of political risk. Baker et al. (2016) conducted a textual analysis of newspapers to identify the frequency of politically relevant words and phrases associated with risk or uncertainty. Thus, at the macro level, Julio & Yook (2012) use national election years to measure political uncertainty. They suggest that political uncertainty impacts firms' investment decisions. At the micro level, political risks may affect different firms and industries. Therefore, using a firm-level political risk, I examine how firm-level political risk affects labor decisions in United States.

At the macroeconomic level, Beland (2015) shows that there is a causal impact of U.S. governors' party allegiance on labor-market outcomes. Guglielminetti (2015) use a measure of disagreement drawn by the Survey of Professional Forecasters (SPF) to measure uncertainty and thus find negative effects of uncertainty on economic performance, employment and wages. Also, the results from Ghosal & Ye (2015) establish that uncertainty negatively impacts the employment growth of smaller businesses, with larger firms being weaker. Leduc & Liu (2012) use uncertainty measures such as CBOE Volatility Index (VIX) and a novel measure of consumers' perceived uncertainty obtain from the Thomson Reuters/University of Michigan Surveys of Consumers. The result shows that a higher uncertainty of consumers and businesses during the 2008 financial crisis reduced employment. I complement this literature by using firms' micro-level data to highlight how labor decisions (wages, employment growth, and labor productivity) respond to firm-level political shock.

Recent work by Di Maggio, Kermani, Ramcharan, Yao & Yu (2022) suggests that wages decrease due to increased firm-level uncertainty. Moreover, Mathä, Millard, Rõõm, Wintr, & Wyszyski (2019) confirm that firms responding to negative shocks were most likely to reduce employment, hourly pay, and hours worked. They also demonstrate that because firms seek the cheapest way to adjust labor expenses, strict employment protection legislation reduces the likelihood that firms will lower pay in the face of negative shocks. Hassan et al. (2019) shows that firms exposed to political risk reduce hiring and investment. Therefore, when the aggregate political risk is high, the dispersion of this firm-level political risk increases. This study deepens and extends the understanding of the effects of firm-level political risk on firm labor outcome since aggregate political risk does not reflect variation in political risk at the firm level over time, nor does it capture heterogeneity in political uncertainty among firms. The findings in this study can help managers make informed labor decisions that safeguard employee interests and company objectives.

Closer to my work, Martínez-Matute & Urtasun (2022) uses a Wage Dynamic Network Survey for 25 European countries, and their results reveal that firms reduce hiring and recur layoffs more frequently when uncertainty increases. However, I contribute to the literature by investigating how firm political risk affects labor decisions, especially labor productivity. Also, I add to the literature by examining the mechanisms such as competition, capital investment, and labor share through which political risk affects labor decisions.

2.1. Development of hypothesis

Firm-level political risk and corporate labor decisions.

Political risk can impact elements of firm's operations, including financial success and employee well-being. Firms may aim to reduce the potential negative consequences of higher

political risk, such as uncertain regulatory environments, policy changes, or unstable political environments, by giving better wages and additional incentive plans to keep and inspire workers (Barr & Diamond, 2006). Also, firms may attract and retain competent staff in this manner, maintaining operational continuity and lowering the negative impact of political risk on their employees, as employees are seen as a key component of production and a critical tool for economic growth and company success.

In economic theory, the relationship between political risk and wages can be described using the concept of compensating wage differentials. According to this hypothesis, workers need higher pay to compensate for the additional risks associated with political instability. Increased political risk creates uncertainty and perceived instability in the job market. Individuals may demand greater pay to offset the perceived risk of undesirable occurrences, such as policy changes or political turbulence, harming job security or income. Employers, realizing the need to attract and keep skilled employees in the face of increased political risk, may respond by giving better compensation and benefits. This is consistent with the economic theory that wages are influenced not just by productivity but also by perceived risks and working conditions.

Hypothesis 1a: Firm-level political risk positively impacts wages.

Conversely, the economic environment in which businesses operate is continually changing due to political events such as government shutdowns, trade wars, tax cuts, elections, etc. Political events could have significant macroeconomic implications, not only through changing aggregate political risk but also by changing the characteristics of the impacted firms and the way political risk is distributed across firms (Hassan et al., 2019; Gulen & Ion, 2016). For instance, a shift in the political environment may give rise to specific concepts like corruption, terrorism, etc., which are tied to the politics of a country and may also have an impact on the laws

of that country. As political regulations keep changing, they may affect resource allocation among firms, lowering total factor productivity and aggregate investment and employment.

Policy uncertainty, regulatory shocks, industry-level policy changes, and other firm-specific variations are the leading causes of firm-level political risk. If political uncertainty matters to firms, they may be required to reduce production, investment, and employee compensation because of an increase in operational cost resulting in a lower profit. Large capital projects with a high degree of irreversibility may be particularly vulnerable to high levels of political uncertainty. Therefore, I hypothesize that

Hypothesis 1b: Firm-level political risk has a negative impact on corporate labor decisions in terms of employment growth and labor productivity.

The interaction effect of competition and political risk on corporate labor decisions

Higher competition and political risk impact corporate labor decisions, with various industries, countries, and periods influencing outcomes. According to classical literature, increased uncertainty causes firms to temporarily suspend their investment and hiring, which in the medium term produces a rapid decrease and rebound in output and employment (Bloom, 2009). If firms freeze on hiring, delay investment, and remain inactive in the face of rising uncertainty, real economic activity suffers. As a result, wait-and-see policies reduce capital through depreciation of the current capital stock, lowering the demand for labor, implying more layoffs and less hiring (Ghosal & Ye, 2015). Also, increased competition during uncertainty can lead to employment cutbacks as firms focus on cost reduction and efficiency to remain competitive. Reduced consumer demand may further increase job losses. Creative destruction and innovation can provide jobs in some industries while displacing them in others. Using microdata from US establishments, Meier

(2014) found that unexpected increases in uncertainty cause firms to freeze investment and labor practices, adopting a gradually greater wait-and-see approach.

Furthermore, firms experiencing increased competitive pressures may use cost-cutting initiatives, such as workforce reductions. This might result in a decrease in employee morale, motivation, and skill development. Furthermore, uncertainty may limit organizations' ability to make long-term investments in training and technology, reducing productivity development. Fear of job insecurity during uncertain times can also lead to a tense work environment, further reducing productivity.

As competition intensifies, firms seeking skilled workers to preserve competitiveness may pay higher compensation to attract and retain talent. The shortage of talented labor in competitive marketplaces can drive up wages as firms prioritize workforce stability in the face of uncertainty, resulting in a bidding effect for skilled workers and overall wage growth. Therefore, I predict that

Hypothesis 2a: Firm-level political risk is expected to negatively affect employment growth and labor productivity while positively affects wages in a competitive environment.

The interaction effect of capital intensity and political risk on corporate labor decisions

Higher capital intensity impacts labor decisions. Political risk introduces uncertainties and challenges to labor management, potentially affecting outcomes. The relationship between capital intensity, political risk, and corporate labor decisions is complex and varies across firms. Reduction in employment growth and labor productivity may be more pronounced in uncertain political situations due to the capacity to lower some fixed costs. Following this argument, firms with a high capital intensity reduce the cost of capital because firms that have previously committed to or invested in a fixed structure may not require new capital investment or

expenditures. High capital intensity can positively affect labor decisions, such as technological advancement, competitive advantage, and compensation and skill development. Investments in advanced technology and automation enhance productivity, increasing demand for skilled labor (Stein & Stone, 2013). Firms may prioritize hiring and training workers with technical expertise, resulting in positive labor decisions. Investing in human capital can attract and retain talented workers, resulting in higher wages, benefits, and training opportunities. Conversely, the capital-skill complementarity concept was suggested by Griliches in 1969 which states that capital intensive production necessitates more skilled labor, resulting in a positive correlation between capital intensity and wages if human capital is properly compensated. I hypothesize

Hypothesis 2b: Firm-level political risk and capital intensity are associated with lower employment growth, and labor productivity but a positive increase in wages.

The interaction effect of higher labor share and higher political risk on corporate labor decisions.

High labor share signals a commitment to workforce investment, resulting in increased job security and stable employment opportunities. This can lead to job preservation and reduced turnover. Additionally, high labor investment involves significant investments in employee training and skill development, maintaining a competitive advantage, and adapting to changing market conditions (Stein & Stone, 2013). Higher political risk could increase costs, including labor-related expenses, to maintain financial stability. This can result in negative effects on wages and employment. Also, higher political risk can create an unstable environment for firms. This would reduce labor productivity as firms face regulatory changes, policy instability, or political challenges. I hypothesize that

Hypothesis 2c: Firm-level political risk and labor share is associated with positive increase in wages, but a negative decrease in employment growth and labor productivity.

3.0 Data, Methods, and Results

3.1. Data Sources

I obtain accounting information on firm-specific variables from the Compustat database from 2002-2022. Furthermore, since the year 2000, the occurrence of political risk in the United States has increased, making the time under consideration appropriate for the empirical analysis. During investor conference calls, investors want to understand the extent to which firms are exposed to political risks. I use the firm-level political risk measure developed by Hassan et al. (2019). The total firm-year observation is 35,314. I exclude financial firms and utility firms from my sample with standard industrial classification (SIC) codes (SIC codes 6000-6999) and (4900-4999), respectively, because these firms are subject to statutory capital requirements and highly regulated base on existing literature (Choi, Chung & Wang, 2021; Ahmed, Muttakin & Khan, 2022)[12]. Also, I exclude firms with negative total assets identify in the existing literature (Jayakody, Morelli & Oberoi, 2023; Zheng, 2022), and the final sample comprises 24,578 firm-year observations and 3,131 U.S. firms. The partisan conflict index of Azzimonti (2014) is obtained from Federal Reserve Bank of Philadelphia.

3.2. Baseline Model Specification

I follow the methodology in Falato & Liang (2016) and construct the labor decision variables. I construct control variables base on previous literature (Choi, Chung & Wang, 2023;

[12] These firms are subjected to state-specific regulations because they have unique industrial characteristics and financial reporting requirements.

Hasan, Alam, Paramati & Islam, 2022) and then merge the labor decision and control variables with firm-level political risk measures. I begin my analysis with a fixed effect model for my baseline regression model to investigate the impact of political risk on firms' labor decisions after controlling for firm and industry characteristics in equation 1.

$$Firm_labor_{it} = \alpha + \beta PolitRisk_{i,t} + \omega(controls)_{i,t} + \gamma(year\ fixed\ effects)_t + \lambda(industry\ fixed\ effects)_i + \varepsilon_{i,t} \quad (1)$$

Political risk can also have an impact on labor decisions through a variety of transmission channels. Equation 2 examines the mechanism by which political risk affects firms' labor decisions, and these channels are competition, capital investment, and labor share.

$$Firm_labor_{it} = \alpha + \beta PolitRisk_{i,t} + \delta PolitRisk_{i,t} * Comp_{i,t} + \phi PolitRisk_{i,t} * capital\ invest_{i,t} + \mu PolitRisk_{i,t} * labor\ share_{i,t} + \omega(controls)_{i,t} + \gamma(year\ fixed\ effects)_t + \lambda(industry\ fixed\ effects)_i + \varepsilon_{i,t} \quad (2)$$

where $Firm_labor_{it}$ measures firms' labor decisions. Decisions made by firms alter how firms operate and their impact on wages, employment growth, and labor productivity. I included a complete set of the year and industry fixed effects. I clustered the standard error by industry and year to address the issue of heteroscedasticity.

Dependent Variables:

Wages

Wages play a significant role from the workers' perspective because they represent a measure of the level and trajectory of their purchasing power and an approximation of their standard of living. Wages are relevant indicator because they are directly related to worker welfare. Wages are one of the most essential components of labor market information. Because wages are a significant source of income for a large part of the economically active population, data on wage levels is critical for assessing workers' living standards and working and living situations. As a result, wages are an essential metric for tracking changes in the working

conditions of employees and the firm. I follow Bacchetta, Benhima & Poilly (2018) and use staff expense variable, denoted by XLR (Compustat data item # 42) which covers salaries, wages, pension costs, profit sharing and incentive compensation, payroll taxes and other employee benefits. Therefore, this measure is less likely to be affected by changes in the composition of earnings when, say, income lowers and health insurance increases. I consider annual log wages as a dependent variable (Lavetti & Schmutte, 2018), and I winsorize log wages by one percent and ninety-nine percentiles to eliminate outliers (Banerjee & Dutta, 2022).

Employment growth

Employment growth is a significant indication for firms' labor decisions since it represents labor demand, business confidence, investment and expansion plans, productivity and efficiency efforts, and overall economic success. It gives valuable insights into enterprises' recruiting and downsizing strategies and the labor market's health, aiding policymakers and businesses in economic planning and labor policy decisions. As in Falato & Liang (2016), I measure employment growth as the ratio of the annual total number of employees (Compustat data item # 29) minus lagged total number of employees divided by the lagged total number of employees. I winsorize employment growth by the top and bottom one percent to eliminate outliers.

Labor Productivity

Labor productivity is an indicator for measuring the labor decisions of firms as it reflects their efficiency, competitiveness, resource allocation, and technological investments (Pietschmann et al., 2016). Therefore, labor productivity can help shape labor market policies and track their effectiveness. High labor productivity is frequently related to high levels or specific types of human capital, signaling priorities for education and training policies.

Productivity indicators can help us understand how labor market performance influences living standards. I measure labor productivity as the ratio of value added to the number of employees (EMP) as in Rogers & Tseng (2000). Differently, Brault & Khan (2022) use aggregate data from FRED to define labor productivity as the ratio of real output to the level of employment. I define value-added for Compustat firms following Brault & Khan (2022) using firm-level data as sales minus cost of goods sold for each firm and industry annually.[13] Value added is the additional value created by a company's operations after deducting the value of intermediate goods and services purchased from other firms. I winsorize labor productivity by the top and bottom one percent to eliminate outliers.

The main variable of interest

Measurement of Political risk ($\boldsymbol{PRisk_{i,t}}$)

The primary measurement of firm-level political risk was created by Hassan et al. (2019). Hassan et al. (2019) developed a novel measure of firm-level political risk faced by individual U.S. firms using textual analysis on transcripts of quarterly earnings conference calls of U.S. listed firms. The authors calculated firm-level political risk by dividing the total number occurrence of words by the number of words in conversation transcripts between call participants and firm management that focuses on risks related to political themes. Hassan et al. (2019) separates political from nonpolitical issues using a pattern-based sequence-classification algorithm developed in computational linguistics (Manning, Raghavan, & Schütze, 2010). The textual analysis of addresses between call participants and corporate management focuses on political hazards, employing synonyms for phrases like "risk" and "uncertainty." Rather than newspaper

[13] XLR in Compustat provides detailed financial data, offering a comprehensive firm-level measure. In contrast, employment variable at the aggregate level from FRED, Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics may lack financial specifics and cannot capture individual firm effects.

articles or financial indicators, this measure of firm-level political risk is based on text written by decision-makers within firms.

The pattern-based sequence classification algorithm helps locate the content connected to "political risk" in the textual data. The authors then counted the number of occurrence bigrams related to political topics that appeared within ten words of a synonym for "risk" or "uncertainty" on either side of each transcript. The result was divided by the total number of bigrams in the firm's transcript. A firm sees a higher level of political risk if more political risk-related content appears in the textual data.

Unlike previous research that used newspaper articles to evaluate risks (Baker et al., 2016; Koijen et al., 2016), this measure uses conference calls as a natural setting to connect the risks that firms confront directly with investors' perceptions. Hassan et al. (2019) view this as a proxy for the political risk and uncertainty that firms experience. They assert that political decisions impact the economy through aggregate and individual political risks.

Hassan et al. (2019) verified this measure by demonstrating a significant connection between perceived political risk and the likelihood of firm lobbying on political issues. Furthermore, some authors have used the Hassan et al. (2019) data and found evidence that firm-level political risks affect corporate outcomes, such as stock return volatility (Hassan et al., 2019), investment (Choi, Chung & Wang, 2022), credit markets (Gad, Nikolaev, Tahoun, & van Lent, 2022) and corporate social responsibility (Chatjuthamard, Treepongkaruna, Jiraporn, & Jiraporn, 2021); dividend payouts (Ahmad, Aziz, El-Khatib & Kowalewski, 2023); debt choice and corporate leverage decisions (Gyimah et al., 2022; Huang, Shen, & Wu, 2023); cash holding (Hasan et al., 2022); Stock liquidity (Das & Yaghoubi, 2023) and tax avoidance (Hossain, Lobo, & Mitra, 2023).

In this study, I employ the firm-level political risk index (Prisk) created by Hassan et al. (2019) to empirically investigate the relationship between firm-level political risk and firms' labor decisions. Hassan et al. (2019) used the quarterly conference calls of firms to construct firm-specific, time-varying political risk indicators. Following the works of Guo & Zheng (2021) and Rehman, Liu & Wu (2022), I annualize the firm-level political risk data by taking an average of the values for the four quarters over a given firm-year to ensure consistency and comparability with the Compustat annual data use in this study[14]. This alignment facilitates more accurate analysis and interpretation. Hence, a high value of the risk measure indicates a higher degree of firm-level political risk. Also, by averaging the quarterly data into annual values, I reduce volatility in the data, allowing you to capture more stable, long-term trends in political risk.

Control Variables

Following previous literature (Choi, Chung & Wang, 2022; Huang, Shen & Wu, 2023; Ben-Nasr, Bouslimi, Ebrahim & Zhong, 2020 and Hasan et al., 2022), I control for firm factors that have been shown to impact corporate labor decisions significantly.

The natural logarithm of the book value of total assets is used to measure firm size. Larger firms might have different labor dynamics due to more diversified operations and greater resources to mitigate the impact of political risk. I expect firm size to be positively related to labor decisions.

[14] The data is available at https://www.firmlevelrisk.com. Some of the earnings call transcripts are publicly accessible. The authors obtained the transcripts from https://www.fool.com/earnings-call-transcripts/
For instance, Apple transcript is found https://www.fool.com/earnings/call-transcripts/2020/07/31/apple-aapl-q3-2020-earnings-call-transcript.aspx.
The original risk index is provided on a quarterly basis per firm. However, the dependent variables and controls in empirical studies, is only accessible annually, I compute and utilize the annual mean for each firm and use the firm-year risk.

