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Firm-level political risk and distance-to-default

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Abstract

This study provides the first empirical evidence of the relationship between firm-level political risk and distance-to-default. Based on our examination of a quarterly dataset of 2,727 U.S. firms covering a period from January 2002 to April 2019, we conclude that firm-level political risk is negatively associated with distance-to-default. We document three economic mechanisms through which political risk increases default risk: information asymmetry, organizational capital, and investment growth. The evidence indicates that the association is more pronounced for firms with low analysts' forecast accuracy, organizational capital, and investment growth. Employing hand-collected data, we also reveal that firms are able to exploit their corporate lobbying to immunize themselves against default risk. Our findings are robust to different endogeneity identifications, including a natural experiment, alternative distance-to-default proxies, and different sub-samples. Overall, we present novel evidence of an adverse impact of firm-level political risk on distance-to-default and how such a negative effect can be mitigated.

Keywords: Political risk, Distance-to-default, Information asymmetry, Organizational capital, Investment growth, Corporate lobbying.

1. Introduction

The impact of political risk on corporate outcomes has been in the spotlight in finance and economics research. Political risk is any government intervention into the workings of the economy that affects a firm's value (Shapiro, 1992). It can alter the value of an economic asset directly or indirectly via different events, such as acts of terrorism, declarations of war, and expropriation of private assets (Bremmer and Keat, 2010). Most studies of political risk have examined national political factors (e.g., elections, regime stability, cabinet reshuffles, etc.) and their effects on sovereign default (Van Rijckeghem and Weder, 2004; Kohlscheen, 2006; Moser, 2007).[1] Moreover, recent studies also examine the impact of country-level economic policy uncertainty on sovereign default risk (Wisniewski and Lambe, 2015; Bales and Burghof, 2021). However, the impact of firm-level political risk on corporate default received little attention creating a lacuna in the corporate finance literature. We attempt to fill this gap by employing Hassan *et al.*'s (2019) firm-level political risk measure and demonstrating its influence on distance-to-default (DTD).[2]

Does firm-level political risk significantly differ from national-level political risk? Hassan *et al.* (2019) find that only a 1% variation in political risk is derived from macro-level political uncertainty. However, an overwhelming 90% variation is attributable to firm-level political risk exposure. Thus, variation in firm-level political risk is not generated by exposure to major country-level events, such as political elections, financial crises, international

[1] A few empirical studies, such as Baum *et al.* (2010), Dam and Koetter (2012), and Eichler and Sobański (2016), also examine the impact of macro-level politics on bank bankruptcy.

[2] Hassan *et al.'s* (2019) firm-level political risk is significantly different from Baker, Bloom, and Davis's (2016) economic policy uncertainty (EPU) index. Hassan *et al.* (2019) employ textual analysis of quarterly earnings conference-call transcripts to construct their firm-level political risk measure. Thus, they quantify the political risk faced by a given firm at a given point in time based on the share of management conversations on risks associated with politics. By contrast, Baker *et al.* (2016) construct EPU from three components – newspaper coverage of policy-related economic uncertainty, reports by the Congressional Budget Office (CBO) on temporary federal tax code provisions, and the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters on policy-related macroeconomic variables. On balance, Hassan *et al.* (2019) measure micro-level political risk based on mangers' responses to how firms' business activities are influenced by political risk, while Baker *et al.* (2016) estimate their index from policy uncertainties related to the macroeconomy.

summits, and so on. Instead, firms face major political risk due to industry-level policy changes and regulatory shocks, local political and policy uncertainties, and purely idiosyncratic circumstances (Hassan *et al.*, 2019). The primary motivation of our study is to recognize that country-level political risk is not the ideal measure to explain the devastating adverse effect firm-level political risk can have on firm value. No prior study in the extant finance literature has examined the relationship between firm-level political risk and DTD, and we find it intriguing to bridge this gap with our investigation. We conjecture that firm-level political risk negatively affects DTD.

Our DTD measure, as developed by the Credit Research Initiative (CRI) of the National University of Singapore, comprises the market value of assets, the value of debts, and the volatility of assets. Political risk is likely to have a significant impact on firms' debt and asset values. We speculate, among others, that firms' political risk affects their information environment, organizational capital, and investment growth, which in turn influences their DTD. Political uncertainty leads to information asymmetry in the equity markets (Pástor and Veronesi, 2012; Boone *et al.*, 2020), which increases analysts' forecast errors (Baloria and Mamo, 2017). Further, Barro (1991), Alesina and Perotti (1996), and Bloom *et al.* (2007) argue that politically risky firms become cautious and spend less on organizational capital (e.g., employee training and apprenticeships, developing business processes, and improving systems). A meagre commitment to organizational capital can reduce the value of a firm leading to its default. In addition, firms experiencing political risk prefer to withhold capital investment until resolving some or all of the uncertainty to avoid future adverse impacts on firm value. Thus, political risk reduces investment growth (Julio and Yook, 2012; Çolak *et al.*, 2016; Jens, 2017; Durnev and Mangen, 2020), which consequently affects firms' DTD.

Evidence suggests that corporate lobbying enables firms to mitigate the negative impact of political risk. Chen *et al.* (2015) and Unsal *et al.* (2016) argue that corporate lobbying helps firms gain access to legislators; and this access then provides firms with valuable and reliable information regarding potential policy changes. Moreover, prior studies have shown that firms engaged in lobbying receive systematic favors, including lower tax (Richter *et al.*, 2009); propitious visas and favorable trade policy (Kerr *et al.*, 2011), prevention of fraud detection (Yu and Yu, 2011); higher likelihood to receive bailout packages (Duchin and Sosyura, 2012) and trouble asset relief program funds (Blau *et al.*, 2013). These preferential treatments in turn motivate firms to engage in lobbying to limit the consequences of political risk. Thus, we also hypothesize that corporate lobbying would mediate the effect of firm-level political risk on DTD.