Market-to-book (MB) ratio is the ratio of asset market value to asset book value. Firms with higher MB ratios may be perceived as growth-oriented and could invest differently in labor compared to value-oriented firms with lower MB ratios. Therefore, I expect both negative and positive associations between MB and labor decisions.

Cash flow (Cashflows) is calculated as the ratio of earnings after interest, dividends, and taxes but before depreciation to the book value of assets. Firms with higher cash flows may be better positioned to retain employees and pay competitive wages even when political risk is high. Net working capital is the difference between working capital and cash scaled by total assets (NWC). I include NWC because it determines a firm's ability to satisfy short-term obligations; those with a greater NWC may better control labor expenditures during politically risky times. R&D intensity is defined as R&D expenses scaled by total assets. Firms with high R&D intensity need to maintain a skilled workforce and could make different labor decisions to retain talent, irrespective of political risk.

Capital intensity (Cap_int) is corporate capital expenditure multiplied by total asset book value. Cash holding (cash hold) is measured as cash scaled by the value of total assets. (Total debt) is the sum of long-term debt and debt in current liabilities scaled by total assets. The total debt reflects how the firm's capital structure and internal financing decisions impact labor decisions. Sale growth (sales growth) is the percentage of sales (sale) growth from the previous year to the current year. Firms with high R&D intensity may need to maintain a skilled workforce and could make different labor decisions to retain talent, irrespective of political risk. Tobin’s q was added to control for the effect of a firm’s growth potential on labor decisions. A dividend dummy indicates 1 if firms pay dividends to common shareholders and 0 if they do not.

Firms that pay dividends might prioritize financial returns to shareholders, which could influence their labor investment decisions under political risk.

Furthermore, the average standard deviation of a firm's cash flow in each industry is represented by industry volatility (industry sigma). To define the industry, I utilized a three-digit SIC code. For the last ten years, the standard deviation of cash flow is firm-level cash flow scaled by total assets. I include industry volatility because industries with higher volatility may have employees who have been exposed to risk, which influences how they respond to political risk. Firm age is the difference between the year under investigation and the first year the firm appears on COMPUSTAT. Older firms with established processes may be less responsive to political risk in labor decisions than younger firms. Altman Z-score, a proxy of financial distress.

Also, Profitability (ROA) is pretax income scaled by total assets. Firms in financial distress may be more sensitive to political risk and make better labor decisions. Return on assets divided by total assets. More profitable firms may have flexibility in making labor decisions in the face of political risk. Competition (HHI) measures the product market competition using Herfindahl–Hirschman Index (HHI) for different industries. The square of revenues of each firm divided by the revenues of all firms in the same industry summed over all firms in the same industry. To eliminate the influence of outliers, I winsorize all continuous variables by the 1st and 99th percentiles. Detailed definitions of all variables are reported in Appendix A.

4.0 Discussion of Results

Table 1A presents the summary statistics of the main variables of labor decisions, the measure of firm-level political risk, firm, industry, and macroeconomic controls used in the study. I present the number of observations, mean, standard deviation, 25th percentile, median, and 75th percentile. The mean value for the political Risk is 0.1163 (11.63 percent) and the

median is 0.0735 (7.35 percent), indicating a significant right skew. The mean value of political risk is different from Hassan et al. (2019) value because of sample differences and years under consideration. A higher political risk percentage indicates greater firm-level political risk impacts. The mean capital investment is 4.5 percent while 7.6 percent for R&D intensity. The average years of firms in the sample are 13 years indicating that the firms are mature to response to political risk impacting labor decisions. The mean wage in the sample is 5.6114, with a standard deviation of 2.0764, indicating a moderate level of variability in wages across firms. The distribution of wages shows that the median wage (5.6189) is slightly higher than the mean, suggesting a right-skewed distribution. Employment growth shows a mean of 90.754, with a standard deviation of 72.774. The median employment growth rate is 101.257, indicating that the distribution is skewed leftward, as the median is higher than the mean. The 25th and 75th percentiles are 85.185 and 111.894, respectively, suggesting that a significant portion of firms experience employment growth. Labor productivity has a mean of 4.678 with a standard deviation of 1.138. This suggests that labor productivity does not vary as widely across firms. The average inflation rate is 2.5%. The firm characteristics considered are usual of Compustat public firms and are comparable to earlier studies (Hasan et al., 2022; Hassan et al., 2019; Hall, 2016).

Table 1A: Summary statistics

	N	Mean	Standard Deviation	25th percentile	Median	75th percentile
Panel A: Main variables of interest						
Political Risk (PRisk)	24578	0.1163	0.1768	0.0353	0.0735	0.1378
(Various political risks)						
Economic	24578	3012.770	4551.108	931.903	1861.041	3497.418
Environment	24578	3310.068	7642.757	820.364	1724.656	3539.080
Trade	24578	2340.114	5135.556	497.926	1162.852	2452.043
Institution	24578	2040.814	3932.511	546.776	1134.599	2215.041
Health	24578	3377.588	8699.715	751.959	1544.156	3227.601
Security	24578	2978.133	5136.376	854.141	1733.696	3339.442
Tax	24578	2907.759	6902.177	779.879	1668.027	3249.030
Technology	24578	2375.466	4454.798	609.206	1306.624	2616.342

Outcome variables						
Wage	24578	5.6114	2.0764	4.2217	5.6189	7.1468
Wage (raw figures)	24578	153.3546	1182.439	82.800	51.713	1410.100
CEO wage	24578	26.5437	140.2789	0.6886	3.0665	13.0657
Employment growth	24578	90.754	72.774	85.185	101.257	111.894
Labor productivity	24578	4.678	1.138	4.100	4.786	5.321
Control variables						
Firm size (size)	24578	6.286	1.746	5.083	6.29	7.5
Firm age (age)	24578	12.920	8.266	6	12	19
Total debt (total_debt)	24578	0.200	0.199	0.004	0.154	0.337
Altman Z score (z-score)	24578	0.004	0.107	-0.027	0.002	.033
Sale growth (sale growth)	24578	4.277	10.305	1.347	3.106	5.687
Net Working capital (NWC)	24578	0.016	0.151	0.003	0.006	0.013
Dividend dummy (divid_dum)	24578	-0.003	0.241	0	0.053	0.099
Cashflow (Cashflow)	24578	-0.003	0.241	0	0.053	0.099
Tobin Q (Q1_Val)	24578	2.041	1.948	0.938	1.438	2.429
R&D intensity (RD_int)	24578	0.080	0.150	0	0.017	0.106
Capital intensity (Cap_int)	24578	0.045	0.059	0.013	0.026	0.052
Market to Book ratio (MB)	24578	4.181	6.577	1.421	2.423	4.333
Cash holding (Cash hold)	24578	0.183	0.189	0.046	0.123	0.252
Profitability (ROA)	24578	0.028	0.266	0.003	0.093	0.149
Industry-level Variables						
Labor Share	24578	2.437	52.283	0.105	0.191	0.344
Competition (HHI_Sic3)	24578	0.233	0.221	0.078	0.139	0.312
Industry volatility (sigma)	24578	7.314	6.354	3.465	6.087	9.527
Panel B: Macroeconomic variables						
Federal interest rate	23	1.622	1.909	0.120	0.980	2.270
High interest	23	0.348	0.487	0	0	1
Inflation rate	23	2.493	1.664	1.586	2.27	3.226
Financial Crisis (2007-2008)	23	0.104	0.306	0	0	1
Real Gross Domestic Product	23	9.701	0.127	9.619	9.683	9.815

Table 1A reports the descriptive statistics for firm characteristics. The sample is drawn from the Compustat North America Database from 2002–2022. The final sample is made up of 24,578 firm-year observations for 3131 firms after matching political risk and Compustat data. Various macroeconomic factors include federal interest rate, inflation rate, financial crisis (2007 to 2008), and real gross domestic product. All the variables are defined in Appendix A.

Table 1B provides correlation coefficients for the main variable of interest and all controls in the main regressions. From this correlation matrix, multicollinearity between the independent variables is unlikely because the correlation coefficients are not large enough in this correlation matrix. Figure 2.1 shows how firm level political risk varies over time. From Table 1C, the manufacturing industry has the highest number of firms, followed by the service industry with agriculture and public administration industries have the least firms. The distribution of the number of firms within an industry is in Table 1C and 1D. The number of firms varies with the number of years. Also, in Table 1E and 1F, Political risk varies significantly across industries.

The manufacturing industry experiences the highest risk, likely due to its exposure to regulatory and economic policies, while no classifiable establishments face the lowest political risk as shown in figure 2.2.

Table 1B: Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Prisk	1.000												
(2) Firm size	-0.057	1.000											
(3) Firm age	0.022	0.231	1.000										
(4) Total debt	-0.020	0.407	0.065	1.000									
(5) Altman Z score	0.016	0.057	-0.038	-0.247	1.000								
(6) Cashflow	-0.064	0.400	0.139	0.057	0.268	1.000							
(7) Tobin Q	0.043	-0.111	-0.089	-0.167	0.449	-0.114	1.000						
(8) R&D intensity	0.054	-0.397	-0.122	-0.222	-0.144	-0.616	0.265	1.000					
(9) Capital intensity	-0.049	0.110	-0.093	0.105	-0.011	0.118	-0.027	-0.161	1.000				
(10) cash holding	0.058	-0.410	-0.162	-0.348	0.054	-0.364	0.309	0.451	-0.196	1.000			
(11) Profitability	-0.067	0.440	0.150	0.095	0.295	0.088	-0.105	-0.693	0.148	-0.390	1.000		
(12) Competition	-0.001	0.136	0.125	0.163	-0.048	0.109	-0.162	-0.228	-0.010	-0.210	0.122	1.000	
(13) Labor share	-0.002	-0.006	0.010	-0.009	0.009	-0.036	0.015	0.039	-0.008	0.019	-0.035	-0.008	1.000

Table 1B displays the Correlation matrix for firm characteristics. The sample is drawn from the Compustat North America Database over the period 2002–2022. The final sample is made up of 24,578 firm-year observations for 3131 firms after matching political risk and Compustat data. Various macroeconomic factors including federal interest rate, inflation rate, financial crisis (2007 to 2008) and real gross domestic product. All the variables are defined in Appendix A.

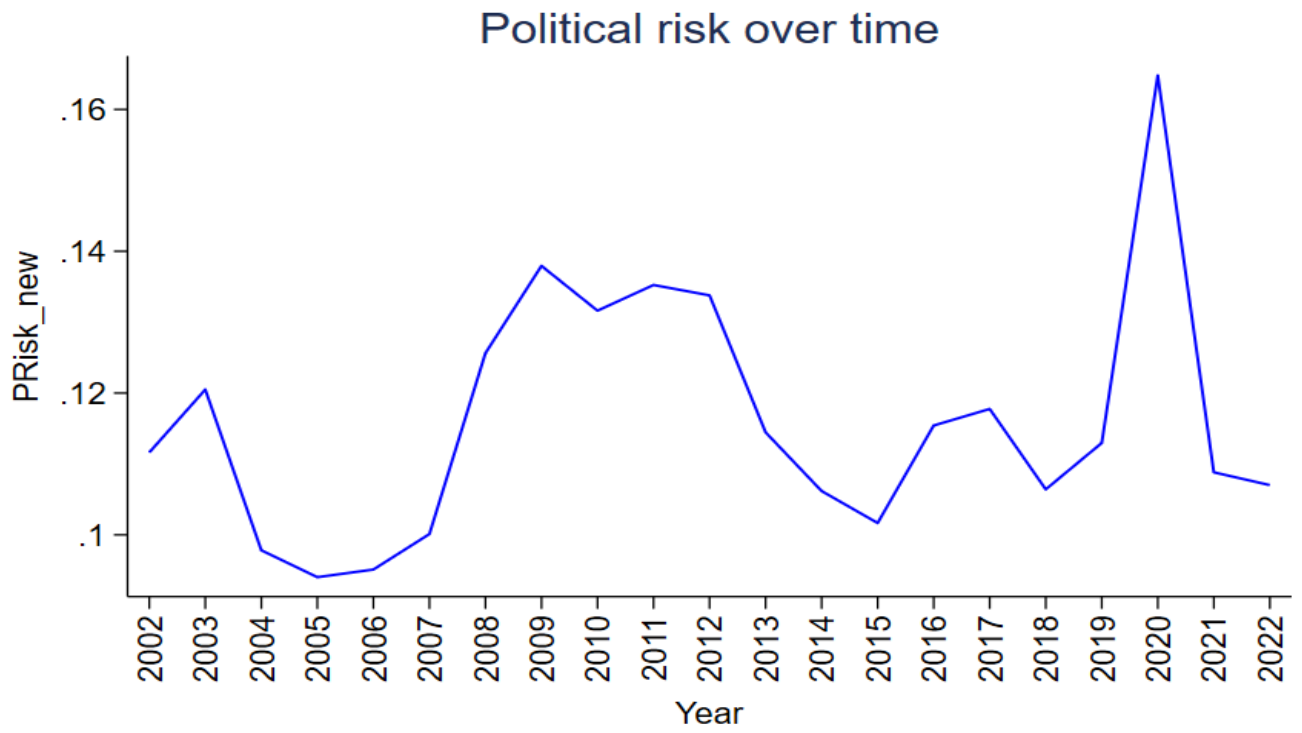

Figure 2.1: Firm-level political risk over years

Table 1C: Number of firms across industries

	Year/Firms																				
Industries	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Agriculture	1	3	3	3	3	2	3	3	3	3	5	5	5	4	3	2	2	3	3	3	3
Mining	30	35	38	46	53	70	77	68	73	72	76	73	82	71	62	78	76	66	47	51	41
Construction	10	13	13	15	17	17	15	14	16	16	13	16	17	17	18	20	20	20	20	22	21
Manufacturing	451	537	561	607	643	678	665	628	629	615	599	551	616	605	576	599	615	588	614	635	493
Wholesale Trade	32	42	44	47	49	48	43	42	40	41	46	45	47	52	54	50	50	48	47	49	42
Retail Trade	88	107	113	115	117	116	114	112	110	107	115	114	117	120	110	109	105	93	89	100	62
Services	280	342	372	386	361	381	371	362	345	343	339	308	324	325	294	314	317	315	304	363	301

This table shows the number of firms by industry

Table 1D: Distinct firms over the year

Year	Unique firms	Year	Unique firms
2002	903	2013	1116
2003	1091	2014	1213
2004	1157	2015	1198
2005	1233	2016	1120
2006	1260	2017	1174
2007	1324	2018	1186
2008	1298	2019	1134
2009	1235	2020	1125
2010	1222	2021	1224
2011	1202	2022	964
2012	1199		

This table presents the number of observations by year.

Table 1E: Political Risk base on 2-digit SIC code industry

SIC Code	Description of industry	Political risk
30	Rubber and Miscellaneous Plastic Products	0.2415
81	Legal Services	0.2325
80	Health Services	0.2248
16	Heamy Construction, Except Building Construction, Contractor	0.1984
01	Agricultural production and services	0.1807
28	Chemicals and Allied Products	0.1541
87	Engineering, Accounting, Research, and Management Services	0.1495
37	Transportation Equipment	0.1427
10	Metal Mining	0.1408
17	Construction - Special Trade Contractors	0.1385
32	Stone, Clay, Glass, and Concrete Products	0.1374
34	Fabricated Metal Products	0.1350
21	Tobacco Products	0.1342
82	Educational Services	0.1331
29	Petroleum Refining and Related Industries	0.1309
79	Amusement and Recreation Services	0.1266
99	Nonclassifiable Establishments	0.1243
12	Coal Mining	0.1189
33	Primary Metal Industries	0.1172
73	Business Services	0.1147
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	0.1126
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	0.1084
13	Oil and Gas Extraction	0.1066
22	Textile Mill Products	0.1027
36	Electronic & Other Electrical Equipment & Components	0.1014
70	Hotels, Rooming Houses, Camps, and Other Lodging Places	0.0988
83	Social Services	0.0982
15	Construction - General Contractors & Operative Builders	0.0968
50	Wholesale Trade - Durable Goods	0.0956
35	Industrial and Commercial Machinery and Computer Equipment	0.0947
55	Automotive Dealers and Gasoline Service Stations	0.0947
25	Furniture and Fixtures	0.0923
39	Miscellaneous Manufacturing Industries	0.0923
51	Wholesale Trade - Nondurable Goods	0.0891
26	Paper and Allied Products	0.0886
31	Leather and Leather Products	0.0852
27	Printing, Publishing and Allied Industries	0.0840
57	Home Furniture, Furnishings and Equipment Stores	0.0823
75	Automotive Repair, Services and Parking	0.0821
24	Lumber and Wood Products, Except Furniture	0.0820
59	Miscellaneous Retail	0.0809

78	Motion Pictures	0.0794
20	Food and Kindred Products	0.0762
53	General Merchandise Stores	0.0728
58	Eating and Drinking Places	0.0721
72	Personal Services	0.0692
56	Apparel and Accessory Stores	0.0606
52	Building Materials, Hardware, Garden Supplies & Mobile Homes	0.0591
54	Food Stores	0.0578
23	Apparel, Finished Products from Fabrics & Similar Materials	0.0572

Table 1F: Categorized Sub-industries into major industries

Major Industries	Political Risk
Agriculture & Fishing	0.1807
Mining	0.4747
Construction	0.4337
Manufacturing	2.2622
Wholesale trade	0.1847
Retail trade	0.5804
Services	1.4088
Nonclassifiable Establishments	0.1243

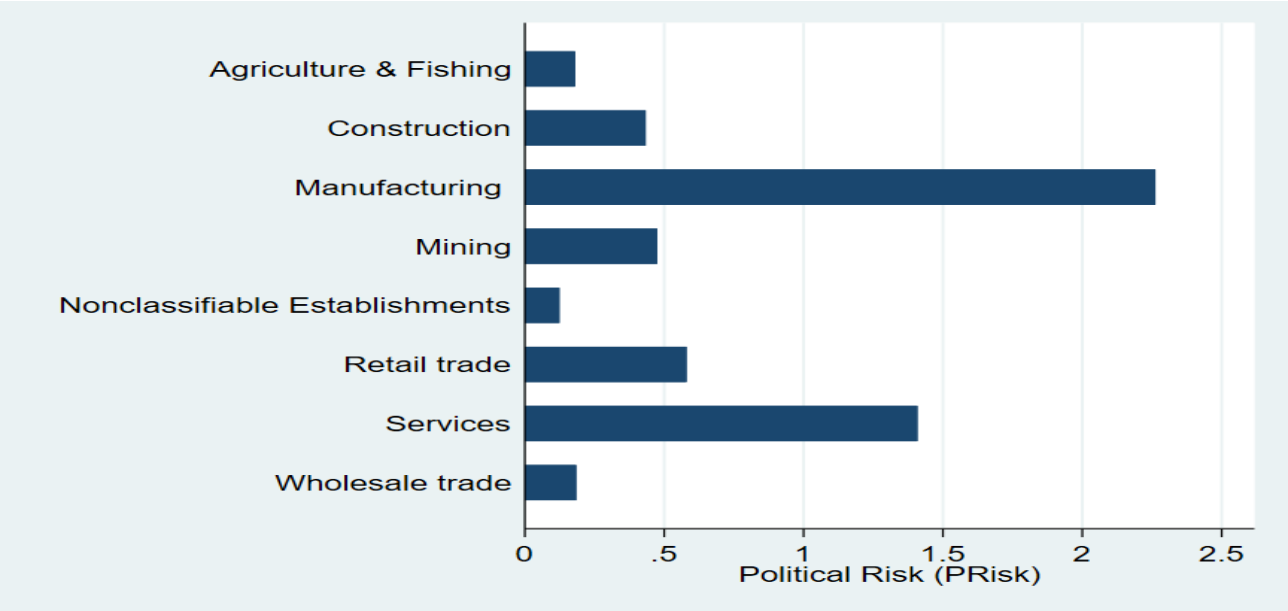

Figure 2.2: A graph showing Political Risk base on major industry

4.1. Empirical Results

Baseline Regressions

How do wages respond to firm-level political Risk?

$$firm_labor_{it} = \alpha + \beta PRisk_{i,t} + \omega(controls)_{i,t} + \gamma(year\ fixed\ effects)_t + \lambda(industry\ fixed\ effects)_i + \varepsilon_{i,t}$$

To examine how firm wages respond to firm-level political risk in hypothesis 1a, I use fixed effects with standard errors adjusted for heteroskedasticity and clustered at the industry level to reduce concerns about within-industry correlation.