We examine a panel of 2,727 firms, from January 2002 to April 2019, amounting to a total of 107,886 firm-quarter observations. We find DTD is negatively associated with firm political risk, indicating that firm-level political risk reduces DTD. We also show that firm-level political risk affects DTD due to low analysts' forecast accuracy, organizational capital, and investment growth. We further demonstrate that firms mitigate the adverse effect of political risk through corporate lobbying. Overall, our results establish a negative causal relationship between firm-level political risk and DTD and identify that corporate lobbying efforts help mitigate such an adverse effect.

Our paper makes several significant contributions to the existing literature. First, our study joins the body of literature investigating the determinants of corporate default risk. Prior studies show that mergers (Furfine *et al.*, 2011), corporate innovation (Hsu *et al.*, 2015), corporate diversification (Singhal and Zhu, 2013), board co-option (Baghdadi *et al.*, 2020), managerial cash use (Arnold, 2014), and board gender diversity (Nadaraja *et al.*, 2021) have a significant impact on corporate default risk. We extend this stream of literature by providing novel evidence that firm political risk is another crucial determinant of default risk.

Second, our paper adds to a group of studies on the role of national political factors (e.g., elections, government turnover rates, government political ideologies) in sovereign default (Balkan, 1992; Van Rijckeghem and Weder, 2004; Kohlscheen, 2007) and bank default (Dam and Koetter, 2012; Eichler and Sobański, 2016). While these studies focus on macro-level political instability, our study is distinct in that we employ the dynamic measure of firm-level political risk. This measure captures industry-, regional-, and national-level political risk in relation to the economy, environment, health, security, tax, technology, and trade that directly and indirectly affects firm-level corporate policies. Thus, using such comprehensive micro-level data, we show that firm political risk is a significant factor in the probability of default.

Third, we examine how firm-level political risk affects DTD. In channel analysis, we show that political risk is more pronounced for firms with low analysts' forecast accuracy, low organizational capital, and low investment growth that in turn adversely impact DTD. Hence, our study adds to the evidence that political risk affects analysts' forecast accuracy (Chen *et al.*, 2010; He and Ma, 2019; Chourou *et al.*, 2020), organizational capital growth (Barro, 1991; Alesina and Perotti, 1996; and Bloom *et al.*, 2007), and investment growth (Julio and Yook, 2012; Jens, 2017).

Fourth, our paper contributes to the bright side of corporate lobbying literature (Richter *et al.*, 2009; Kerr *et al*., 2011; Yu and Yu, 2011; Duchin and Sosyura, 2012; Blau *et al*., 2013). We argue that firms engaged in lobbying enjoy a range of financial and non-financial benefits due to their preferential access to policy information, thus helping them mitigate the negative impact of political risk. Our empirical findings show that firms' lobbying efforts help attenuate their political risk exposure.

Endogeneity is a potential concern for our study because the association between firm-level political risk and DTD could be spurious and inconsistent due to the omitted variable bias and unobserved firm-level heterogeneity. We employ three empirical strategies to mitigate these endogeneity concerns. First, we perform a unique natural experiment of 'redistricting electoral boundaries' in the 2010 decennial census, with a difference-in-differences (DID) framework. The redistricting event acts as a possible exogenous shock expected to substantially affect the variation in firm-level political risk. We place redistricted firms into the treatment group. Our empirical evidence shows that the adverse effect of political risk on DTD remains unchanged. Second, to address unobserved firm-level heterogeneity, following Rosenbaum and Rubin (1983), we use a propensity score matching (PSM) analysis to find firms with similar characteristics and different levels of political risk. Our post-match empirical results show that the firm-level political risk remains negatively associated with DTD. Third, in line with D'Mello and Toscano (2020), we employ the partisan conflict index (PCI) as an instrumental variable (IV) for firm-level political risk. Again, we reconfirm the negative relationship between firm-level political risk and DTD after extracting exogenous components from our variable of interest. Overall, our identification strategies provide reliable evidence that firm-level political risk has a negative causal relationship with DTD.

The remainder of the paper is structured as follows: Section 2 outlines the literature review and hypotheses development. Section 3 presents a description of the data and sample statistics. Section 4 reports empirical findings. Section 5 addresses the endogeneity concerns, and Section 6 highlights robustness checks. Section 7 elaborates on channel analysis. Section 8 discusses how firm political risk can be mitigated via corporate lobbying. Finally, Section 9 concludes the paper.

2. Related literature and hypotheses development

This section presents findings from a review of the extant literature. First, we consider the relevant literature on the relationship between political risk and default risk. We then highlight the potential economic mechanisms through which political risk affects DTD. Finally, we discuss the literature on corporate lobbying and how it enables firms to mitigate the negative consequences of political risk.

2.1 Political risk and DTD

While no previous empirical studies have examined the relationship between firm-level political risk and DTD, there have been investigations of the links between macro-level political risk measures and sovereign default risk. For example, the seminal work of Citron and Nickelsburg (1987) finds that political instability – as measured by the number of changes of governments in the preceding five years – significantly increases the probability of sovereign default. Similarly, Brewer and Rivoli (1990) conclude that regime instability – proxied by changes in heads of government and governing groups – leads to sovereign default. Balkan (1992) developed a political instability index (including events such as assassinations, anti-government protests, general strikes, riots, and government crises) and find a statistically significant association between their index and the probability of default. In the same vein, Van Rijckeghem and Weder (2004) and Kohlscheen (2006) document that political turnover increases the probability of sovereign default; and in the context of Latin America, Moser (2007) finds that cabinet reshuffles considerably increase the spread of sovereign bonds.

Some empirical studies have also shown that national political factors affect bank default risk. For instance, Baum *et al.* (2010) find that bank efficiency was significantly lower around the time of Turkey's elections, which affected rates of bank default. In Germany, Dam and Koetter (2012) report that electoral cycles, government parliamentary majority, and CEO political affiliation all significantly influence the probability of bank bailout. Eichler and Sobański (2016) show that, in Eurozone member countries, national electoral cycles, government power, and the government's political ideologies substantially affect bank default risk. Owing to the impact of macro-political instability on sovereign and bank default, we hypothesize that there would be a greater likelihood of default for firms with higher political risk. Hence, our first hypothesis is as follows:

H1: Firm-level political risk is negatively associated with DTD.

2.2 Potential Channels: How does political risk affect DTD?

In this section, we argue that, among others, information asymmetry, organizational capital, and investment growth are the potential channels through which political risk affects distance-to-default.

2.2.1 Political risk and DTD: the role of information asymmetry

A multitude of evidence suggests that information asymmetry is one of the means that cause political risk to affect DTD. During times of political uncertainty, managers become conservative in their information disclosure decisions, as comprehensive disclosure regarding risk and uncertainty negatively affects firm value (Graham *et al.*, 2006; Kothari *et al.*, 2009). In particular, Gubernatorial elections create political uncertainty (i.e., the effect of the election on cash flows), which increases information asymmetry among stakeholders (e.g., Pástor and Veronesi, 2012; Boone *et al.*, 2020). Baloria and Mamo (2017) find that analysts' forecast accuracy declines during presidential election periods. Çolak *et al.* (2017) document that firms relying on government contracts experience a higher degree of complications, related to asymmetric information prior to gubernatorial elections, negatively affecting initial public offerings. Thus, political uncertainty increases information asymmetry between managers and investors.

We argue that high information asymmetry makes it difficult to signal the quality of the firm to investors and lenders (Wu, 1993), which has strong implications for default risk. Similarly, Berger *et al*. (2005) show that information asymmetry, by influencing debt maturity, affects credit risk. Moreover, if information is opaque, firms experience instability through the dissemination of systemic shocks between firms in the same industry (De Bandt and Hartmann, 2000; Acharya and Yorulmazer, 2008). Overall, we argue that political risk creates a vacuum of information in the financial markets, leading to a negative impact on DTD. Reflecting on this, we develop the following hypothesis:

H2a: Firm-level political risk negatively affects DTD through information asymmetry.

2.2.2 Political risk and DTD: the role of organizational capital

We argue that organizational capital could be another channel by which firm political risk may influence their default risk. Lev *et al.* (2009) define organizational capital as the cluster of technologies that consists of business practices, processes, and designs leading to cost savings. We speculate that firms exposed to political risk may reduce or delay projects related to organizational capital. Barro (1991) and Alesina and Perotti (1996) report that politically risky firms cut back their allocations on different components of organizational capital, while Bernanke (1983) and Bloom *et al.* (2007) show that firms follow a cautious approach in spending to organizational capital when they face uncertainty.

While political risk could slow down investments in organizational capital, extant literature highlights that organizational capital plays an important role in improving firm performance. Lev and Radhakrishnan (2005), and Hasan and Cheung (2018) report that organizational capital is a source of sustainable competitive advantage that increases firm value. In line with this, firms with low organizational capital are likely to have lower productivity and efficiency that may increase their default risk. This leads to our next hypothesis:

H2b: Firm-level political risk negatively affects DTD when organizational capital is low.

2.2.3 Political risk and DTD: the role of investment growth

In a seminal work on investment growth, Bernanke (1983) presents a model based on the theory of irreversible choice under uncertainty that demonstrates the relationship between uncertainty and real investment. Given investment irreversibility, firms encountering rising political risk tend to defer investment decisions until the arrival of new information that resolves some or all of the uncertainty. Moreover, uncertainty and capital irreversibility create positive option value that induces firms to defer investment to avoid future adverse impacts on firm value at the expense of immediate loss (Dixit and Pindyck, 1994).

Empirical studies have estimated the impact of political uncertainty on costly investment activities. Julio and Yook (2012) document that, during election years, firms reduce their investments by an average of 4.8%, relative to non-election years, indicating that firms prefer to withhold investment until uncertainty has been resolved. Likewise, during U.S. gubernatorial elections (Jens, 2017) and changes in government officials in China (An *et al.*, 2016), corporate investment reduces significantly. Policy uncertainty can also affect firms' investment decisions. Gulen and Ion (2016) report a 10% decrease in capital investments during the recent global financial crisis, which they attribute to an increase in economic policy uncertainty. Thus, we conclude that political risk leads to delays in investment, which consequently affects DTD. Accordingly, we postulate the following hypothesis:

> *H2c: Firm-level political risk negatively affects DTD when investment growth is low.*

2.3 Corporate lobbying and DTD

The previous theoretical discussion implies that political risk significantly reduces a firm's DTD. A natural follow-up question is thus how a firm can reduce the adverse effects of political risk. In response, we conjecture that firms would lobby to mitigate their political risk exposure.