The first column of Table 2 shows the estimation results for the baseline specification of the regression equation (1). The result indicates that one standard deviation increase in firm-level political risk corresponds to a 9.22 percentage points wage increase and is statistically significant at a 5% significance level. When all controls are accounted for in column 4 of Table 2, the economic significance reveals that one standard deviation increase in political risk leads to a 0.61 percentage point wage increase. My finding contrasts with Di Maggio et al. (2022) and Mathä (2019), as their finding shows that wages decrease with increased uncertainty. My result is in line with hypothesis 1a. Firm size and age show positive effects on wages, indicating larger and older firms tend to pay higher wages. Total debt and R&D intensity have negative impacts, implying firms with higher debt or investment in R&D tend to pay lower wages. Market-to-book ratio (MB) and cash holdings positively affect wages, reflecting that firms with better growth opportunities might offer higher wages.

I obtain the chief executive officers (CEO) compensation data from Execucomp and examine how firm-level political risk influences CEO wages. Before examining how political risk influences CEO wages, I plot a graph as shown in figure 3 to illustrate trends between CEOs and regular employees' wages from 2000 to 2022. From figure 3, average CEO compensation

data remains relatively flat, hovering around a lower mean value, while regular employment wages exhibit significant fluctuations, peaking around 2015 and then declining. In column 1 of Table 3, firm-level political risk has no influence on CEO wages. Also, I disaggregate the CEO wage from the regular employee and run a regression analysis using the dependent variable as wage disparity in column 2. There is no significant relationship between firm-level political risk and wage disparity. This shows that the effects of political risk on wages results are not driven by changes in CEO wages.

Table 2: Firm-level political firm-level and Wages

Dependent variable: Wages				
	(1) Wages	(2) Wages	(3) Wages	(4) Wages
PRisk	0.0526***	0.0043***	0.0044***	0.0035***
	(0.0191)	(0.0015)	(0.0015)	(0.0013)
Firm size		0.0013***	0.0013***	0.0014***
		(0.0002)	(0.0002)	(0.0003)
Firm age		0.0001**	0.0002***	0.0002***
		(0.0001)	(0.0001)	(0.0001)
Total debt		-0.0077**	-0.0077**	-0.0061*
		(0.0032)	(0.0034)	(0.0035)
Altman Z score		-0.0001*	-0.0001*	-0.0001**
		(0.0001)	(0.0001)	(0.0001)
Dividend dummy		0.0033***	0.0032***	0.0038***
		(0.0010)	(0.0010)	(0.0010)
Tobin Q		-0.0025**	-0.0025**	-0.0026**
		(0.0010)	(0.0011)	(0.0011)
R&D intensity		-0.0112***	-0.0131***	-0.0074**
		(0.0035)	(0.0038)	(0.0033)
Capital intensity		0.0051	0.0048	0.0148***
		(0.0034)	(.0034)	(0.0044)
MB		0.0010**	0.0011**	0.0010**
		(0.0005)	(0.0005)	(0.0005)
Cash hold		0.0072***	0.0084***	0.0078***
		(0.0023)	(0.0026)	(0.0024)
Profitability		-0.0038	-0.0042*	-0.0062***
		(0.0023)	(0.0023)	(0.0023)
Competition			0.0008	0.0039**
			(0.0011)	(0.0017)
Labor share			0.0003	0.0003
			(0.0002)	(0.0002)

Constant	0.0238***	-0.0068***	-0.0048	-0.0132
	(0.0025)	(0.0016)	(0.0361)	(0.0488)
Observations	24, 578	23, 994	23, 654	23, 654
R-squared	0.0004	0.0157	0.0163	0.0220
Industry Effect	No	No	Yes	Yes
Firm Effect	No	No	No	Yes
Year Effect	No	No	No	Yes
Additional controls	No	No	Yes	Yes

This table shows the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is wages. The variable of interest is political risk described by Hassan et al. (2019). Model 1 clusters standard errors but without industry effects, year effects, firm effects, and firm controls. Model 2 includes controls but without year, firm, and industry effects. Model 3 presents the regression with industry effects, firm controls, and macroeconomic factors but no firm and year effects. Model 4 shows the regression results with all controls. Additional controls include net working capital, sale growth, cashflow, industry volatility, financial crisis, inflation, interest rate and real gross domestic product. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

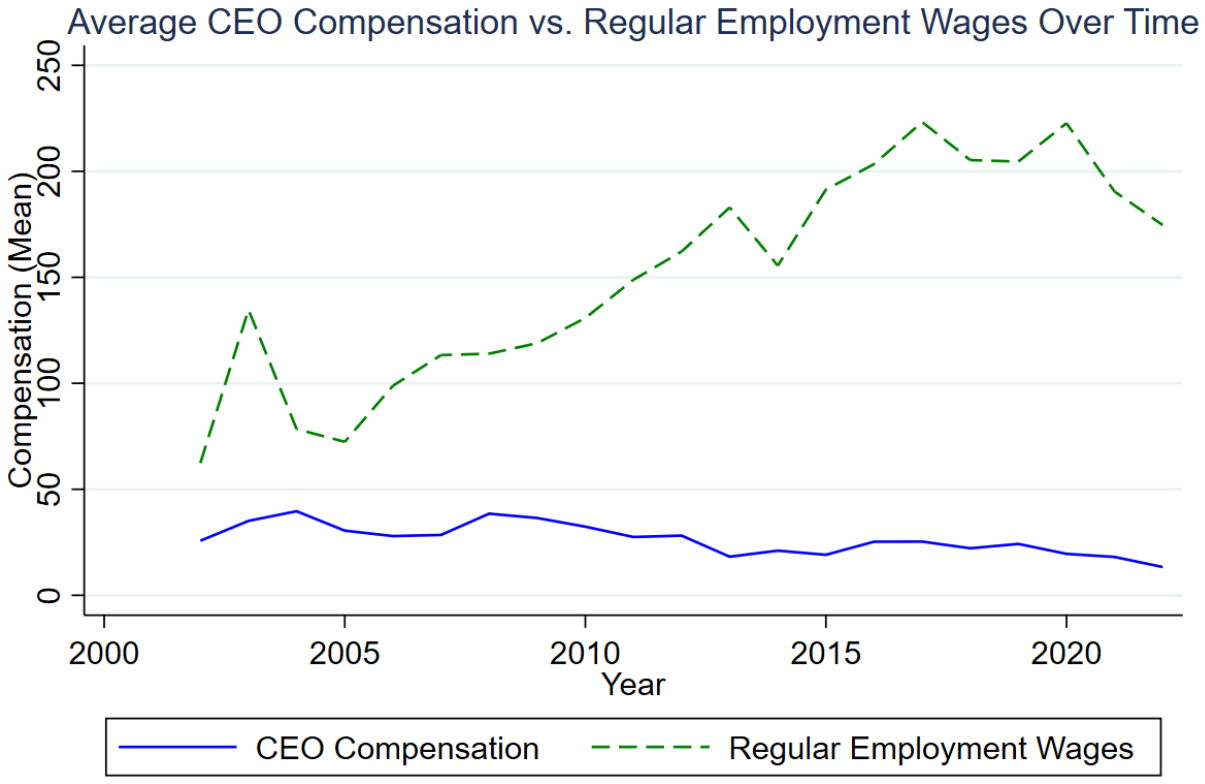

Figure 2.3: A graph showing a relationship between CEO compensation and regular employee compensation

Table 3: Firm-level political firm-level and CEO compensation and wage dispersion

	(1) CEO Wage	(2) Wage Dispersion
PRisk	0.0115	1.5190
	(0.0306)	(4.714)
Firm size	-1.0135***	22.2648***
	(0.0088)	(1.9896)
Firm age	0.0005	-1.5318***
	(0.0016)	(0.2647)
Total debt	-0.0081	-2.5763
	(0.049)	(7.331)
Altman Z score	-0.0006	1.4145***
	(0.0008)	(0.4234)
Dividend dummy	0.0059	-4.2122
	(0.0209)	(3.553)
Tobin Q	0.0052	-9.3682***
	(0.0052)	(2.373)
R&D intensity	0.1011	14.5794
	(0.0941)	(26.7391)
Capital intensity	-0.0758	5.7236
	(0.135)	(14.7395)
Market to Book ratio	-0.0016	0.1814
	(0.0011)	(0.2575)
Cash hold	-0.0442	17.3079*
	(0.0489)	(9.7957)
Profitability	0.0986	121.9914**
	(0.0634)	(47.4121)
Competition	-0.0719	-5.5296
	(0.053)	(5.2606)
Industry volatility	0.0006	0.0399
	(0.0018)	(0.311)
Global financial crisis	0.0116	-9.0163
	(0.0345)	(6.0129)
Inflation	0.0016	-1.6176**
	(0.0091)	(.7247)
Real GDP	0.1522	42.187**
	(0.1435)	(20.8613)
Interest Rate	-0.061	3.7047
	(0.0508)	(3.2475)
Constant	6.1882***	-54.7292***
	(1.3713)	(200.2907)
Observations	21790	20798
R-squared	0.7397	0.1309
Industry Effect	No	Yes
Firm Effect	Yes	Yes
Year Effect	Yes	Yes

This table shows the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variables are CEO pay (TDC1/total asset) and wage disparity (total wage-CEO wage). The variable of interest is political risk described by Hassan et al. (2019). Models 1 and 2 show the regression results with all controls. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the firm level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

The effect of firm-level Political Risk on Employment Growth

To test the hypothesis that employment growth responds negatively to increased firm-level political risk, I run baseline regression in equation (1), with employment growth being the dependent variable. Table 4 reports the regression results. Model 1 of Table 4 shows firm-level political risk negatively affects employment growth and statistically significant at 5%. This is consistent with hypothesis 1b stating that firm-level political risk has a negative impact on labor productivity. For economic significance, one standard deviation increase in firm-level political risk relates to an 8.94 percentage point decrease in employment growth without firm controls. However, when firm characteristics and year and industry effects were accounted for, the economic significance one standard deviation increase in political risk was associated with a 17.99 percentage point decrease in employment growth at a 5% significance level. On average, political risk is likely to reduce firm's employment growth by $5.445 million.

The results for the control variables are usually in line with intuitions. Employment growth is negatively associated with firm size, age, total debt, net working capital, dividend dummy, R&D intensity, MB, cash holding, and profitability. On the other hand, employment growth increases as cash flow and sale growth.

Table 4: Firm-level political risk and Employment growth

Dependent variable: Employment growth				
	(1) Employment growth	(2) Employment growth	(3) Employment growth	(4) Employment growth
PRisk	-0.0510**	-0.0538**	-0.0434**	-0.1026**
	(0.0208)	(0.0214)	(0.0213)	(2.1418)
Firm size		0.0128***	0.0112***	3.9925***
		(0.0032)	(0.0030)	(0.4865)
Firm age		-0.0037***	-0.0034***	-0.5588***
		(0.0008)	(0.0009)	(0.1180)
Total debt		0.0150	0.0195	-12.4834***
		(0.0438)	(0.0474)	(4.2683)
Altman Z score		0.0009*	0.0008	0.0095

		(0.0005)	(0.0005)	(0.0598)
Dividend dummy		-0.0542***	-0.0506***	-5.8011***
		(0.0103)	(0.0108)	(1.1847)
Tobin Q		0.0334***	0.0335***	1.8564***
		(0.0043)	(0.0039)	(0.3348)
R&D intensity		-0.1307***	-0.1571***	6.7292
		(0.0495)	(0.0524)	(5.0545)
Capital intensity		0.1166	0.1047	16.6014
		(0.0707)	(0.0705)	(10.1237)
MB		-0.0005	-0.001	-0.4735***
		(0.0012)	(0.0011)	(0.0840)
Cash hold		-0.0256	-0.0405	-14.7652***
		(0.0303)	(0.0254)	(2.6347)
Profitability		-0.0358	-0.0492	-1.8308
		(0.0447)	(0.0481)	(5.0391)
Competition			-0.0487***	-4.0921**
			(0.0155)	(1.7633)
Labor share			4.18e-06	0.0058
			(0.0001)	(0.0041)
constant	1.1059***	1.0282***	0.9620	-240.5116***
	(0.006)	(0.0218)	(0.7652)	(39.0550)
Observations	20, 278	19, 814	19, 612	23, 654
R-squared	0.0002	0.0136	0.0141	0.0876
Industry Effect	No	No	Yes	Yes
Firm Effect	No	No	No	Yes
Year Effect	No	No	No	Yes
Additional controls	No	No	Yes	Yes

This table shows the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is employment growth. The variable of interest is political risk described by Hassan et al. (2019). Model 1 clusters standard errors but without industry effects, year effects, firm effects, and firm controls. Model 2 includes controls but without year, firm, and industry effects. Model 3 presents the regression with industry effects, firm controls, and macroeconomic factors but no firm and year effects. Model 4 shows the regression results with all controls. Additional controls include net working capital, sale growth, cashflow, industry volatility, financial crisis, inflation, interest rate and real gross domestic product. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

The effect of firm-level political risk on labor productivity

I tested the hypothesis that increased political risk negatively reduces labor productivity. Employment growth responds negatively to increased firm-level political risk; I run baseline regression in equation (1) with labor productivity as the dependent variable. Table 5 reports the regression results. One standard deviation increase in political risk is associated with 30.48 percentage point decrease in labor productivity without accounting for firm characteristics, year,

and industry effects.

In Column 4 of Table 5, when firm controls, year, and industry effect were accounted for, one standard deviation increase in political risk is associated with a 31.73 percentage point decrease in labor productivity. Firm age, market-to-book ratio, total debt and labor share have negative effects on labor productivity while R&D intensity, firm size and cash holding have a positive effect on labor productivity.

Table 5: Firm-level political risk and Labor Productivity

Dependent variable: Labor Productivity				
	(1) Labor productivity	(2) Labor productivity	(3) Labor productivity	(4) Labor productivity
PRisk	-0.1738***	-0.1293*	-0.1203*	-0.1809***
	(0.0547)	(0.0728)	(0.0711)	(0.0568)
Firm size		0.1374***	0.1145***	0.1008***
		(0.0087)	(0.0073)	(0.0058)
Firm age		-0.0038***	-0.0087***	-0.0111***
		(0.0012)	(0.0010)	(0.0009)
Total debt		0.0576	-0.1191	-0.2748***
		(0.1005)	(0.0954)	(0.0608)
Altman Z score		0.0017*	0.0017*	-0.0002
		(0.0009)	(0.0010)	(0.0010)
Dividend dummy		-0.0791***	-0.0659***	-0.1241***
		(0.0213)	(0.0197)	(0.0172)
Tobin Q		0.0664***	0.0512***	0.0623***
		(0.0083)	(0.0085)	(0.0077)
R&D intensity		3.7161***	3.8163***	3.2633***
		(0.2103)	(0.2252)	(0.2030)
Capital intensity		0.8430	0.9586	-0.9675
		(0.9585)	(0.9381)	(0.6443)
MB		-0.0066***	-0.007***	-0.0009
		(0.0022)	(0.0021)	(0.0016)
Cash hold		0.8570***	0.7342***	0.7251***
		(0.0662)	(0.0660)	(0.0518)
Profitability		1.2685***	1.4700***	1.6962***
		(0.1726)	(0.1755)	(0.1742)
Competition			-0.1136**	-0.0172
			(0.0558)	(0.0819)
Labor share			-0.0058***	-0.0057***
			(0.0007)	(0.0006)
Constant	4.6975***	3.2328***	-13.2075***	-12.6369***
	(0.0095)	(0.0986)	(2.6254)	(1.4640)

Observations	22, 231	21, 696	21, 696	21, 696
R-squared	0.0070	0.1625	0.1861	0.3184
Industry Effect	No	No	No	Yes
Firm Effect	No	No	No	Yes
Year Effect	No	No	No	Yes
Additional controls	No	No	Yes	Yes

This table shows the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is employment growth. The variable of interest is political risk described by Hassan et al. (2019). Model 1 clusters standard errors but without industry effects, year effects, firm effects, and firm controls. Model 2 includes controls but without year, firm, and industry effects. Model 3 presents the regression with industry effects, firm controls, and macroeconomic factors but no firm and year effects. Model 4 shows the regression results with all controls. Additional controls include net working capital, sale growth, cashflow, industry volatility, financial crisis, inflation, interest rate and real gross domestic product. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

The interaction effects of explaining how firm-level political risk affects labor decisions.