Lobbying is a strategic choice in which corporations are engaged in influencing legislators and politicians at various levels of the government to co-opt the process of policy formation and direct benefits toward them. Yu and Yu (2011) and Cao *et al.* (2018) argue that lobbying is an effective tool to help forge stronger relationships with the government as it is less affected by election cycles and less regulated compared to other forms of political connections. These relationships then provide the connected firms access to valuable and reliable information regarding future government policies (Unsal *et al.*, 2016; Cao *et al.*, 2018). For example, Enron, one of the corporations that spent heavily on lobbying, received a large quantity of policy-related information from political and government offices between 1999 and 2002 (Drutman and Hopkins, 2013).

Corporate lobbying is a key resource for generating a competitive advantage over competitors (Li and Liu, 2014). A wealth of empirical evidence suggests that firms that spend on lobbying enjoy a better financial performance, including higher stock prices (Hill *et al.*, 2013) and superior returns (Chen *et al.*, 2015). Lobbying spending also helps firms to achieve a specific objective successfully, such as lower tax rates (Richter *et al.*, 2009), favorable visa and trade policy (Kerr *et al.*, 2011), and control regulations on tobacco (Glantz and Begay, 1994) and greenhouse gas (Markussen and Svendsen, 2005). Moreover, Duchin and Sosyura (2012) and Blau et al. (2013) show that lobbying efforts increase the likelihood of securing bailout assistance and trouble asset relief program funds, respectively. Finally, lobbying is also found to prevent corporate fraud detection (Yu and Yu, 2012) and promote accounting conservatism (Kong *et al.*, 2017).

In summary, we argue that firms spending heavily on lobbying enjoy a range of financial and non-financial benefits due to their preferential access to policy information that allows them to take strategic decisions to immunize against default. This finding underpins our final hypothesis:

H3. Corporate lobbying helps reduce the negative impact of firm political risk on DTD.

3. Data and econometric model

3.1. Data description

Our sample begins in January 2002 to align with the firm-level political risk data, and it ends in April 2019. We obtain data on DTD from the National University of Singapore's Credit Research Initiative (CRI) dataset, which is widely used in the literature (e.g., Duan and Van Laere, 2012; Duan *et al.*, 2012; Duan and Wang, 2012; Nadarajah *et al.*, 2021). We collect the stock return data from CRSP and the accounting data from COMPUSTAT. The analysts' forecast data are from I/B/E/S. All board-related data come from BoardEx. We exclude financial firms with standard industrial classification (SIC) codes between 6000 and 6999 from our sample, as these firms are subject to statutory capital requirements. The final sample comprises 2,727 firms and 107,886 firm-quarter observations. We introduce the firm-level political risk (*PRisk*) and DTD measures below:[3]

Firm-level Political Risk (PRisk)

The firm-level political risk measure, *PRisk*, captures news on the manifestation of political shock. Hassan *et al.* (2019) employed firms' quarterly conference calls to derive firm-specific, time-varying measures of political risk. The authors then applied machine-learning algorithms to analyze conference calls transcripts and identify the proportion of the narratives that were political in nature. To distinguish between political and non-political topics, Hassan *et al.* (2019) developed bigrams (two-word combinations) using training sets of political ($\mathbb{P}$) and non-political ($\mathbb{N}$) themes. To create themes for the training set, the authors draw on

[3] We also use probability of default (PD), actuarial spread (AS), Altman Z-score, and Whited-Wu financial constraints index as alternative measures of default risk. The description of the alternative variables is provided in Appendix A.

undergraduate textbooks on U.S. politics and political narrative linguistics of the major U.S. newspapers. They also consulted undergraduate financial accounting textbooks and news items on corporate events to develop a system that could decipher political conversations embedded in conference calls. The authors constructed their political risk measure by counting the number of political bigrams near a synonym for risk or uncertainty, then dividing this by the total number of bigrams in the conference call transcript:

$$PRisk_{it} = \Sigma_b^{B_{it}} \left(1\left[b \in \frac{\mathbb{P}}{\mathbb{N}}\right]\right) \times 1[|b-r| < 10] \times \frac{f_{b,p}}{B_p}) \tag{1}$$

where r is the position of the nearest synonym for risk or uncertainty and $b = \{0,1,\dots,B_{it}\}$ indexes bigrams in firm *i*'s conference call at time *t*. Each bigram is weighted with a score reflecting the strength of the bigram's political association, where $f_{b,p}$ is the frequency of bigram b in the political training set and B_p is the total number of bigrams in the training set. Hassan *et al.* (2019) perform a variety of validity tests, such as (i) human verification of whether the algorithm had correctly identified conversations about the risk associated with political topics; (ii) an inspection of how the measure aligned with political events over time; (iii) tests to ensure that the measure did not reflect news about the mean value of political exposure (i.e., it did not reflect sentiments about political events in a firm's conference call); and (iv) a set of tests to establish that *PRisk* was different from non-political risk.

The variance decomposition of *PRisk* makes a case for our study. In contrast to the conventional wisdom that political and regulatory decisions have a relatively uniform impact across firms in a developed economy (Pástor and Veronesi, 2012), Hassan *et al.* (2019) find approximately 91.69% firm-level variation, with 19.87% being permanent differences across firms (i.e., between-firm variation) and 71.82% was changed over time (i.e., changes within firms in a given sector). This suggests that political risk directly affects firm-level variations, thereby, justifying our examination of its effects on DTD.

Distance to default (DTD)

The DTD is a volatility adjusted measure of the leverage of a firm. The CRI estimates DTD for each firm using Merton's (1974) structural model with the same assumptions on the debt maturity and size as Moody's KMV implementation (Duan *et al.,* 2005). In this model, the debt level in defining the default point includes a firm's current liabilities plus half of the long-term debt plus the fraction δ multiplied by other liabilities. As firms release their financial statements quarterly, it is difficult to have a stable estimate for δ for individual firms. To address this concern, the fraction δ is shared on the calibration group level but differentiated by Bloomberg 10-industry sectors. Therefore, our DTD is computed as follows:

$$DTD_t = \frac{\log\left(\frac{V_t}{L}\right) + \left(\mu - \frac{\sigma^2}{2}\right)(T - t)}{\sigma\sqrt{T - t}} \quad (2)$$

where V_t is the asset value following a geometric Brownian motion with drift μ and volatility σ, L is the default point with value equal to short-term liabilities plus half of long-term liabilities, and $\sqrt{T - t}$ is set to one year.

One input into the DTD of a firm is the estimated drift μ of the implied asset value of the firm. To have a better prediction of default, the CRI DTD measure also uses σ, which is the volatility of the market value of a firm's assets that calibrates daily instead of monthly, to have a timely reflection on asset volatility caused by a change in capital structure, market capitalization, and so on.

Our adapted DTD measure overcomes several drawbacks identified in the literature (e.g., Duan *et al.,* 2012) by implementing a range of special treatments such as (a) adding a fraction (δ) of other liability to the Moody's KMV default point; (b) setting μ to improve the stability of DTD estimation; and (c) standardizing a firm's market value by its book value to address the scale alteration because of any key financing and investment.

3.2. Empirical model and variables

To investigate the impact of firm-level political risk on DTD, we estimate the following baseline model:

$$DTD_{i,t} = \alpha + \beta_1 PRisk_{i,t} + \beta_2 ln\_equity_{i,t} + \beta_3 ln\_debt_{i,t} + \beta_4 1/\sigma E_{i,t} + \beta_5 excess\ return_{i,t} + \beta_6 Income/asset_{i,t} + \beta_7 tobin's\ q_{i,t} + \varepsilon_{i,t} \quad (3)$$

where $DTD_{i,t}$ denotes distance-to-default and $PRisk_{i,t}$ is the firm-level political risk. Closely following Bharath and Shumway (2008) and Brogaard *et al.* (2017), we control six variables in our baseline model. $ln\_equity_{i,t}$ is the natural logarithm of the market value of equity (in million U.S. dollars), calculated as the product of the number of shares outstanding and the stock price at the end of the quarter, while $ln\_debt_{i,t}$ is the natural logarithm of the sum of the face value of debt (in millions of U.S. dollars) in current liabilities and one-half of long-term debt. The $Income/Assets_{i,t}$ is the ratio of net income to total assets, and we calculate $excess\ return_{i,t}$ as the difference between a firm's stock return and market return. Annualized stock return volatility ($1/\sigma E_{i,t}$) is the standard deviation of monthly stock returns over the prior year. Finally, $tobin's\ q_{i,t}$ is the market value of assets over the book value of assets. We winsorize all variables at the 1st and 99th percentiles to mitigate the influence of outliers. We use the Fama-French 10 industries classification to control for industry effects (Table A1 in the Appendix defines all variables used in this study).

Table 1 presents the summary statistics. The average DTD of a firm in our sample is 5.062. The DTD is skewed to the right, as the median is 4.592, and the maximum value is large, at 14.026. The standard deviation of DTD is low, at 2.905. The mean value of our variable of interest – firm political risk ($PRisk_{it}$) – is 1.054. The minimum value for political risk is zero, while the median and maximum values are 0.549 and 9.446, respectively. This suggests that, like DTD, $PRisk_{it}$ is skewed to the right.

The control variables appear standard. For example, the value of equity ranges from $13.5 million to $12 billion, and the average market value of equity is $6.3 billion. On average, debt value is $922 million, and the excess return is 0.02%. Mean stock return volatility and income/assets are 12% and -0.2%, respectively. Overall, our descriptive statistics are qualitatively similar to those of Brogaard *et al.* (2017).[4]

[Insert Table 1 about here]

Table A2 in the Appendix documents the average DTD across five portfolios of stocks, sorted on political risk. We find that DTD decreases monotonically as political risk increases meaning that firms with higher political risk have lower DTD. The final row presents the average DTD of high minus low political risk portfolios. The difference is statistically significant at 1% level, indicating that firms with higher political risk have significantly lower DTD.

Figure 1 illustrates the variation in political risk and its relationship with DTD. Both political risk and DTD increased between 2002 and 2019. As expected, there was high volatility in political risk (the solid line) during the Iraq war (2002-2004) and following the election of President Obama (2008-2009), the re-election of President Obama (2012-2013), and the election of President Trump (2016-2017). On this basis, we conclude that DTD (dotted line) has an inverse relationship with political risk.

[Insert Figure 1 about here]

[4] Our unreported Pearson correlations show a significant negative correlation between firm political risk and DTD. We document a positive relationship between DTD and all control variables except stock return volatility. Overall, we identify low correlation coefficients between political risk and other control variables, which reduces multicollinearity concerns.