Here, I focus on the mechanism through which political risk affects labor decisions, as shown in Table 6-8. Explicitly, I examine three mechanisms: competition, capital intensity and labor share. The regression result reveals significant and positive coefficients for firm-level political risk and competition in their relationships with wages. The coefficients indicate that higher political risk and increased competition relate to higher wages, statistically significant at 5%. Moreover, my result supports capital investment and labor share mediating roles. The interaction term between firm-level political risk and capital investment simply means that high firm-level political risk and capital investment is associated with an increase in wages. Similarly, a higher labor share leads to an increase in wages, as displayed in Table 6.

In Table 7, the regression result shows a significant negative interaction effect between firm-level political risk, competition, capital investment, and labor share on employment growth. The negative interaction effect indicates that high political risk and intense competition might generate an unfavorable business environment. Because of uncertainties and regulatory constraints, firms may hesitate to hire more people. Therefore, an increase in competition may

necessitate cost-cutting measures, such as downsizing or hiring restrictions, and the overall effect is a reduction in employment growth.

The main model includes firm-level political risk, competition, capital investment, labor share as independent variables and labor productivity as the dependent variable. I also incorporate control variables, year, and industry effects to account for potential confounding factors. The regression result reveals a significant negative impact on labor productivity due to increased firm-level political risk and interaction between competition, capital investment, and labor share.

Table 8 shows evidence of how firm-level political risk interacts with competition, capital intensity and labor share to affect labor productivity. The findings show that an increase in political risk is associated with a decrease in labor productivity. However, it is statistically significant only in models (2) and (3). The interaction term is negative and significant in model 1. This implies that the negative effect of political risk on labor productivity is more pronounced as competition increases. The negative impact of political risk on labor productivity is stronger when interacted with capital intensity and labor share.

Table 6: Channels through which political Risk affects firms' labor decisions.

Dependent variable: Wages			
	(1) Wages	(2) Wages	(3) Wages
PRisk	0.0005	0.0034**	0.0034***
	(0.0008)	(0.0016)	(0.0012)
PRisk x Competition	0.0140***		
	(0.0053)		
PRisk x Capital intensity		0.0046**	
		(0.0216)	
PRisk x labor share			0.0035**
			(0.0024)
Competition	0.0023	0.0039**	0.0039**
	(0.0014)	(0.0017)	(0.0017)
Capital intensity	0.0146***	0.0144***	0.0148***
	(0.0043)	(0.0038)	(0.0043)
Labor share	0.0003	0 .0003	-0.0002

	(0.0002)	(0.0002)	(0.0002)
Firm size	0.0014***	0.0014***	0.0014***
	(0.0003)	(0.0003)	(0.0003)
Firm age	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)
Total debt	-0.0061*	-0.0061*	-0.0061*
	(0.0035)	(0.0035)	(0.0035)
Altman Z score	0.0001**	0.0001**	0.0001**
	(0.0001)	(0.0001)	(0.0001)
Sale growth	-0.0003	-0.0003	-0.0004
	(0.0005)	(0.0005)	(0.0005)
Dividend dummy	0.0038***	0.0038***	0.0038***
	(0.0010)	(0.0010)	(0.001)
Cashflow	0.0008	0.0008	0.0007
	(0.0017)	(0.0017)	(0.0017)
Tobin Q	-0.0026**	-0.0026**	-0.0026**
	(0.0011)	(0.0011)	(0.0011)
R&D intensity	-0.0072**	-0.0074**	-0.0075**
	(0.0033)	(0.0033)	(0.0033)
MB	0.0010**	0.0010**	0.0010**
	(0.0005)	(0.0005)	(0.0005)
Cash hold	0.0078***	0.0078***	0.0079***
	(0.0024)	(0.0024)	(0.0024)
Profitability	-0.0062***	-0.0062***	-0.0060***
	(0.0023)	(0.0023)	(0.0023)
Industry volatility	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)
Financial crisis	0.0020	0.0020	0.0022
	(0.0014)	(0.0014)	(0.0014)
Inflation	-0.0008	-0.0008	-0.0008
	(0.0005)	(0.0005)	(0.0005)
RGDP	-0.0001	-0.0001	0.0001
	(0.0051)	(0.0051)	(0.0051)
High interest	0.0073*	0.0073*	0.0077*
	(0.0039)	(0.0039)	(0.0039)
Constant	-0.0131	-0.0133	-0.0145
	(0.0488)	(0.0490)	(0.0486)
Observations	23, 654	23, 654	23, 654
R-squared	0.0221	0.0220	0.0234
Industry Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes

This table reports the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is wages. The variable of interest is political risk described by Hassan et al. (2019). Model 1 shows the regression of the interaction effect of competition and political risk on wages. Model 2 shows the regression of the interaction effect of capital intensity and political risk on wages. Model 3 presents the regression of interaction effect of labor share and political risk on wages. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

Table 7: Channels through which political Risk affects firms' labor decisions.

Dependent variable: Employment growth			
	(1) Employment growth	(2) Employment growth	(3) Employment growth
PRisk	0.7025	0.4987	-0.1086
	(2.6974)	(2.4278)	(2.1443)
PRisk x Competition	-2.7829		
	(7.4705)		
PRisk x Capital intensity		-19.2685	
		(5.0871)	
PRisk x labor share			-0.1087
			(0.1747)
Competition	-3.7783*	-4.0774**	-4.0924**
	(1.9513)	(1.7705)	(1.7635)
Capital intensity	16.6400	18.4867	16.5993
	(10.1383)	(11.9981)	(10.1244)
Labor share	0.0058	0.0058	-0.0029
	(0.0041)	(0.0041)	(0.0140)
Firm size	3.9892***	3.9925***	3.9923***
	(0.4863)	(0.4864)	(0.4866)
Firm age	0.5589***	0.5591***	0.5587***
	(0.1179)	(0.1182)	(0.1180)
Total debt	-12.5034***	-12.4674***	-12.4834***
	(4.2835)	(4.2661)	(4.2684)
Net working capital	-22.5877***	-22.5989***	-22.5794***
	(3.6405)	(3.6452)	(3.6427)
Altman Z score	0.0094	0.0094	0.0094
	(0.0598)	(0.0598)	(0.0598)
Sale growth	-10.1666***	-10.164***	-10.1614***
	(3.6597)	(3.6600)	(3.6583)
Dividend dummy	-5.7995***	-5.8055***	-5.8015***
	(1.1845)	(1.1864)	(1.1847)
Cashflow	9.9208**	9.9167**	9.9083**
	(4.3830)	(4.3853)	(4.3884)
Tobin Q	1.8577***	1.8575***	1.8559***
	(0.3347)	(0.3346)	(0.3348)
R&D intensity	6.7020	6.7601	6.7254
	(5.0738)	(5.0917)	(5.0530)
MB	-0.4736***	-0.4738***	-0.4735***
	(0.0840)	(0.084)	(0.0840)
Cash hold	-14.768***	-14.769***	-14.7629***
	(2.6336)	(2.6353)	(2.6351)
Profitability	-1.8277	-1.8147	-1.8260
	(5.033)	(5.0616)	(5.0392)
Industry volatility	0.5434***	0.5436***	0.5433***
	(0.2010)	(0.2009)	(0.2011)
Financial crisis	-67.1265***	-67.1234***	-67.1264***
	(3.6752)	(3.6805)	(3.6767)
Inflation	-3.0939**	-3.0922**	-3.0979**
	(1.1933)	(1.1945)	(1.1949)

RGDP	250.1702***	250.1323***	250.1836***
	(3.9982)	(4.0108)	(4.0093)
High interest	16.517**	16.5123**	16.5382**
	(8.0981)	(8.1083)	(8.1072)
Constant	-2405.5342***	-2405.1441***	-2405.5528***
	(39.0123)	(39.0703)	(39.0734)
Observations	23, 654	23, 654	23, 654
R-squared	0.0876	0.0876	0.0876
Industry Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes

This table reports the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is employment growth. The variable of interest is political risk described by Hassan et al. (2019). Model 1 shows the regression of the interaction effect of competition and political risk on employment growth. Model 2 shows the regression of interaction effect of capital intensity and political risk on employment growth. Model 3 presents the regression of the interaction effect of labor share and political risk on employment growth. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

Table 8: Channels through which political Risk affects firms' labor productivity.

Dependent variable: Labor Productivity			
	(1) Labor Productivity	(2) Labor Productivity	(3) Labor Productivity
PRisk	-0.1190	-0.3222***	-0.148***
	(0.0869)	(0.082)	(0.0513)
PRisk x Competition	-0.2107**		
	(0.1824)		
PRisk x Capital intensity		-4.3642**	
		(1.7869)	
PRisk x labor share			-1.7492***
			(0.4183)
Competition	0.0059	-0.0202	-0.0076
	(0.0913)	(0.0815)	(.0809)
Capital intensity	-0.9650	-1.3961**	-0.9531
	(0.6444)	(0.6778)	(0.6443)
Labor share	-0.0057***	-0.0058***	-0.0452***
	(0.0006)	(0.0006)	(0.0124)
Firm size	0.1006***	0.1008***	0.1004***
	(0.0058)	(0.0058)	(0.0057)
Firm age	-0.0110***	-0.0111***	-0.0109***
	(0.0009)	(0.0009)	(0.0009)
Total debt	-0.2763***	-0.2788***	-0.2879***
	(0.0603)	(0.0605)	(0.0614)
Net working capital	-0.1634**	-0.1573*	-0.1649**
	(0.0807)	(0.0808)	(0.0805)
Altman Z score	-0.0002	-0.0002	-0.0001
	(0.0010)	(0.0010)	(0.0010)
Sale growth	0.7757***	0.7764***	0.7752***
	(0.1988)	(0.1992)	(0.1987)

Dividend dummy	-0.1241***	-0.1234***	-0.1164***
	(0.0173)	(0.0171)	(0.0175)
Cashflow	0.3243**	0.324**	0.3304**
	(0.1573)	(0.1575)	(0.1569)
Tobin Q	0.0624***	0.062***	0.0593***
	(0.0077)	(0.0077)	(0.008)
R&D intensity	3.2622***	3.2559***	3.2489***
	(0.2029)	(0.2021)	(0.1992)
MB	-0.0009	-0.0008	0.0001
	(0.0016)	(0.0016)	(0.0016)
Cash hold	0.7244***	0.7250***	0.7333***
	(0.0518)	(0.0514)	(0.0527)
Profitability	1.6975***	1.6945***	1.6956***
	(0.1746)	(0.1738)	(0.1745)
Industry volatility	-0.0014	-0.0015	-0.0017
	(0.0020)	(0.0020)	(0.0020)
Financial crisis	0.1382***	0.1385***	0.1394***
	(0.0328)	(0.0331)	(0.0323)
Inflation	0.0123	0.0112	0.0109
	(0.0147)	(0.0148)	(0.015)
RGDP	1.5820***	1.5944***	1.5927***
	(0.1548)	(0.1567)	(0.1556)
High interest	0.0977*	0.1021*	0.1043*
	(0.0551)	(0.0549)	(0.0545)
Constant	-12.6351***	-12.7277***	-12.7360***
	(1.4612)	(1.4812)	(1.4685)
Observations	21, 696	21, 696	21, 696
R-squared	0.3184	0.3191	0.3238
Industry Effect	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes

This table reports the estimates from fixed effects models explaining the effects of political risk on firms' labor decisions. The dependent variable is labor productivity. The variable of interest is political risk described by Hassan et al. (2019). Model 1 shows the regression of the interaction effect of competition and political risk on labor productivity. Model 2 shows the regression of the interaction effect of capital intensity and political risk on labor productivity. Model 3 presents the regression of the interaction effect of labor share and political risk on labor productivity. The sample consists of U.S. listed non-financial and non-utility firms drawn from Compustat from 2002–2022. The standard errors are clustered at the industry level to adjust for heteroskedasticity. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are explained in Appendix A.

Addressing endogeneity concerns

Two-stage residual-based regressions

I employ the two-stage least squares (2SLS) instrumental variable technique to address the challenges of unobservable characteristics and endogeneity in examining the impact of firm-specific political risk on labor decisions.

I use two-stage least squares (2SLS) to incorporate the exogenous factor from firm

political risk and re-estimate Eq. (1). However, to use the 2SLS technique, I employ the Partisan Conflict Index (PCI) as an instrumental variable, which is correlated to the firm-level political risk but uncorrelated with the error term. To select such PCI, I draw on relevant research (Gulen & Ion, 2016; Hasan et al., 2022; Azzimonti, 2018). This index is important because it captures policy disagreements between and within political parties, as well as between Congress and the President, at any time. Given the measurement, it is a valid instrument for our model, as firm political risk is expected to be high when country-level partisan conflict is high. PCI has a negative relationship with firm-level political risk and the result is reported in Table 9.

First, I estimate the first-stage regression where the dependent variable is Prisk*,* and independent variables include PCI and other control variables in the baseline model. I report the estimation of this first-stage regression in the first column of Table 9. As predicted, PCI is negatively related to Prisk, which confirms the satisfaction relevance of the instrumental variable because policy uncertainty increases the firm-level political risk faced by each firm.

In columns 2-4 of Table 9, I present the findings of the second-stage regression. I obtained the predicted value of Prisk from the first regression and used it to estimate labor decisions. At the 5% level, the instrumented firm political risk variable (Prisk fitted) exhibits a positive and significant coefficient between wages while a negative relationship between employment growth and labor productivity.

Also, the Kleibergen-Paap statistics in the second-stage regressions are all greater than the 10% Stock-Yogo critical value, demonstrating that the instrumental variable is not weak. This finding is consistent with the result from my baseline regressions. When I adopted the instrumental variable approach, my findings remain consistent; this alleviates the issue that omitted variables influence my conclusions.

Table 9: Instrumental Variable Regression

	First stage	Second stage		
	(1)	(2)	(3)	(4)
	First stage	Wages	Employment growth	Labor productivity
Partisan conflict	-0.0015***			
	(0.0002)			
PRisk residual		0.0035**	-0.2234**	-0.1923***
		(0.0013)	(2.2552)	(0.0587)
Firm size	-0.0040***	0.0014***	4.0626***	0.1019***
	(0.0012)	(0.0003)	(0.5025)	(0.0059)
Firm age	0.0010***	0.0002***	0.6032***	-0.0105***
	(0.0002)	(0.0001)	(0.1239)	(0.0008)
Total debt	0.0178***	-0.004	-12.8868***	-.2672***
	(0.0065)	(0.0028)	(4.4682)	(0.0634)
NWC	0.0016	0.0018	-22.9678***	-0.1525*
	(0.0105)	(0.0012)	(3.7384)	(0.0827)
Altman Z score	0.0007***	0.0001**	0.0115	-0.0003
	(0.0002)	(0.0001)	(0.0610)	(0.0010)
Sale growth	-0.0063	-0.0002	-10.0832***	0.7616***
	(0.0051)	(0.0004)	(3.6464)	(0.1914)
Dividend dummy	-0.0003	0.0033***	-5.8195***	-0.1282***
	(0.0038)	(0.0009)	(1.2268)	(0.0172)
Cashflow	-0.0261*	0.0004	9.5372**	0.2960*
	(0.0154)	(0.0014)	(4.5025)	(0.1602)
Tobin Q	0.0019	-0.0020**	1.8264***	0.0634***
	(0.0012)	(0.0009)	(0.3450)	(0.0079)
R&D intensity	0.0001	-0.0056**	6.3162	3.2438***
	(0.0142)	(0.0025)	(5.2023)	(0.2069)
Capital intensity	-0.0744***	0.0143***	17.4355*	-0.9266
	(0.0223)	(0.0045)	(10.372)	(0.6547)
MB	-0.0003	0.0007*	-0.4897***	-0.0010
	(0.0002)	(0.0004)	(0.0874)	(0.0017)
Cash hold	0.0063	0.0065***	-15.5584***	0.7229***
	(0.0092)	(0.0019)	(2.6542)	(0.0528)
Profitability	-0.0241**	-0.0054***	-1.8833	1.7016***
	(0.0115)	(0.0020)	(5.2055)	(0.1827)
Competition	0.0257***	0.0041**	-4.2080**	-0.0175
	(0.0077)	(0.0017)	(1.8489)	(0.0846)
Industry volatility	-0.0005	-0.0001**	0.5345**	-0.0012
	(0.0003)	(0.0001)	(0.2153)	(0.0021)
Labor share	-0.0004**	0.0003	0.0039	-0.0057***
	(0.0002)	(0.0002)	(0.0032)	(0.0006)
Financial crisis	-0.0140	0.0020	-67.0159***	0.1368***
	(0.0131)	(0.0013)	(3.6794)	(0.033)
Inflation	-0.0086***	-0.0008	-3.0807**	0.0136
	(0.0017)	(0.0005)	(1.1990)	(0.0147)
RGDP	0.2728***	0.0006	24.6441***	1.5566***
	(0.0427)	(0.0048)	(4.1636)	(0.1555)
High interest		0.0010	14.6497***	0.0430

		(0.0010)	(1.6266)	(0.0323)
Constant	-2.4116***	-0.0198	-240.9681***	-12.3948***
	(0.4005)	(0.0457)	(40.5904)	(1.4692)
Observations	22741	22741	22741	20858
R-squared	0.0287	0.0202	0.0877	0.3156
Industry Effect	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes
Kleibergen-Paap LM test		19.93**		

The table displays the results of two-stage least squares (2SLS) regressions. Column 1 contains the first-stage regression findings, with PRisk as the dependent variable. Column 2 contains the coefficients of the second-stage regression. The partisan conflict index proposed by Gulen & Ion (2016) and Hasan, Alam, Paramati & Islam, 2022 serves as the instrumental variable. I use the partisan conflict index developed by Azzimonti (2018) and the political stability index. Control variable definitions are provided in Appendix A. At the firm level, I group standard errors. The robust standard errors are in parentheses and clustered at the industry level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Cross sectional analysis: Leader firms and Laggard firms

In this section, I perform a cross-sectional analysis. First, I investigate whether our results remain the same for leading and laggard firms. Following Gutiérrez & Philippon (2017), I define leader firms as those firms above 75th percentiles of market concentration (HHI) and laggard firms are those below. Such an investigation is motivated by the fact that it would provide insights for stakeholders and policymakers to address policy implications for a stable labor market. Understanding firms' responses to political uncertainties helps predict future adaptability and competitiveness among these two groups.