4. Baseline results

We begin by investigating the relationship between firm political risk and DTD. Table 2 shows the baseline results using OLS estimations. Column 1 of Table 2 presents the results of the univariate regression (without controls) for political risk and DTD, with industry and year fixed effects. The finding indicates that firm-level political risk has a statistically significant negative relationship with DTD, with a coefficient of -0.033 (at 1% significance level). This means a one standard deviation shock to a firm's political risk is associated with a decrease of 0.051 [= -0.033×1.534] in DTD. Hence, the size of the coefficient is also economically significant. Column 2 presents the results with all control variables but the political risk measure. In columns 3 to 5, we include control variables with different combinations of industry and year fixed effects. Column 6 shows the results of Fama-MacBeth regression, while the regressions in columns 7 and 8 include firm-fixed effects and log transformation of political risk, respectively. For all the above specifications, we find that political risk significantly reduces firm DTD, even when controlling for firm characteristics known to be linked to default risk. The results are consistent with the findings of macro-level studies (Van Rijckeghem and Weder, 2004; Kohlscheen, 2006), which show that political turnover increases the likelihood of sovereign default. Overall, these findings provide strong evidence for our first hypothesis (*H1*). Consistent with the findings of Brogaard *et al.* (2017), our control variables *ln_equity,* $1/\sigma_E$, *Income/Assets*, and *Tobin's q* have significant positive associations with DTD. Conversely, as expected, *ln_debt* and *excess return* have significant negative relationships.[5]

[Insert Table 2 about here]

[5] We also estimate the association between different types of political risks and DTD. Hassan *et al.* (2019) classify their political risk measures into seven sub-categories: economy, environment, health, security, tax, technology, and trade. Our untabulated results show that all sub-categories of political risk are negatively associated with DTD at a 1% significance level, suggesting that the impact of political risk on DTD is not limited to a particular type of political risk.

The negative relationship between firm political risk and DTD shown in Table 2 could arguably be driven by high-tech industries, with many high-tech firms filing for bankruptcy during the dot.com bubble (Brogaard *et al.*, 2017). To alleviate this concern, we estimate Eq. 3 separately for each of the Fama and French 10 industry classifications. Table A3 in the Appendix summarizes the results, with each row including a regression using firm-quarter observations for a particular industry, though we only report the coefficients and *p*-values for brevity. Our results indicate that the impact of firm political risk on DTD is not limited primarily to high-tech industries. In fact, there is a significant negative relationship for 7 out of the 10 industries, thus highlighting the generalizability of our findings. Overall, our findings are qualitatively similar across a range of models: hence, the firm-level political risk has a robust negative impact on DTD.

5. Addressing endogeneity

Endogeneity concerns may pose a question to the finding of a causal relationship between firm political risk and DTD. For example, any policy change could create a substantial exogenous shock that significantly affects firm-level political risk without directly affecting DTD. Moreover, a firm's DTD could be affected by an unknown factor also linked to firm political risk, thereby generating a spurious correlation. We employ three different identification strategies to overcome these potential endogeneity concerns. First, we conduct a natural experiment using the redistricting of electoral boundaries in 2010 as an exogenous policy shock. We expect the new electoral boundaries to cause potential exogenous variations in firms' political risk exposures. Second, we use a propensity score-matched sample to reduce heterogeneities between firms with high and low political risk. Finally, in line with D'Mello and Toscano (2020), we use the Partisan Conflict Index (PCI) as an instrumental variable (IV) for firm-level political risk and excerpted the exogenous elements from it.

5.1. A natural experiment: Redrawing of federal electoral district boundaries

Redistricting is the mandated practice of redrawing congressional electoral boundaries after new population data become available following each decennial census. Following a series of rulings by the U.S. Supreme Court in the 1960s, the Single-Member District Mandate of 1967 requires that congressional districts are made as equal in population as practicable so that communities have equal access to political representation. When congressional district boundaries are redrawn, firms may encounter new political landscapes, being assigned new congressional representatives with different political priorities and outlooks. As a result, firms must take new approaches to re-establish connections with those regulatory institutions and politicians. Since the primary responsibility for redistricting belongs to the state legislature or independent bipartisan redistricting commissions or independent bodies, firms have little or no influence on the redistricting outcomes. Therefore, this phenomenon offers a plausible exogenous variation in the political risk that firms experience (Denes *et al.*, 2017; Gad *et al.*, 2020). Within their political vicinity, firms usually prefer trusted, long-term relationships with the regulatory bodies and congressional representatives in their home districts. However, redistricting reshuffles the long-established relationships between the parties, thereby exposing the firms to greater political uncertainty.

Taking the 2010 census and the redistricting that followed, we employ a Difference-in-Difference (DID) approach to estimate the causal impact of political risk on DTD. We obtain the redistricting data by determining the congressional districts in which each given firm is located on the basis of the longitude and latitude of the COMPUSTAT address. Our sample comprises 2,727 unique firms; and we are able to obtain the headquarters address data (i.e., the first line of address, ZIP code, and state) for 2,521 of these firms from COMPUSTAT. We remove from the sample 24 firms whose headquarters addresses were in Canada. For each firm in our sample, we use Google geocoding to determine the latitude and longitude of the address. The latitudes and longitudes are then matched with congressional districts. Data on the geographic boundaries of the congressional districts over time are taken from the U.S. Census Bureau website and shapefiles compiled by Lewis *et al.* (2013). We then identify any changes in a given firm's district (i.e., redistricting).

The 2010 census led to the redrawing of 243 congressional electoral districts across 18 states, accounting for 1,431 firms. Some firms were unaffected by redistricting, as they remained in the same district. A total of 941 (37%) firms were placed into new congressional districts, and these constitute our *treated* firms.

In line with Gad *et al.* (2020), we examine the following model for DID estimation:

$$DTD_{i,t} = \alpha + \beta_1 Treated\ firm_{i,t} \times Post\ event_{i,t} +$$

$$\beta_2 Treated\ firm_{i,t} + \beta_3 Post\ event_{i,t} + \beta_4 control\ variables + \varepsilon_{i,t} \quad (4)$$

The treated firm variable captures the shift in firms' political risk due to redistricting. For this purpose, we take all firms located in a given congressional district in the five years prior to redistricting and sort them into three groups based on their political risk ranking. We then repeat the process, based on the political risk ranking of all the firms located in the new districts, as measured over the five years preceding the redistricting. In this way, we create a categorical treatment variable, ranging from -1 to +1. A firm is assigned the value of +1 (-1) when it moved into a higher (lower) tercile after the redistricting. The categorical variable takes the value of zero if the firm remains in the same tercile after redistricting. *Post event* is a dummy variable, equal to one after all federal redistricting of 2010 had been finalized (that is, after 2011), and otherwise equal to zero.[6] Our interest is in the interaction term $Treated\ firm_{i,t} \times Post\ event$.

[6] Redrawing of the electoral districts often results in legal challenges by concerned political stakeholders in the states; and the final legal challenges to the proposed new district lines of the 2010 census were not settled in court until 2011. Thus, the new redistricting came into effect after 2011.

Table 3 presents the results of our natural experiment (i.e., the DID regressions). Columns 1 and 2 report the results of OLS regression, including the industry and year fixed effects, while Column 2 shows the results for firm-fixed effects. The coefficient for $Treated\ firm_{i,t} \times Post\ event$ is negative and statistically significant at the 5% level in both columns. This suggests that firms with higher political risk after redistricting had lower DTD than the firms that were unaffected by redistricting. Overall, the results presented in Table 2 are consistent for the periods of exogenous shocks.[7]

[Insert Table 3 about here]

5.2. Propensity score matching (PSM)

We employ the PSM approach to overcome any omitted variable biases due to functional form misspecification and systematic differences between firm characteristics. For this purpose, we match the DTD for firms with high political risk (above median political risk) with those for firms with low political risk (below median political risk). We also assign firm-quarter observations with high (low) political risk to the treatment (control) group. To begin, we estimate the probability that a firm has high political risk. We then estimate a logit regression to explain the firm's political risk dummy (set as one if a firm has a political risk above the median, and zero otherwise), using the control variables included in Eq. 3. The regression results are presented in Column 1 of Table 4. In the pre-match sample, we find that most of our explanatory variables are significant, with the exception of Tobin's q.

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[7] One may argue that a shift in a firm's political risk due to Congressional redistricting comes from changes in the comparison group (different firms being included in the old and new district boundaries) rather than changes in the level of political risk for the firm itself. To mitigate this concern, we also perform another DID estimation using the same Congressional redistricting but focusing on changes in a firm's political risk after the redistricting. In this case, for example, Streamline Health Solutions Inc.'s political risk changed from an average of 0.235 to an average of 1.616 after the redrawing of the electoral boundaries. Thus, we create a *'Treated'* dummy variable that takes the value of 1 if the political risk has changed due to Congressional redistricting and zero if the political risk has remained unchanged. *Post event* is an indicator variable that equals to 1 after 2011, and 0 otherwise. We find qualitatively similar results (untabulated) as reported in Table 3.

In the next stage, we use the nearest neighbor matching method to ensure that firms with high political risk (the treatment group) are adequately similar to the matched firms with low political risk (the control group). In each firm-quarter, the firms in the treatment group are matched with those in the control group, based on their closest propensity scores. In addition, we ensure that the largest difference between the propensity score of each firm-quarter observation and that of its matched peer are within 0.1% in absolute value.

We re-run the logit regression in our post-match sample to confirm that the treatment and control groups' firm-quarter observations are identical. The results (shown in Column 2 of Table 4) show that all coefficients for the explanatory variables are statistically insignificant, implying no differences in terms of DTD between the two groups. Moreover, the coefficients in Column 2 are generally smaller than those in Column 1, suggesting that degrees of freedom decline in the restricted sample. Overall, the diagnostic tests reveal that the PSM analysis eliminates the apparent differences between the control variables.

In the next stage, we estimate the impact of political risk on DTD in the matched sample. The results are presented in Column 3 of Table 4. The coefficient of political risk is negative and significant at the 1% level, suggesting that a firm's political risk continues to negatively affect DTD after the removal of firm-specific characteristics. For robustness purposes, we also consider firm-quarter observations with political risk in the treatment group and those without political risk in the control group. The results, shown in Columns 4-6, suggest that firm-level political risk leads to a decrease in DTD, and this is not triggered by other firm-specific differences in characteristics. Overall, the PSM verifies that the results presented in Table 2 are attributable to the variations between firm-quarter observations for high and low political risk.

[Insert Table 4 about here]

5.3. Instrumental variable approach

Our third attempt to mitigate the endogeneity concern is the IV approach. For this, we conduct a two-stage least squares (2SLS) analysis and re-estimate Eq. 3 to remove the exogenous element from the firm-level political risk. The major challenge in employing 2SLS is the identification of an exogenous IV with no explicit connection to DTD. In line with D'Mello and Toscano (2020), we use the Partisan Conflict Index (PCI) as an IV for firm political risk. The PCI index captures policy disagreement at a certain point in time on two fronts: (i) between and within the political parties and (ii) between Congress and the President. Greater partisan conflict increases the political and policy uncertainty that escalates firm political risk (Gulen and Ion, 2016). On the contrary, partisan conflict should not affect DTD in any way other than its impact on firm political risk. Therefore, partisan conflict is deemed a valid instrument, and we expect the PCI to be positively associated with firm-level political risk.

The results for the IV regression are reported in Table 5. The findings from the first-stage regression are presented in Column 1 of Table 5, where the dependent variable is firm political risk. We have included the same control variables used in our baseline model in Eq. 3. Consistent with the requirements for a valid IV, PCI has a significant and positive relationship with firm political risk, indicating the relevance of the IV. The Wu-Hausman endogeneity test statistic validates our endogeneity concern. The Kleibergen-Paap underidentification test statistic and the Cragg-Donald weak identification test statistic reject the null hypothesis of a weak instrument (Cragg and Donald, 1993; Stock and Yogo, 2005). The second-stage regression findings are presented in Column 2 of Table 5. We use the fitted values of PCI from the first-stage regression to estimate DTD. The coefficient of the instrumented firm political risk variable (instrumented-PCI) is positive and significant at the 1% level. This finding is consistent with our baseline regression that firm-level political risk significantly decreases DTD.