The results displayed in Table 10 show that wages increase more in the leading firms than in the laggard firms as political risk increases. The high wage increase in the leading firm can be associated with employee retention, market power, talent attraction, and during uncertain seasons. The decrease in employment growth and labor productivity is higher in leading firms than in laggard firms. During periods of high political risk, firms become cautious and risk-averse, resulting in decreased hiring decisions and overall employment growth. Also, employees are not sure of the certainty of their jobs, resulting in their level of productivity, thus, a fall in labor productivity.

Table 10: Firm-level political risk and labor decisions among firm leaders and laggard

	Leader firms			Laggard firms		
	(1) Wages	(2) Employment growth	(3) Labor Productivity	(4) Wages	(5) Employment growth	(6) Labor Productivity
PRisk	0.0082***	-11.9003***	-0.0739**	0.0044**	-4.1567	-0.0160
	(0.0015)	(4.4469)	(0.0792)	(0.0017)	(4.0291)	(0.0952)
PRisk x lead	0.0173***	-15.6872***	-0.4130***			
	(0.0046)	(4.5863)	(0.1155)			
Leader	0.0044***	10.8746***	-0.1046***			
	(0.0009)	(2.0265)	(0.0202)			
PRisk x follow				0.0069***	-0.6901**	-0.2312**
				(0.0025)	(9.4413)	(0.1854)
Follower				-0.0055***	3.4899	-0.0229
				(0.0011)	(2.1448)	(0.1072)
Firm size	0.0009***	1.3492*	0.1416***	0.0014***	4.6273***	0.0499***
	(0.0002)	(0.7331)	(0.0072)	(0.0003)	(0.6279)	(0.0124)
Firm age	0.0002***	0.6873***	-0.013***	0.0002***	0.3630***	-0.0115***
	(0.0001)	(0.1312)	(0.0009)	(0.0001)	(0.1290)	(0.0025)
Total debt	-0.0054	-10.5465	-0.2248***	-0.0086**	-13.5552***	-0.5970***
	(0.0040)	(7.4851)	(0.0836)	(0.0041)	(4.1373)	(0.1044)
NWC	0.0005	-20.2071***	-0.1526	0.0008	-25.2073***	-0.1874**
	(0.0013)	(6.6527)	(0.1180)	(0.0013)	(3.9903)	(0.0924)
Sale growth	-0.0008*	-9.6652*	0.7794***	-0.0006	-12.2010***	0.6301**
	(0.0004)	(5.0733)	(0.2485)	(0.0004)	(4.0021)	(0.2648)
Dividend dummy	0.0039***	-6.447***	-0.0924***	0.0036***	-0.1740	-0.1469***
	(0.0010)	(1.5442)	(0.018)	(0.001)	(2.4832)	(0.0524)
Cashflow	0.0019	11.6940	0.2782**	0.0013	6.9811**	0.2842
	(0.0017)	(7.4454)	(0.1308)	(0.0018)	(3.3249)	(0.2849)
Tobin Q	-0.0024**	0.9130**	0.0530***	-0.0022**	3.8346***	0.0908**
	(0.0009)	(0.4402)	(0.0081)	(0.0009)	(1.1162)	(0.0376)
R&D intensity	-0.0078**	6.0485	3.9806***	-0.0074**	3.4230	2.1153***
	(0.0036)	(9.9755)	(0.2025)	(0.0035)	(5.9620)	(0.2177)
Capital intensity	0.0123***	17.6549	-2.0065***	0.0112***	4.7703	1.3679*
	(0.0040)	(12.6341)	(0.5936)	(0.0037)	(13.375)	(0.7001)
MB	0.0010**	-0.2937**	-0.0017	0.0010**	-0.6633***	0.0050*
	(0.0004)	(0.1203)	(0.0018)	(0.0004)	(0.1095)	(0.0028)
Cash hold	0.0070***	-20.0864***	0.7693***	0.0083***	-7.2489*	0.5976***
	(0.0024)	(3.334)	(0.0568)	(0.0026)	(4.1052)	(0.0941)
Profitability	-0.0050**	-7.1989	1.8850***	-0.0041**	2.5516	1.7418***
	(0.0019)	(9.0969)	(0.1325)	(0.0017)	(3.7700)	(0.3339)
Competition	0.0011	0.6949	0.1521**	-0.0011	-8.7793**	-0.2356**
	(0.0011)	(2.1633)	(0.0683)	(0.0010)	(3.4167)	(0.1180)
Industry volatility	-0.0002**	0.4478*	-0.0003	-0.0002**	0.6953***	-0.0048
	(0.0001)	(0.2539)	(0.0020)	(0.0001)	(0.1537)	(0.0039)
Labor share	0.0003	0.0052*	-0.7500***	0.0004	0.0103	-0.0051***
	(0.0002)	(0.0030)	(0.0395)	(0.0002)	(0.0099)	(0.0003)
Constant	-0.0073***	-25.0045***	2.0740***	-0.0116***	-21.7034*	3.2382***
	(0.0023)	(5.7098)	(0.1332)	(0.0029)	(11.267)	(0.1860)
Observations	17, 000	17, 268	16, 266	6, 654	6, 386	5, 430
R-squared	0.0225	0.0815	0.3693	0.0236	0.1268	0.3012

Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the regression results of the mechanism in which political risk affects firms' labor decisions among U.S. leaders and followers. I regress wage, employment growth, and labor productivity on the leading firms' control variables and industry and year-fixed effects. I repeat the specification for the laggard firms. Following Gutiérrez & Philippon (2019), I define leader firms as those above or equal to the median value of market concentration and Laggard firms (below the median of market concentration). I control industry, firm, and year effects. The standard errors are adjusted for heteroskedasticity and are clustered at the industry level. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. A detailed explanation of the variables is in Appendix A.

Additional test

I rerun the baseline model with wages as the dependent variable and the various alternative measure of firm-level political risk, and the results are shown in Table 11. The findings suggest that different dimensions of political risk are associated with firm wages. Economic, environmental, health, security, tax, and technology risks have significant impacts on wages. Economic and environmental risks tend to increase wages, potentially compensating for the increased risk. Also, health, security, and technology risks also positively affect wages. Institutional and trade risks do not show a significant effect on wages in this model. I found evidence that increased political risk is associated with increased wages. This supports the baseline findings that firm-level political risk is related to higher wages.

Robustness test

Alternative political risk measures: political risk elements

Table 11: Alternative Measures of firm political risk and Wages

	(1) Economic	(2) Environment	(3) Trade	(4) Institutions	(5) Health	(6) Security	(7) Tax	(8) Technology
Economic	0.0003***							
	(0.0001)							
Environment		0.0001**						
		(0.0003)						
Trade			0.0001					
			(0.0001)					
Institution				0.0002***				
				(0.0001)				
Health					0.0002**			
					(0.0001)			
Security						0.0002**		
						(0.0001)		
Tax							0.0001*	
							(0.0001)	
Technology								0.0001***
								(0.0001)
size	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0014***	0.0013***	0.0014***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm age	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Total debt	-0.0062*	-0.0060*	-0.0060*	-0.0061*	-0.0062*	-0.0061*	-0.0060*	-0.0061*
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
NWC	0.0013	0.0013	0.0013	0.0014	0.0014	0.0013	0.0014	0.0014
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Altman Z score	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sale growth	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Dividend dummy	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***	0.0038***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)

Cashflow	0.0009	0.0009	0.0009	0.0009	0.0009	0.0008	0.0009	0.0008
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Tobin Q	-0.0026**	-0.0026**	-0.0026**	-0.0026**	-0.0026**	-0.0026**	-0.0026**	-0.0026**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
R&D intensity	-0.0072**	-0.0073**	-0.0074**	-0.0074**	-0.0076**	-0.0073**	-0.0075**	-0.0074**
	(0.0033)	(0.0032)	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0033)
Capital intensity	0.0149***	.01431***	0.0146***	0.01473***	0.0152***	0.0148***	0.0147***	0.0147***
	(0.0044)	(0.0043)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)
MB	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Cash hold	0.0079***	0.0078***	0.0078***	0.0078***	0.0078***	0.0078***	0.0079***	0.0079***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0025)	(0.0024)	(0.0024)	(0.0024)
Profitability	-0.0062***	-0.0063***	-0.0063***	-0.0063***	-0.0061***	-0.0062***	-0.0064***	-0.0062***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Competition	0.0038**	0.0039**	0.0039**	0.0039**	0.0039**	0.0039**	0.0039**	0.0039**
	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0017)
Industry volatility	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Labor share	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0085	-0.0131	-0.0132	-0.0136	-0.0047	-0.0133	-0.0123	-0.0139
	(0.0491)	(0.0488)	(0.0489)	(0.0486)	(0.0487)	(0.0484)	(0.0482)	(0.0483)
Observations	23, 654	23, 654	23, 654	23, 654	23, 654	23, 654	23, 654	23654
R-squared	0.0224	0.0220	0.0219	0.0221	0.0231	0.0221	0.0222	0.0220
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effect	No	No	No	No	No	No	No	No
Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table shows the regression results of a firm's wages on several political risk measures. Hassan et al. (2019) used machine learning from business conference calls to construct eight different indicators of firm-level political risk. Each measure of firm-level political risk relates to economic policy and budget, environment, health, institutions, political process, security and defense, tax policy, technology and infrastructure, and trade. Control variable definitions are provided in Appendix A. The standard errors are adjusted for heteroskedasticity and are clustered at the industry level. Standard errors are included in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. A detailed explanation of the variables is in the Appendix A.

5.0 Conclusion

Political shocks impact economic activity, investment, and capital decisions, but less attention is given to labor decisions. This paper investigates how labor market decisions of U.S. firms respond to firm-level political risk.

The study employs a novel firm-level political risk measure established by Hassan et al. (2019), and the results show that firms increase labor wages when political risk is high. However, employment growth and labor productivity decrease as political risk increases. Also, an increase in competition and firm-level political risk increase wages. However, when political risk interacts with a high labor share reduces labor productivity. Additionally, the interaction between political risk, capital investment and labor share are associated with a negative impact on labor productivity.

Firms facing decreasing labor productivity and employment growth due to increasing political risk should adopt proactive measures like practicing financial prudence. Policymakers must pay attention to several types of political risks since they significantly impact labor decisions. This paper contributes to the expanding literature on the political motivations of labor decisions of firms. The findings highlight that firms react to political risk by increasing wages but reducing employment growth and decreasing labor productivity.

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Appendix A

Table Variable Definitions

Variable	Definition	Source
Political Risk (Prisk)	The proportion of each firm's quarterly earnings conference calls is devoted to political risks. The annual political risk is the average of quarterly political risk values for a specific year. For my analysis, I scaled it by 1000.	(Hassan et al., 2019).
Political Risk-Economic	The economic policy-specific component of political risk is equal to the proportion of individual firms' quarterly earnings conference calls related to economic policy-related political risk.	(Hassan et al., 2019).
Political Risk-Environment	The environmental policy-specific measure of political risk is equal to the proportion of individual firms' quarterly earnings conference calls related to economic policy-related political risk. This includes air act, renewable energy, climate change, clean air, greenhouse gas, and other ecological issues	(Hassan et al., 2019).
Political Risk-Trade	This comprises free trade, trade agreements, trade barriers, globalization, and labor standards.	(Hassan et al., 2019).
Political Risk-Institution	The environmental policy-specific measure includes campaign finance, finance reform, federal elections, and political system	(Hassan et al., 2019).
Political Risk-Health	Health risk contains issues related to prescription drugs, medicare, government takeover, and drug plan	(Hassan et al., 2019).
Political Risk-Security	Incorporates issues like terrorism, nuclear weapons, and the U.S. troops	(Hassan et al., 2019).
Political Risk-Tax	Covers estate tax, tax relief, bush tax, and tax reform	(Hassan et al., 2019).
Political Risk-Technology	It considers fairness doctrine, cyber warfare and high-tech jobs, among others	(Hassan et al., 2019).
Wages or labor compensation	Wages are a measure of the amount and trend of workers' purchasing power and an estimate of their standard of life. Total Wages is the total labor expenses deflated by 10000.	Author's calculation. Compustat
Employment growth	The ratio of the total number of employees minus lagged total number of employees divided by the lagged total number of employees.	Author's calculation Compustat
Labor productivity	Sales minus cost of goods sold divided by employees.	Author's calculation Compustat
Firm size (size)	The natural logarithm of total assets	Author's calculation Compustat
Firm age (age)	Firm age is measured as the time between its going public and the current time (also in years).	Author's calculation
Total debt	Sum of short-term debt (current liabilities) and total long-term debt scaled by total assets	Author's calculation Compustat
Altman Z score (z-score)	I use the Altman Z-score model to measure financial distress. The Z-score of a firm is computed as per Altman (1968, 2000). The sum of 1.2 times net working capital, 1.4 times retained earnings, 3.3 times pretax income, sales, 0.6 times market value, and 1 times sale all divided by total asset	Author's calculation Compustat

Sale growth	Annual sales growth rate. Percentage of sales growth from the previous year to the current year.	Author's calculation Compustat
Net Working capital	The difference between working capital and cash, scaled by total assets.	Author's calculation Compustat
Dividend dummy	A dummy variable equals 1 if firm pays a dividend to common shareholders and 0 otherwise.	Author's calculation Compustat
Cashflow	Sum of total income before extraordinary items and depreciation expense divided by total assets.	Author's calculation Compustat
Tobin Q	Total assets less the book value of equity scaled by the market value of equity over total assets	Author's calculation Compustat
R&D intensity	R&D expenses scaled by total assets. For missing R&D expenses, the value of R&D is set to zero	Author's calculation Compustat
Capital intensity	Capital expenditure scaled by total assets.	Author's calculation Compustat
Market to Book ratio	Market-to-book ratio. The market value of the firm divided by the enterprise value	Author's calculation Compustat
Cash holding	Cash scaled by the book value of total assets	Author's calculation Compustat
Profitability	Operating income before depreciation scaled by total assets	Author's calculation Compustat
Labor Share	It is measured as staff expenses scaled by total sale	Author's calculation Compustat
Competition	HHI is measured as the sum of squared market shares of each firm in each industry (three-digit SIC code). Therefore, higher HHI indicates concentration and less competitive markets.	Author's calculation Compustat
Industry volatility	The average standard deviation of a firm's cashflow in each industry. To define industry, I utilize a three-digit SIC code. The standard deviation of cash flow is calculated by dividing firm-level cash flow by total assets.	Author's calculation Compustat
Federal interest rate	Federal funds rate is the overnight interest rate for depository institutions trading federal funds held at Federal Reserve Banks.	Federal Reserve Bank of St. Louis (FRED)
High interest	A dummy variable that equals 1 if the federal interest rate is higher than the median value and 0 otherwise.	FRED
Inflation rate	Consumer price index measures inflation as an annual percentage change in average consumer's cost of goods and services.	FRED
Financial Crisis (2007-2008)	A dummy variable that equals 1 if the year equals 2007-2008 and 0 otherwise.	Author's calculation
Real Gross Domestic Product	The real GDP is the inflation-adjusted worth of goods and services made by labor and property in the United States.	FRED
Partisan Conflict	Tracks the level of political disagreement among federal lawmakers in the United States. It is Developed by Azzimonti (2018). Index values higher indicate greater political conflict.	Federal Reserve Bank of Philadelphia

Chapter 3

Effects of Debt Financing Decisions on Profitability: A Comparison of USA and Europe Biopharmaceutical Industry

Abstract

Debt financing is important for financing major investments in the biopharmaceutical industry. Debt financing allows companies to raise funds without giving up ownership or control through indenture and covenants of the company. In this study, I analyze the effects of debt financing decisions on profitability in the biopharmaceutical industry. I find that short-term debt, long-term debt and total debt negatively impacts return on assets (ROA) as a firm's profitability measure. A comparison is made between the US and Europe biopharmaceutical firms and the result shows the negative effects of short-term and long-term debt on profitability persist more for US biopharmaceutical firms than Europe firms. Short-term and long-term debt both impact profitability negatively with 10-year lagged R&D intensity and financial distress. Short-term debt's negative impact is stronger in post-Covid-19, indicating increased financial strain. Long-term debt consistently affects profitability negatively, with relative stable effects during the pre- and post-Covid-19.

1.0 Introduction

Debt financing is important for financing major investments like R&D in the biopharmaceutical industry. Debt financing allows companies to raise funds without giving up ownership or control through indenture and covenants of the company. Debt financing provides greater flexibility for firms in biopharmaceutical industry to finance highly intensive research and development (R&D).

Debt financing is a factor that can significantly impact a company's net revenue (Spazek, 2020). Debt financing or borrowing of funds to finance company's operations and investments can have two impacts on a firm. Debt financing provides the necessary capital for expansion and innovation. On the other hand, it imposes financial obligations that can strain a firm's resources, especially in sectors with high capital intensity and competitive innovation. The biopharmaceutical industry in the United States is an example of such a sector, making it an ideal place to investigate these relationships. When firms are selecting debt to finance their operations and investments, they face decisions regarding the appropriate types of debt.

The choice of debt financing is an important decision for companies aiming to fund their projects. This paper poses research questions: How do short-term and long-term debt impact profitability within the biopharmaceutical industry? What are the ways through which short-term and long-term debt affect profitability? The diverse range of debt instruments, both short- and long-term, provides flexibility in financial strategies. The impact of debt on profitability remains a subject of debate, with conflicting findings in previous studies. While some suggest that debt can lower the cost of capital and enhance profitability (Tailab, 2014; Abor, 2005; Trabelsi & Bouallegui, 2004), others argue that higher interest payments may decrease overall profitability (Harris & Raviv (1991) and Rajan & Zingales, 1995).

Focusing specifically on the biopharmaceutical industry, my interest in analyzing the impact of debt financing is driven by the industry's unique characteristics. The biopharmaceutical sector attracts significant attention due to continuous advancements in R&D, strong investor demand for higher returns and the imperative for companies to replenish their pipelines. Furthermore, the industry's critical role in addressing global health challenges, such as the Covid-19 pandemic, underscores its financial and economic significance.

Debt financing is essential to the biopharmaceutical industry, allowing companies to undertake large R&D activities, grow medication pipelines, and respond quickly to global health emergencies. In this capital-intensive industry, debt provides the financial resources required to drive innovation, maintain competitive market positions, and cover operating costs. It helps biopharmaceutical companies negotiate the complexity of medication discovery, manufacturing, and market dynamics, hence promoting long-term growth and breakthroughs in healthcare.

As the biopharmaceutical industry stands at the intersection of innovation, health care, and economic impact, understanding the dynamics of debt financing and its influence on profitability is important because debt financing minimizes agency costs (Jensen and Meckling, 1976), serve as indicators of firm quality (Myers and Majluf, 1984), and might influence firm's profit. The strategic decisions made by companies in this sector not only shape their financial performance but also contribute to advancements in healthcare, making it a focal point for financial and strategic analysis (Thakor & Lo, 2015). The strategic decisions made by companies in this sector not only shape their financial performance but also contribute to advancements in healthcare, making it a focal point for financial and strategic analysis. Therefore, debt financing decisions raise important questions regarding how biopharmaceutical firms use their financial structures to influence profitability.

I study 687 public-traded US and Europe biopharmaceutical firms with data on Compustat between 1990-2022 (4284 firm-year observation two-way fixed effects and dynamic panel estimations, I find evidence that total debt, both long-term and short-term, affects profits negatively. This is because the more the short-term debt and long-term debt increases, the more it will increase the firm's interest expense which in turn reduces its profit. In terms of economic significance, a one-standard-deviation increase in the short-term debt leads to 13.7 percent decrease in profitability after controlling for firm-level and macroeconomic characteristics. This

negative effect on profitability is more pronounced for US biopharmaceutical firms than European firms.

In addition, the result shows that long-term debt reduces profitability for biopharmaceutical firms. The economic significance of the negative relationship between long-term debt and profitability is that an increase of one standard deviation of long-term debt relates to a 2.55 percent standard deviation decrease in profitability. This suggests a strong negative impact of long-term debt on profitability for pharmaceutical firms in the USA.

Total debt, which combines both short-term and long-term debt, has a negative effect on profitability and is statistically significant at 1 percent. There is a strong negative impact of long-term debt on profitability for pharmaceutical firms in the USA as compared to European biopharmaceutical firms.

Furthermore, I examine the mechanisms through which debt financing affects profitability. The results show that short-term and long-term debt impact profitability negatively with 10-year lagged R&D intensity and financial distress. Biopharmaceutical firms heavily invest in R&D, often necessitating debt financing. However, the finding reveals that long-term debt negatively impacts profitability when combined with 10-year lagged R&D intensity and financial distress. This suggests that while R&D is essential for innovation, high levels of R&D spending paired with long-term debt can strain profitability. Similarly, financial distress exacerbates the negative effects of long-term debt, highlighting the need for effective financial distress management.

This paper contributes to the existing literature that relates how the composition of debt affects profitability. Some studies (Tyagi & Nauriyal, 2016; Pervan et al., 2019; Aashna and Thyagarajan, 2016) overlook how short-term and long-term debt impact profitability separately.

This study contributes to the literature by offering a comprehensive analysis of the interplay between long-term debt, lagged R&D and financial distress in the biopharmaceutical industry. It

provides practical implications for financial managers and policymakers aiming to balance debt financing with sustainable profitability.

This study focuses on the biopharmaceutical industry, which is characterized by increased competitiveness, which drives innovation. In response to the need for constant innovation, biopharmaceutical businesses frequently rely on higher debt to fund projects. However, my findings show that increased debt levels are associated with a decrease in profitability, defying the understanding that debt drives growth and financial success in this dynamic market.

The rest of this paper is organized as follows. Section 2 examines relevant theoretical and empirical literature. Section 3 outlines the research methodology, which includes empirical estimation methods. The empirical findings are presented in Section 4. In Section 5, the study's summary and conclusion are presented. The data and variables used in the study are described in the Appendix.

2.0 Literature review and development of hypotheses

According to Modigliani and Miller (MM) (1958), debt does not affect the value of the firm, so any structure of debt adopted by any firm at any point in time is as good as any other in the absence of corporate tax. Relaxing some of the assumptions of M&M from their initial proposition in prior literature revealed that capital structure affects profitability[15]. Tyagi & Nauriyal (2016) examined the profitability of the Indian biopharmaceutical sector. Their study employed an OLS regression model with Driscoll-Kraay standard errors and used inflation-adjusted panel data from 2000 to 2013. Export intensity, advertising and market intensity, firm

[15] Some of the assumptions of MM model are there are no taxes of any kind. Also, transaction costs for securities are nonexistent, and bankruptcy costs do not apply. Information is perfectly symmetrical, allowing investors equal insights to those of corporations, leading to rational investment behaviors. Borrowing costs are identical for both investors and corporations, and there are no additional expenses associated with issuing securities, such as underwriting fees, payments to bankers, advertising costs, or taxes on corporate dividends.

market power, and a stronger patent regime benefit profitability. The MM theory implies that firms can raise their profitability by maximizing their debt financing and reaping the benefits of tax savings as a result. Hence an increase in leverage leads to a positive effect on profitability.

Some authors, including Myers (1976), Jensen & Meckling (1976), Grossman & Hart (1983), Jensen (1986), Harris & Raviv (1990), Ahmed, Abdullahi, & Roslan (2012), and Fosu (2013), have improved the classic capital structure by incorporating control variables. The authors conducted empirical studies based on several capital structure theories. Various theories include trade off, pecking-order, information asymmetry, signaling, product/input market interaction, and market-timing theories.

Consequently, in 1958, Modigliani-Miller's MM theory was developed into trade-off theory[16]. The trade-off theory focuses on debt repayment and costs of debt issuance, and it predicts that a desirable target debt ratio would add value to the business. Rather than constantly issuing debt to improve firm value, the trade-off theory asserts that firms must strive towards a specific level of debt financing to achieve the optimal company value. Kraus & Litzenberger (1973) stated firms should aim for debt levels that maximize tax benefits while minimizing bankruptcy risks. Jawade (2014) analyzed the effect of capital structure on biopharmaceutical company performance across a range of market capitalizations. The author showed that capital structure provides growth prospects, maintains solvency, and provides an excellent return to stakeholders without dilution of management control; firms must trade-off between the tax benefits of debt and the consequences of bankruptcy.

[16] Static and dynamic trade-off theory are two types of trade-off theory. Using debt against equity offers both advantages and downsides, according to the static trade-off hypothesis. As a result, businesses should choose an optimal debt that balances these factors at the margin (Scott 1977). the dynamic trade-off hypothesis shows that, even in a trade-off environment with a fixed cost of issuing stock, firms can deviate from their goal capital structure by altering leverage. when it exceeds extreme boundaries because when a company makes money, it frequently pays down debt, lowering influence (Fischer, Heinkel, and Zechner, 1989)

Myers and Majluf (1984) posited the pecking order theory as an alternative to the trade-off theory. According to this hypothesis, when a company needs external funding, it favors debt over equity. It also predicts that riskier firms will have higher leverage ratios. Investors and managers have a greater incentive to take on riskier projects when a firm's debt financing allocation rises. Mohammadzadeh, Rahimi, Aarabi, & Salamzadeh (2013) examined the relationship between capital structure and profitability in Iranian biopharmaceutical enterprises. The top 30 Iranian biopharmaceutical businesses were studied, and their financial data was collected from 2001 to 2010. This study used the net margin profit and the debt ratio as profitability and capital structure indices, respectively, with sales growth as a control variable. The findings revealed a significant negative association between debt and profitability. Also, the result supports the pecking order theory in the Iranian biopharmaceutical companies. The results show that increased debt financing negatively impacts profitability in Iranian biopharmaceutical firms, aligning with the pecking order theory by prioritizing internal over external financing due to debt's cost and risk. Other authors concluded that internal funding, such as retained earnings, is the best first alternative, followed by debt securities if internal funds are insufficient to finance the firm (Frank & Goyal, 2003; Rasiah & Kim, 2011).

Thus, the use of debt to finance investments projects in the biopharmaceutical industry can positively or negatively affect profitability in a competitive environment. I argue that debt financing does not only affect profitability directly but also influences biopharmaceutical firms' profitability indirectly through 10-year lagged R&D and financial distress.

2.1. Development of hypotheses

Three key testable hypotheses are established based on theoretical predictions and historical empirical evidence.

Relationship between debt financing and profitability

Debt financing involves borrowing funds to support business operations or investments, which is either short-term or long-term debt (Allen, 2015). The combination of short-term and long-term debt is the total debt. Debt requires firms to make periodic interest payments, which not only reduce profits in the current accounting period but may also limit available cash for operations in the subsequent period (Sarkar and Sarkar, 2008). Debt financing can provide a tax shelter for profits associated with high financial risk; hence, all firms should consider how much debt capital they should maintain to benefit from such trade-offs. The costs of obtaining new external funding are higher than those of internal financing, as internal funds do not incur any transaction costs. Past research has discovered a positive link between debt financing and profitability (Habib et al., 2016; Margaritis & Psillaki, 2010), while others argue that debt and profit have a negative relationship (Habib et al., 2016; Sadiq & Sher, 2016). However, Weill (2008) shows that debt financing can positively or negatively impact a firm's performance when industrial histories, current economic conditions, and other macroeconomic factors are accounted for. To make appropriate debt decisions, it is necessary to test the relationship between levels of debt and firm profitability. In this light, I test the following:

Hypothesis 1: Debt finance has a significant relationship with profitability.

Short-term debt refers to obligations that last shorter than a year and are typically related to internal or external company concerns while long-term debt refers to a company's borrowing or external finance that is repayable over a longer period of time. Short-term debt is riskier and has a greater impact on profitability than long-term debt due to several factors. The frequent and immediate repayment schedules associated with short-term debt create significant liquidity pressures, forcing

firms to allocate substantial cash flow to debt servicing. This can strain resources, limit funds available for strategic investments like R&D and reduce overall financial flexibility. Additionally, short-term debt often comes with higher and more volatile interest rates, increasing interest expenses and financial uncertainty. Short-term debt has a greater negative influence on biopharmaceutical industry profitability than long-term debt because of higher periodic interest payments and the urgency of repayment. I hypothesize that

Hypothesis 2: Short-term debt has a more negative impact on profitability than long-term debt.

Mechanisms through which debt financing affects Profitability

Interaction between debt and lagged of R&D on Profitability

R&D investments in the biopharmaceutical industry typically take considerable time to impact on a firm's profitability. Firstly, new drugs undergo extensive preclinical and clinical trials spanning approximately 10 years. Secondly, FDA approval is essential to ensure safety, efficacy, and quality, adding complexity and time to the process. Thirdly, translating successful R&D into economic benefits involves patenting innovations, a time-consuming process to protect against competitors. Therefore, immediate financial gains from R&D investments may not be realized if the benefits of innovative products do not sufficiently outweigh their costs. Thus, the impact of debt on profitability when combined with lagged R&D investments in the biopharmaceutical industry can vary. Zhao & Wu (2013) and Lu & Wang (2011) found a negative impact of current expenditure on performance using ROA, but a positive and significant effect of one-year lagged expenditure on profitability. Debt may provide necessary funding for R&D activities, contributing positively to future profitability through innovation and market competitiveness. However,

excessive debt levels could increase financial risk and interest expenses, potentially negatively impacting profitability. I hypothesized that

Hypothesis 3a: There is a significant effect of debt and lagged R&D on a firm's profitability.

Interaction between debt and financial distress on Profitability

Financially distressed biopharmaceutical firms with high debt face adverse impacts on profitability due to increased interest expenses, risk of default, reduced investor confidence and market valuation, strategic constraints on R&D and growth investments, heightened regulatory scrutiny, and competitive disadvantages against financially stable peers. These factors collectively hinder financial stability, operational effectiveness, and long-term growth prospects in a competitive industry reliant on innovation and regulatory compliance. Therefore, I hypothesize that

Hypothesis 3b: There is a negative effect of debt and financially distressed firms on a firm's profitability.

3.0 Data and empirical methodology

3.1. Data and data Sources

This study uses unbalanced panel data consisting of publicly traded biopharmaceutical firms with data available on COMPUSTAT. I consider all audited financial data for biopharmaceutical companies based on 4-digit Standard Industrial Classification (SIC) code (SIC 2833: Medicinal Chemicals and Botanical Products, SIC 2834: Pharmaceutical Preparations, SIC 2835: In Vitro and In Vivo Diagnostic Substances, SIC 2836: Biological Products, Except Diagnostic Substances) retrieved from COMPUSTAT. I merge the resulting sample of the COMPUSTAT data with macroeconomic data (Inflation, real gross domestic product per output

and interest rate) from the Federal Reserve Economic (FRED) from 1990-2022. The final sample comprises 687 US and European public-traded biopharmaceutical firms and 4284 firm-year observations from 1990-2022. 485 firms belong to US while 202 firms belong to Europe. The European countries with biopharmaceutical firms are Belgium, Switzerland, Germany, Denmark, Spain, France, United Kingdom, Ireland, Luxembourg, Netherlands, Norway, Sweden. Out of 687 firms, 45 firms did not report R&D. Therefore, R&D expenses were set to zero when they were not reported, and those firms are found in Appendix.

3.2. Definition and measurement of variables

The definition of all variables with expected signs is found in the Appendix. I defined the dependent and independent variables to be used in this study so that they were consistent with those of Rajan and Zingales (1995), Loderer & Waelchli (2010), Abor's (2005), Fosu (2013), and Pervan, Pervan, & Ćurak (2019).

3.3. Empirical model and estimation strategy

Theoretically, the leverage-profitability relationship is expressed in equation 1 after controlling for firm-specific characteristics. These variables were chosen based on prior literature and their theoretical significance in determining a firm's profitability.

$$ROA_{it} = \alpha + \beta debt_{it} + \omega controls_{it} + \varepsilon_{it} \quad (1)$$

ROA_{it} is firm i's profit in year t. The return on assets (ROA) has been used in prior research and by managers and other stakeholders, supporting the use of ROA as a measure of profitability (Bettis, 1981; Baum et al., 2007; Kebewar, 2013; Pervan, Pervan, & Ćurak, 2019). As a result, this study employs ROA as a profitability metric, and it is the dependent variable in the data analysis. It is measured as earnings before interest, taxes, depreciation, and amortization. The main explanatory variable is debt. $Debt$ measures the debt financing decisions such as total debt, long-

term, and short-term debt and they are measured in percentages. $Controls$ are the firm-level variables that include firm age, firm size, R&D intensity, cash holding, capital intensity, growth opportunity and macroeconomic variables such as real GDP, interest rate, inflation and global financial crisis (2007-2009). I lag the variables to address endogeneity and reverse causality issues.

3.4. Method of estimation

The relationship between debt and a firm's profitability at time t can be expressed in equation 2 using two fixed effects estimations:

I expect that companies in the sample may have other unobserved idiosyncrasies that distinguish them from one another. To determine and control for the unobserved individual-specific firm and year effects, I use two-way fixed as depicted in Equation 2:

$$Prof_{it} = \alpha + \beta Debts_{it} + \theta' x + \mu_i + \varepsilon_{it} \quad (2a)$$

Mechanisms through which debt financing influences profitability

$$Prof_{it} = \alpha + \beta Debts_{it} + \theta' debts * mechanism + \emptyset controls + \mu_i + \varepsilon_{it} \quad (2b)$$

where $Prof_{it}$ represents the profitability of firm i at time t, i = 1, …, N and t = 1, …, T. $\epsilon_{it} = \mu_i + \varepsilon_{it}$ in that $\mu_i$captures the time-invariant firm-specific effects, accounts for unobserved heterogeneity, and ε_{it} is the white noise. $Mechanism$ are 10-year lagged of R&D and financial distress.

The fixed-effects model controls for the potential correlation between regressors' and unobservable individual effects. The fixed effects approach takes to be a group-specific constant term in the regression model (Wooldridge, 2012). The use of the fixed effects helps to address the problem of possible endogeneity concerns. By analyzing the within-firm variance in profitability across time, I include firm-fixed effects and firm-specific controls like age, tangibility, etc. address this concern. Also, I introduce year-fixed effects to account for unobserved time-specific shocks

influencing all firms (Grullon, Larkin & Michaely, 2018). I use cluster-robust standard error estimations at the firm level to control for possible heteroscedasticity and autocorrelation.

4.0 Results and discussions

4.1. Summary statistics

Table 1A shows how number of firms varies across years. 2022 has the highest firms with 1990 having the lowest number of biopharmaceutical firms. Table 1B presents the summary statistics for dependent and independent variables. I winsorize all continuous variables at the 1st and 99th percentiles in the analysis to reduce the influence of outliers (Campbell, Hilscher & Szilagyi, 2008; Loderer & Waelchli, 2010). I use two measures for firm profitability. The first measure is calculated as the ratio of earnings before interest, taxes, depreciation and amortization over total assets (EBITDA/TA). and it is the main measure. The second measure is measured as the ratio of net income over total assets (NI/TA). A firm's profitability as measured by return on assets (ROA) depicts an average of 6 percent decrease of total assets. Having a negative ROA indicates that biopharmaceutical firms have a downward trend in profitability. The average short-term debt ratio of 18.9 percent indicates that biopharmaceutical firms utilize a relatively large portion of their total debt (28.9 percent) for short-term financing needs relative to long-term debt of 10.52 percent. This suggests that biopharmaceutical firms rely heavily on short-term debt to fund their operations. The average firm age of around 9 years suggests that many firms in the biopharmaceutical industry are relatively young. This reflects the dynamic and innovative nature of the sector, with many new entrants focused on breakthrough technologies and treatments. R&D intensity, which measures R&D expenditure as a percentage of total asset, is about 21.56 percent. This high R&D intensity shows the industry's commitment to innovation and the significant resources allocated to developing new drugs and treatments.

Table 1C shows the descriptive statistics in the subsample of firms in US and Europe. US biopharmaceutical firms have a mean profitability of 7.87 percent, while European firms have a mean of 2.36 percent. This indicates that US firms, on average, generate higher profitability relative to their total assets compared to European firms, suggesting potentially higher efficiency in asset utilization or stronger market positioning. Also, US biopharmaceutical firms maintain a mean short-term debt ratio of 16.31 percent, compared to 14.52 percent for European firms. This difference implies that US firms rely more on short-term debt relative to their total assets, which may indicate varying strategies in managing liquidity and financing short-term obligations. US firms have a mean long-term debt ratio of 10.66 percent, while European firms have a mean of 8.82 percent. The higher mean long-term debt ratio among US firms suggests a greater reliance on long-term financing for capital investments and strategic initiatives relative to their total asset base. Figure 1 shows how short-term debt and long-term debt vary across years.

Table 1A: Number of firms across years

Year	Number of firms
1990	34
1991	59
1992	66
1993	89
1994	103
1995	103
1996	111
1997	126
1998	138
1999	142
2000	134
2001	157
2002	160
2003	151
2004	155
2005	160
2006	157
2007	150
2008	131
2009	115
2010	99
2011	97
2012	93
2013	92
2014	103
2015	118
2016	125
2017	132
2018	135
2019	191
2020	201
2021	218
2022	239

Table 1B: Descriptive Statistics

	N	Mean	Std. Dev.	p25	Median	p75	p99
Outcome variables							
Profitability_1 (ROA_1)	4284	-0.0623	0.3105	-0.2421	0.0361	0.1534	0.4032
Profitability_2 (ROA 2)	4284	-0.1467	0.3466	-0.3055	-0.0401	0.0750	0.3357
Main Explanatory variables							
Total debt	4284	0.2890	0.3270	0.0774	0.2060	0.3907	1.4417
Short term debt	4284	0.1838	0.3070	0.0435	0.1500	0.3460	1.3566
Long term debt	4284	0.1052	0.1118	0.0029	0.0135	0.0448	0.4629
Control variables							
Firm age	4284	9.1041	7.8820	7	15	32	41
Firm size	4284	6.2258	2.1511	4.6286	5.8536	7.4414	11.7563
R&D intensity	4284	0.2156	0.2818	0.0570	0.1380	0.3012	1.0789
R&D-lag 10	4284	0.0119	0.0456	0.0021	0.0033	0.0069	0.1796
Cash holding	4284	0.3839	0.2836	0.1251	0.3259	0.6324	0.9426
Capital intensity	4284	0.0374	0.0407	0.0114	0.0257	0.0494	0.2030
Growth opportunity	4284	2.6531	2.3850	1.1594	1.9916	3.3544	11.498
Panel B: Macroeconomic variables							
Real GDP	33	1.5327	1.7141	0.7712	1.6551	2.6583	5.1866
Interest rate	33	2.6288	2.3205	0.18	2.16	4.68	7.31
Inflation	33	2.6479	1.5146	1.6400	2.6074	3.1568	8.0028
Global financial crisis	33	0.0909	0.2919	0	0	0	1

This table reports the summary of descriptive statistics of the dependent variable (ROA) and the main explanatory variables: debt (shot term debt, long-term and total debt) with other control variables. The sample contains 687 biopharmaceutical firms, making a total of 4284 firm-year observations from 1990-2022. All the firm-specific variables were winsorize at the 1st and 99th percentiles.

Table 1C: Summary statistics

All Biopharmaceutical Firms

	USA Biopharmaceutical firms			Europe Biopharmaceutical firms		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Main dependent variables						
Profitability_ 1	3595	0.0787	0.3180	689	0.0236	0.2513
Profitability_ 2	3595	0.1638	0.3563	689	0.0572	0.2744
Main explanatory variables						
Total Debt	3595	0.2697	0.3412	689	0.2334	0.2322
Short-term debt	3595	0.1631	0.3205	689	0.1452	0.2172
Long-term debt	3595	0.1066	0.1182	689	0.0882	0.0685
Control variables						
firm age	3595	9.3366	7.8366	689	7.8911	8.0117
firm size	3595	5.9451	1.9957	689	7.6902	2.3325
R&D intensity	3595	0.2256	0.2996	689	0.1639	0.1492
R&D-lag 10	3595	0.0132	0.0495	689	0.0050	0.0066
cash holding	3595	0.3961	0.2846	689	0.3202	0.2697
Capital intensity	3595	0.0380	0.0419	689	0.0338	0.0336
Growth opportunity	3595	2.7065	2.4459	689	2.3744	2.0166

This table reports the summary of descriptive statistics between US and Europe biopharmaceutical firms. The dependent variable is profitability measured as (EBITDA/TA) and is income before depreciation and amortization divided by book value of assets. The main explanatory variables are debt financing (shot term debt, long-term and total debt) with other control variables. The sample contains 687 biopharmaceutical firms, making a total of 4284 firm-year observations from 1990-2022. All the firm-specific variables were winsorize at the 1st and 99th percentiles.

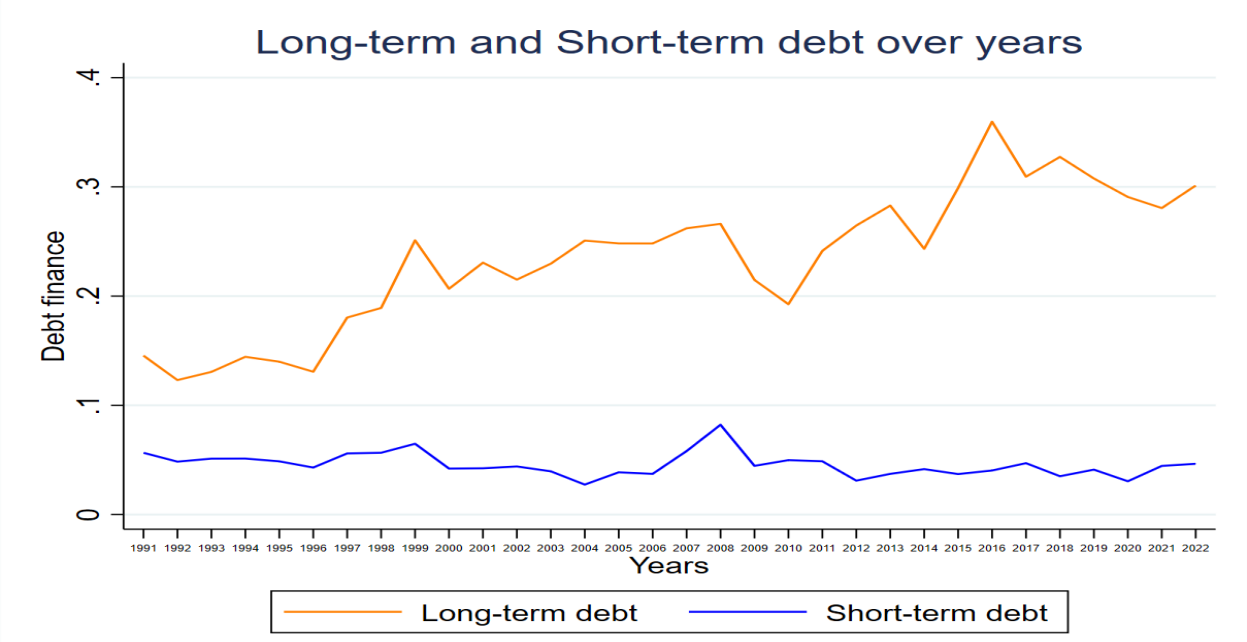

Figure 3.1: A graph showing a relationship between short-term and long-term debt across years

4.2. Correlation matrix

The correlation matrix is displayed in Table 1D. From Table 1D, short-term debt and long-term debt are negatively correlated with ROA. The variance inflation factors (VIF) for the rest of the main explanatory variables and controls are within the acceptable limits (1.24-3.82).

Table 1D: Correlation Coefficients

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	VIF
(1) Profitability (ROA)	1.0000									
(2) Short Term debt	-0.1580	1.0000								1.06
(3) Long-term debt	-0.2490	0.0030	1.0000							1.02
(4) Firm age	0.2760	0.0390	-0.0530	1.0000						1.29
(5) Firm size	0.4350	-0.1130	-0.0230	0.0450	1.0000					1.20
(6) R&D intensity	-0.4440	-0.0450	0.0620	-0.1260	-0.1970	1.0000				1.31
(7) cash holding	-0.5260	-0.1620	0.0210	-0.3020	-0.2640	0.4510	1.0000			1.57
(8) Capital intensity	-0.0840	-0.0580	-0.0680	0.0250	-0.1580	0.1230	0.1900	1.0000		1.90
(9) Growth opportunity	-0.0580	-0.0660	-0.0350	0.0290	-0.0280	0.2490	0.2550	0.1660	1.0000	1.15

This table reports the correlation coefficients among the variables employed in this study. All continuous variables are winsorize at the 1st and 99th percentiles.

4.3. Discussion of empirical results

Table 1E shows the result of hypothesis test using paired t-test. The result is to prove whether the short-term and long-term debt variables individually have an influence on profitability. The result shows that p-value is less than 1 percent meaning that short-term and long-term debt individually have an influence on profitability.

Test difference between short-term debt and long-term debt

t = 39.8290
Degrees of freedom = 4283

Hypothesis:
Null hypothesis: There is no difference between short-term debt and long-term debt
Alternative hypothesis: There is no difference between short-term debt and long-term debt

Table 1E: Test difference between short-term debt and long-term debt

Variable	Observation	Mean	Standard error	Standard deviation
Long term debt	4,284	0.2438	0.0047	.3069
Short term debt	4,284	0.0452	0.0017	.3069

Pr (T > t) = 0.0000

Table 2 shows the regression of how short-term debt affects profitability. Without any controls, short-term debt affects profitability negatively by 44.7 percent and statistically significant at 1 percent. For economic significance, one standard deviation increase in short-term debt leads to 13.7 percent decrease in profitability. Column 2 shows that Short-term debt has a statistically significant negative effect on profitability (ROA) with all controls. From economic significance, one standard deviation increase in short term relates to 13.1 percent decrease in profitability. Columns 3 and 4 display how short-term debt affects profitability among US and Europe biopharmaceutical industry. The coefficient for short-term debt shows a negative effect on profitability and is statistically significant at 1 percent. This suggests that, in the USA, an increase in short-term debt is associated with a substantial and significant decrease in profitability but there is no statistically significant relationship between short-term debt and profitability for European biopharmaceutical firms.

Table 2: The effect of short-term debt on profitability

			USA	**Europe**
	(1)	(2)	(3)	(4)
	ROA	ROA	ROA	ROA
Short term debt	-0.4475***	-0.4256***	-0.5349***	-0.3152
	(0.131)	(0.1212)	(0.1332)	(0.2552)
Firm age		0.0026***	0.003***	0.0013*
		(0.0007)	(0.0008)	(0.0007)
Firm size		0.0437***	0.0468***	0.0375***
		(0.0026)	(0.0031)	(0.0042)
R&D intensity		-0.2688***	-0.2571***	-0.4611***
		(0.0797)	(0.0788)	(0.0999)
Cash holding		-0.3821***	-0.3993***	-0.2629***
		(0.0306)	(0.0318)	(0.0509)
Capital intensity		0.0386	0.0405*	0.024
		(0.025)	(0.0241)	(0.0731)
Growth Opportunity		0.0102***	0.0079***	0.0271***
		(0.0028)	(0.0029)	(0.0049)
Real GDP		0.022***	0.0202***	0.0277***
		(0.0014)	(0.0016)	(0.0037)
Interest rate		0.0627***	0.0631***	0.0537***
		(0.0039)	(0.0043)	(0.0081)
Inflation		-0.0516***	-0.053***	-0.0403***

		(0.0028)	(0.003)	(0.0062)
Global Financial Crisis		-0.0291***	-0.0391***	0.0364***
		(0.0056)	(0.0065)	(0.0097)
Constant	0.1529***	-0.1415***	-0.1571***	-0.1481***
	(0.0074)	(0.0262)	(0.0302)	(0.0502)
Observations	4284	4284	3595	689
R-Squared	0.0694	0.4967	0.483	0.6111
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes

Table 2 examines the effect of short-term debt on profitability. Columns 3 and 4 compare the effect of short-term debt on profitability among US and Europe biopharmaceutical firms. In all regression models, I control for year fixed effects and firm fixed effects. Robust standard errors clustered by firms are presented in parentheses. *, **, *** denote a two-tailed p-value of <0.10, 0.05, and 0.01, respectively. Definitions of variables and their estimation methods are provided in Appendix.

Table 3 displays the effect of long-term debt on profitability. Long-term debt affects profitability negatively by 22.85 percent and statistically significant at 1 percent without any controls. Column 2 shows that the coefficient of long-term debt has a negative effect on profitability and is statistically significant at 1 percent when controls were included. From economic significance, one standard deviation increase in long-term debt leads to 2.2 percent decrease in profitability. Columns 3 and 4 display how long-term debt affects profitability among US and Europe biopharmaceutical industry. The coefficient for long-term debt shows a negative effect on profitability and is statistically significant at 1 percent. The negative impact of long-term debt on ROA is statistically significant in the USA, suggesting a clear relationship between increased long-term debt and decreased profitability. However, in Europe, the relationship is not statistically significant, indicating no clear impact of long-term debt on profitability. This is in line with hypothesis 2 which states that short-term debt impacts profitability more than long-term debt.

Table 3: The effect of long-term debt on profitability

			USA	**Europe**
	(1) ROA	(2) ROA	(3) ROA	(4) ROA
Long-term debt	-0.2285***	-0.1948***	-0.2078***	-0.0276
	(0.0267)	(0.0227)	(0.0261)	(0.0518)
Firm age		0.0029***	0.0033***	0.0012*
		(0.0008)	(0.0008)	(0.0007)
Firm size		0.0465***	0.0511***	0.0369***

		(0.0025)	(0.0029)	(0.0038)
R&D intensity		-0.2572***	-0.245***	-0.468***
		(0.0757)	(0.0744)	(0.1014)
Cash holding		-0.3447***	-0.3549***	-0.2535***
		(0.0291)	(0.0303)	(0.0526)
Capital intensity		0.0326	0.0354	0.008
		(0.0247)	(0.0231)	(0.0835)
growth Opportunity		0.0094***	0.0072***	0.0273***
		(0.0024)	(0.0025)	(0.005)
Real GDP		0.0174***	0.0164***	0.0234***
		(0.0015)	(0.0016)	(0.0021)
Interest rate		0.0527***	0.0548***	0.0451***
		(0.004)	(0.0044)	(0.0062)
Inflation		-0.0452***	-0.048***	-0.0337***
		(0.0028)	(0.003)	(0.0041)
Global Financial Crisis		-0.0345***	-0.0517***	0.0463***
		(0.0049)	(0.0055)	(0.0081)
Constant	0.1608***	-0.1587***	-0.1785***	-0.1594***
	(0.0039)	(0.0267)	(0.0288)	(0.0444)
Observations	4284	4284	3595	689
R-squared	0.0929	0.4983	0.4878	0.6049
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	No

This table reports the results from the regression of the effect of long-term debt on profitability. The dependent variable is profitability measured as (EBITDA/TA) and is income before depreciation and amortization divided by book value of assets. The main explanatory variable is long-term with other control variables. Models (3) and (4) are for the sample of firms in USA and Europe. All other variables are defined in Appendix. The sample period is from 199 to 2020. I control for year fixed effects and firm fixed effects. Standard errors are clustered by firm, and standard errors are reported in parentheses. The *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

In Table 4, there is a negative impact of total debt on ROA and is statistically significant at 1 percent. This shows a clear relationship between increased total debt and decreased profitability. This is in line with hypothesis 1 that states that debt financing (total debt) has a significant effect on profitability.

Table 4: The effects of total debt on profitability

			USA	**Europe**
	(1)	(2)	(3)	(4)
	ROA	ROA	ROA	ROA
Total debt	-0.2534***	-0.2345***	-0.2484***	-0.0552
	(0.0306)	(0.0285)	(0.0315)	(0.0468)
Firm age		0.003***	0.0034***	0.0012*
		(0.0007)	(0.0008)	(0.0007)
Firm size		0.0438***	0.048***	0.0362***
		(0.0022)	(0.0026)	(0.0036)
R&D intensity		-0.2517***	-0.2396***	-0.4682***

		(0.0736)	(0.0724)	(0.1002)
Cash holding		-0.3657***	-0.3764***	-0.2629***
		(0.0277)	(0.0291)	(0.048)
Capital intensity		0.0225	0.0229	0.0073
		(0.0246)	(0.0237)	(0.0846)
Growth Opportunity		0.0091***	0.0071***	0.0267***
		(0.0023)	(0.0024)	(0.005)
Real GDP		0.0162***	0.0149***	0.0233***
		(0.0013)	(0.0015)	(0.0015)
Interest rate		0.049***	0.0503***	0.0442***
		(0.0036)	(0.0039)	(0.0048)
Inflation		-0.0423***	-0.0443***	-0.0334***
		(0.0025)	(0.0028)	(0.0034)
Global Financial Crisis		-0.0334***	-0.0500***	0.0465***
		(0.0048)	(.0052)	(0.0075)
Constant	0.1788***	-0.1175***	-0.1344***	-0.1409***
	(0.0062)	(0.0264)	(0.0292)	(0.0411)
Observations	4284	4284	3595	689
R-Squared	0.1128	0.5205	0.5131	0.6065
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	No

This table reports the results from the regression of the effect of long-term debt on profitability. The dependent variable is profitability measured as (EBITDA/TA) and is income before depreciation and amortization divided by book value of assets. The main explanatory variable is total debt with other control variables. Models (3) and (4) are for the sample of firms in USA and Europe. All other variables are defined in Appendix. The sample period is from 199 to 2020. I control for year fixed effects and firm fixed effects. Standard errors are clustered by firm, and standard errors are reported in parentheses. The *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 5 and 6 examine the channels through which short-term and long-term debt affect profitability. In column 1 of Table 5, the interaction suggests that although short-term debt alone might reduce profitability, combining it with 10-year lagged R&D intensity can potentially enhance profitability. This implies that there is a synergistic effect, meaning firms that have invested in R&D in the past might use short-term debt more effectively. This could be because the innovative products developed from earlier R&D efforts eventually become profitable. However, the interaction term between long-term debt and 10-year lagged R&D suggests a positive relationship on profitability but not statistically significant as shown in Table 6.

The interaction term between short-term debt and financial distress is negative and statistically significant. This means that when short-term debt and financial distress occur together,

they significantly worsen profitability. Biopharmaceutical firms facing financial distress are particularly harmed by short-term debt, likely because of higher borrowing costs and less financial flexibility. In Table 6, when both long-term debt and financial distress are present, the negative impact on profitability worsens. Firms in financial distress situation may find long-term debt especially burdensome, likely due to increased difficulties in managing and servicing debt over a long period.

The coefficients for short-term debt in models (1) and (2) show a significant negative impact on profitability both before and after the Covid-19 pandemic. Before Covid-19, the effect is quite negative, meaning that higher levels of short-term debt are linked to lower profitability in biopharmaceutical firms. After Covid-19, this negative effect becomes even stronger. The pandemic likely made short-term debt more burdensome for firms due to increased financial uncertainty and operational disruptions. Similarly, the coefficients for long-term debt in models (3) and (4) indicate a clear negative impact on profitability both before and after the Covid-19 pandemic. Before Covid-19, long-term debt reduces profitability. This negative effect remains significant but becomes slightly less severe after Covid-19. The persistent negative effect of long-term debt on profitability implies that long-term debt imposes a continuous financial strain on biopharmaceutical firms, likely due to the ongoing costs associated with servicing the debt as displayed in Table 7.

Table 5: The effect of short-term debt on profitability through 10-year lag of R&D, financial distress and total productivity

	(1) ROA	(2) ROA	(3) ROA
Short term debt	-0.5385***	0.0482	0.4542**
	(0.1233)	(0.057)	(0.1873)
$R\&D_{t-10}$	-0.1016**		
	(0.0453)		
Short-term debt x $R\&D_{t-10}$	1.4842**		
	(0.6015)		
Financial distress		-0.1819***	
		(0.0141)	
Short term debt x financial distress		-0.5454***	
		(0.1513)	
Firm age	0.0026***	0.0025***	-0.0007***
	(0.0007)	(0.0006)	(0.0002)
Firm size	0.0438***	0.0313***	0.0193***
	(0.0026)	(0.002)	(0.0012)
R&D	-0.2688***	-0.221***	0.0011
	(0.0797)	(0.0641)	(0.0283)
Cash holding	-0.3824***	-0.3398***	-0.0796***
	(0.0306)	(0.0248)	(0.0165)
Capital intensity	0.0386	0.0116	-0.0344**
	(0.0251)	(0.0191)	(0.0175)
Growth Opportunity	0.0102***	-0.0016	0.014***
	(0.0028)	(0.0021)	(0.0017)
Real GDP	0.0223***	0.0106***	0.009***
	(0.0014)	(0.0011)	(0.0005)
Interest rate	0.0634***	0.0313***	0.0245***
	(0.0039)	(0.0031)	(0.0011)
Inflation	-0.052***	-0.0261***	-0.0148***
	(0.0027)	(0.0022)	(0.0009)
Global Financial Crisis	-0.0297***	0.0076**	0.0358***
	(0.0055)	(0.0031)	(0.0028)
Constant	-0.141***	-0.0322	0.3004***
	(0.0261)	(0.0215)	(.0216)
Observations	4284	4284	2555
R-Squared	0.4972	0.5693	0.4693
Year Effects	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes

This table reports the results from the regression of the effect of long-term debt on profitability. The dependent variable is profitability measured as (EBITDA/TA) and is income before depreciation and amortization divided by book value of assets. The main explanatory variable is short-term debt with other control variables. The moderating variables are 10-year lag of R&D and financial distress. All other variables are defined in Appendix. The sample period is from 199 to 2020. I control for year fixed effects and firm fixed effects. Standard errors are clustered by firm, and standard errors are reported in parentheses. The *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 6: The effect of long-term debt on profitability through 10-year lag of R&D, financial distress and total productivity

	(1) ROA	(2) ROA	(3) ROA
Long term debt	-0.1936***	-0.0027	0.0552
	(0.0239)	(0.050)	(0.1178)
$R\&D_{t-10}$	0.0746		
	(0.1017)		
Long-term debt x $R\&D_{t-10}$	0.1695		
	(0.2827)		
Financial distress		-0.1667***	
		(0.0172)	
Long term debt x financial distress		-0.1117**	
		(0.0561)	
Firm age	0.0029***	0.0026***	-0.0008***
	(0.0008)	(0.0007)	(0.0003)
Firm size	0.0464***	0.0349***	0.0193***
	(0.0026)	(0.0022)	(0.0012)
R&D	-0.2571***	-0.2201***	0.002
	(0.0757)	(0.0636)	(0.0264)
Cash holding	-0.3444***	-0.313***	-0.0816***
	(0.029)	(0.0256)	(0.0158)
Capital intensity	0.0331	0.0100	-0.0355**
	(0.0247)	(0.0203)	(0.0177)
Growth Opportunity	0.0093***	-0.0009	0.0138***
	(0.0024)	(0.002)	(0.0018)
Real GDP	0.0172***	0.0105***	0.008***
	(0.0015)	(0.0012)	(0.0006)
Interest rate	0.0521***	0.0332***	0.0223***
	(0.004)	(0.0035)	(0.0013)
Inflation	-0.0448***	-0.0279***	-0.013***
	(0.0028)	(0.0025)	(0.0011)
Global Financial Crisis	-0.0339***	0.0028	0.0353***
	(0.005)	(0.0035)	(0.0031)
Constant	-0.1593***	-0.0657***	0.3091***
	(0.0264)	(0.0233)	(0.0342)
Observations	4284	4284	2555
R-Squared	0.4984	0.5521	0.4692
Year Effects	Yes	Yes	Yes
Firm Effects	No	No	No

This table reports the results from the regression of the effect of long-term debt on profitability. The dependent variable is profitability measured as (EBITDA/TA) and is income before depreciation and amortization divided by book value of assets. The main explanatory variable is long-term debt with other control variables. The moderating variables are 10-year lag of R&D and financial distress. All other variables are defined in Appendix. The sample period is from 199 to 2020. I control for year fixed effects and firm fixed effects. Standard errors are clustered by firm, and standard errors are reported in parentheses. The *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Table 7: The effects of short-term and long-term debt on profitability

	Short-term debt		Long-term Debt	
	(1)	(2)	(3)	(4)
	Pre-Covid-19	Post Covid-19	Pre-Covid-19	Post Covid-19
Short term debt	-0.3934***	-0.6195***		
	(0.0816)	(0.3406)		
Long term debt			-0.1937***	-0.183***
			(0.0251)	(0.0398)
Firm age	0.0033***	0.0019	0.0037***	0.0006***
	(0.0008)	(0.0013)	(0.0009)	(0.0001)
Firm size	0.0433***	0.0535***	0.0449***	0.0655***
	(0.0027)	(0.0016)	(0.0025)	(0.0107)
R&D intensity	-0.2577***	-0.5425**	-0.245***	-0.5937***
	(0.0793)	(0.2109)	(0.0747)	(0.1662)
Cash holding	-0.3838***	-0.2198***	-0.3538***	-0.1714***
	(0.0301)	(0.0847)	(0.0293)	(0.0047)
Capital intensity	0.0386	0.127***	0.0338	0.0228
	(0.0265)	(0.0297)	(0.0258)	(0.0374)
Growth Opportunity	0.0096***	0.0134**	0.0087***	0.0119***
	(0.003)	(0.0068)	(0.0025)	(0.0039)
Real GDP	-0.0051***	-0.0256***	-0.0058***	-0.0283***
	(0.0016)	(0.0008)	(0.0017)	(0.0098)
Interest rate	0.0519***	0.0544*	0.0458**	0.0619*
	(0.0021)	(0.0032)	(0.002)	(0.0041)
Inflation	-0.0288***	-0.0449***	-0.0301***	-0.0491***
	(0.0016)	(0.0004)	(0.0015)	(0.0147)
Global Financial Crisis	0.0152*	0.0415***	-0.0059	0.0346***
	(0.009)	(0.0004)	(0.0096)	(0.0024)
Constant	-0.222***	-0.0571***	-0.212***	-0.0467***
	(0.027)	(0.0011)	(0.0316)	(0.0031)
Observations	3827	457	3827	457
R-Squared	0.4881	0.5882	0.5078	0.4249
Year Effects	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	No

Robustness Check

For robustness test, I employ the system dynamic panel data (DPD) estimator to estimate the econometric model in equation 1. The DPD integrates equations involving differences and levels. In this System GMM approach (Blundell & Bond, 1998), lagged levels act as instruments for the differenced equations, while lagged differences are employed as instruments for the level equations. I measure ROA as the net income divided by total assets, and it is the dependent variable in the data analysis. It is measured as earnings before interest, taxes, depreciation, and

amortization. The main explanatory variable is debt. Debt measures the debt financing decisions such as total debt, long-term, and short-term debt and they are measured in percentages. The findings from Table 8 highlight that both short-term and long-term debt negatively affect profitability in biopharmaceutical firms. Short-term debt has a more negative effect compared to long-term debt. When considering total debt, the negative impact on profitability remains significant, emphasizing the need for careful management of debt financing to sustain profitability in the biopharmaceutical industry.

Table 8: The effect of debt financing on alternative measure of profitability

	(1)	(2)	(3)
Variables	Short-term	Long-term	Total debt
ROA_{t-1}	0.0773***	0.0668***	0.0432***
	(0.0003)	(0.0003)	(0.0001)
ROA_{t-2}	-0.1098***	-0.1290***	-0.1393***
	(0.0003)	(0.0002)	(0.0001)
Short term debt	-0.3682***		
	(0.0009)		
Long-term debt		-0.1683***	
		(0.0001)	
Total debt			-0.2388***
			(0.0001)
Firm age	0.0127***	0.0170***	0.0151***
	(0.0004)	(0.0004)	(0.0004)
Firm size	0.1444***	0.1465***	0.1416***
	(0.0003)	(0.0002)	(0.0001)
R&D intensity	-0.1821***	-0.1753***	-0.1758***
	(0.0002)	(0.0002)	(0.0002)
Cash holding	0.0740***	0.0910***	0.0653***
	(0.0005)	(0.0003)	(0.0002)
Capital intensity	-0.0031***	0.0118***	0.0080***
	(0.0005)	(0.0002)	(0.0001)
growth Opportunity	0.0035***	0.0039***	0.0032***
	(0.0000)	(0.0000)	(0.0000)
Real GDP	0.0023***	0.0015***	0.0010***
	(0.0000)	(0.0000)	(0.0000)
Interest rate	0.0038***	0.0027***	0.0033***
	(0.0001)	(0.0001)	(0.0000)
Inflation	-0.0044***	-0.0025***	-0.0025***
	(0.0000)	(0.0001)	(0.0000)
Global Financial Crisis	-0.0004***	-0.0018***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)
Constant	-1.4391***	-1.5679***	-1.4413***
	(0.0108)	(0.0115)	(0.0113)

Observations	2,780	2,780	2,780
Number of firms	445	445	445
Observation	2780	2780	2780
AR (1)	-4.497	-4.488	-4.484
AR (2)	1.353	1.036	0.898
Sargan	291	291.2	290.6

This table shows the results of two-step System GMM (SGMM) regressions of profitability from 1990 to 2020. The dependent variable is ROA, measured as the ratio of net income divided by total assets. The proxy for corporate debt is total debt. Sargan statistic is a Sargan-Hansen test of overidentifying restrictions. AR (2) is the test for the null of no residual serial correlation. Instrument: two lags of ROA and the rest of the explanatory variables are exogenous. Significant levels are indicated by *** p<0.01, ** p<0.05, * p<0.1

5.0 Conclusions and Recommendations

Debt financing is important for financing major investments like R&D in the biopharmaceutical industry. Debt financing allows companies to raise funds without giving up ownership or control through indenture and covenants of the company. Debt financing provides greater flexibility for firms in biopharmaceutical industry to finance highly intensive research and development (R&D).

The choice of debt financing is an important decision for companies aiming to fund their projects. This paper poses research questions: How do short-term and long-term debt impact profitability within the biopharmaceutical industry? What are the ways through which short-term and long-term debt affect profitability? The diverse range of debt instruments, both short- and long-term, provides flexibility in financial strategies.

The results show that short-term debt, long-term debt and total debt negatively impacts return on assets (ROA) as a firm's profitability measure. A comparison is made between the US and Europe biopharmaceutical firms and the result shows the negative effects of short-term and long-term debt on profitability persist more for US biopharmaceutical firms than Europe firms. Short-term and long-term debt both impact profitability negatively with 10-year lagged R&D intensity and financial distress. Short-term debt's negative impact is stronger in post-Covid-19,

indicating increased financial strain. Long-term debt consistently affects profitability negatively, with relative stable effects during the pre- and post-Covid-19.

The empirical findings from this research have some interesting implications for policymakers in the biopharmaceutical industry. Firstly, they emphasize the importance of prudent debt management strategies, particularly for US biopharmaceutical firms, where the negative impact of both short-term and long-term debt on profitability is more pronounced compared to European counterparts. This suggests a need for careful monitoring and sustainable debt practices to mitigate financial strain, especially post-Covid-19.

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Appendix

Table 9A: 45 firms reporting zero R&D

Company legal name	Company legal name
NBTY Inc	MedMen Enterprises Inc
Nabi Biopharmaceuticals-Old	Green Thumb Industries Inc
Sigma-Aldrich Corp	Trulieve Cannabis Corp
HST Global Inc	Curaleaf Holdings Inc
Unigene Laboratories Inc	Cresco Labs Inc
Natural Alternatives International Inc	cbdMD Inc
	The Cannabist Company
Acelity Holdings Inc	Holdings Inc
Avid Bioservices Inc	Ayr Wellness Inc
NewAge Inc	4Front Ventures Corp
MariMed Inc	Upexi Inc
PDK Labs Inc	Glass House Brands Inc
Bradley Pharmaceuticals Inc.	Smart for Life Inc
Dura Pharmaceuticals Inc	Xstelos Holdings Inc
Pml Inc	BMP Sunstone Corp
Catalytica Inc	Transgene SA
NSA International Inc	Nextera Enterprises Inc
Rexall Sundown Inc	AXM Pharma Inc -Old
NovelStem International Corp	Life Sciences Research Inc
IVC Industries Inc	IGC Pharma Inc
Derma Sciences Inc	Marizyme Inc
Nanobac Pharmaceutical	Youngevity International Inc
Bactolac Pharmaceutical Inc	Item 9 Labs Corp
	Goodness Growth Holdings Inc

Table 9B: Definition of variables, Expected signs, and Data sources

Variable	Description and Definition	Expected sign	Data Source
Dependent Variables:			
Profitability indicators			
Return on Asset (ROA_1)	Measures how well a company can handle its assets to generate profit over time. Calculated as earnings before interest, taxes, depreciation, and amortization, (ebitda) divided by total assets(at).		COMPUSTAT
Return on Asset (ROA_2)	Calculated by net income (ni) divided by total assets(at)		COMPUSTAT
Main explanatory variables			
Debt:			
Short term debt	short-term debt is a form of debt that matures in less than a year. short term liabilities (debt)/total assets	+/-	COMPUSTAT
Long-term debt	Long-term debt is a form of debt that matures in more than a year. long term liabilities (debt)/ total assets	+/-	COMPUSTAT
Total debt	It is the combination of short-term and long-term debt. Total debt/total assets	+/-	COMPUSTAT
Other Controls			
Firm size (size)	natural logarithm of the company's total assets	+/-	COMPUSTAT
Capital Intensity	Capital expenditure/total assets	+/-	COMPUSTAT
Growth opportunity	market to book ratio: market value of common equity/book value of common equity The market value was scaled by thousands. i.e. (prcc_f* csho*1000)/1000000 The book value is calculated by subtracting total liabilities from total assets.	+/-	COMPUSTAT
Research and Development Intensity	Research and development expense divided by total assets	+/-	COMPUSTAT
Firm age	The difference between the year under investigation and the year in which the firm is included in COMPUSTAT.	+/-	COMPUSTAT
Altman Z-score/ Financial distress	The Z-score is a financial indicator that uses various inputs from company income	+/-	COMPUSTAT

	statements and balance sheets to measure a company's financial status. It is calculated as 1.2 (working capital / total assets) + 1.4 (retained earnings / total assets) + 3.3 (earnings before interest and tax / total assets) + 0.6 (market value of equity / total liabilities) + 1.0(sales / total assets). I use the above and below the grey zone of the Altman z-score to create a dummy. 1=No financial non-distress if the Altman z-score is less than 1.8 0= financial non distress if the Altman z-score is above 1.8		
Inflation rate (Infl)	Proxy use is a Consumer price index. It is the consumer price index for all urban consumers (entire items U.S. City). It is percent change, seasonally adjusted annually	+/-	FRED St. Louis
Real Gross Domestic Product (RGDP)	Real Gross domestic product per capita as a measure. It is measured as chained 2012 Dollars and seasonally adjusted annual rate. I scale it by taking the log of it	+/-	FRED St. Louis
Interest Rate	Federal funds rate is the overnight interest rate for depository institutions trading federal funds held at Federal Reserve Banks		Federal Reserve Bank of St. Louis (FRED)