[Insert Table 5 about here]

6. Robustness checks

In this section, we present a battery of robustness tests for our findings. First, a good number of studies (e.g., Demir and Ersan, 2017; Liu and Zhang, 2020) report that policy uncertainty affects corporate policies significantly. To address the argument that our baseline results may simply capture the impact of economic policy uncertainty, we control Baker *et al.*'s (2016) economic policy uncertainty index along with the other variables specified in Eq. 3. As presented in Table A4, we still document a negative association between firm political risk and DTD.

Second, another concern is that a firm's political risk growth might have a substantial degree of persistence. To capture any effect of past political risk, we re-run Eq. 3 as a dynamic panel by adding a lagged dependent variable as an additional control. Table 6 Panel A includes the regression result.[8] When controlling for the dynamic effect, we find qualitatively similar results.[9] Third, we exclude the 'sin' industries from our sample because these are more likely to experience high political risk, and this could affect our findings. Hong and Kacperczyk (2009) and Kim and Venkatachalam (2011) define sin industries as alcohol-, gambling-, tobacco-, and sex-related industries, as well as weapons manufacturers. The results in Panel B of Table 6 show that the negative relationship between firm political risk and DTD persists, even after sin industries are excluded from the sample.

[Insert Table 6 about here]

Fourth, we examine whether periods of heightened political risk drive our baseline results. As depicted in Figure 1, firm political risk peaks during the Iraq war (in 2002Q4),

[8] The regression also includes the control variables as specified in Eq. 3. For brevity, we only report the coefficient of the firm political risk.
[9] We also use one-year lagged variables to mitigate the effects of contemporaneous associations in our baseline regressions. Our unreported results confirm the baseline findings.

following the election and re-election of President Obama (in 2008Q4 and 2012Q3), and after Trump was elected as president (2017Q1). Panel C of Table 6 presents the results after excluding these peak political risk quarters. Our results suggest a significant negative impact of firm political risk on DTD, implying that the effect we find is not limited to extreme political risk periods. Finally, we investigate the impact of political risk on alternative measures of bankruptcy risk. Previous studies have employed a three-month probability of default, actuarial spread, Altman Z-score, and Whited Wu index as proxies for bankruptcy risk (see, for example, Carling *et al.*, 2007; Yildirim, 2020). Table 7 presents the regression results for alternative measures of default risk. Our results indicate that firm political risk significantly increases default risk across all the alternative measures. Taken together, these results support our baseline findings.[10]

[Insert Table 7 about here]

7. Channel analysis

In this section, we examine how firm political risk negatively affects DTD. Specifically, we investigate whether information asymmetry, organizational capital, and investment growth are the channels by which firm political risk influences DTD. For this purpose, we follow two procedures. First, we examine the direct association between political risk and information asymmetry, organizational capital, and investment growth. Then, we re-investigate the association between firm political risk and DTD across different firm subsamples based on information asymmetry, organizational capital, and investment growth.

We measure information asymmetry proxied by analysts' forecast accuracy (Thomas, 2002; Chen *et al.*, 2010; Baloria and Mamo, 2017). Analyst forecast accuracy is the negative

[10] Besides firm characteristics, corporate governance factors may also influence firm default risk. Thus, we further control for board characteristics by including board size, number of female directors, board independence, and institutional ownership in our Eq. 3. Our unreported results reconfirm our baseline findings.

of the absolute value of the consensus forecast error at time *t* scaled by the stock price at time *t*. The analysts' forecast error is measured as follows:

$$Accuracy = (-1)\left(\frac{|Forecast_{t-1} - EPS_t|}{PRICE_t}\right) \quad (5)$$

We follow Eisfeldt and Papanikolaou (2013) and Hasan *et al.* (2021) and estimate organization capital based on selling, general and administrative (SG&A) expenses. Specifically, we calculate organizational capital as follows:

$$OC_{i,t} = (1 - \delta_{oc})OC_{i,t-1} + (SG\&A_{i,t} \times \lambda_{oc}) \quad (6)$$

We estimate the initial stock of overall organizational capital as:

$$OC_{i,0} = \frac{SG\&A_{i,t} \times \lambda_{oc}}{g + \lambda_{oc}} \quad (7)$$

where $OC_{i,t}$ is organizational capital of firm *i* at time *t*. δ_{oc} is the depreciation rate of OC, $SG\&A_{i,t}$ is the SG&A expenses of firm *i* in year *t*, λ_{oc} denotes the percentage of SG&A expenses that is invested in OC, and *g* is the long-term growth rate of SG&A. Following prior literature (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017; Hou *et al.*, 2020), we assume a value of λ_{oc} equal to 30% of SG&A expenses (i.e., λ_{oc} = 0.30). Similar to Peters and Taylor (2017), we consider a depreciation rate of 20% (δ_{oc}= 0.20). As per Hou *et al.* (2020), we assume 10% as the long-term growth rate in SG&A expenses. We scale OC by total assets (OC/TA) to get our *OCA* measure.

We calculate growth in investment as the difference between the current and prior year's investment.[11] We expect negative relationships between firm-level political risk and analysts' forecast accuracy, organizational capital, and investment growth. We also predict

[11] The change in investment is $\Delta Investment = Investment_t - Investment_{t-1}$; where $Investment = \frac{CAPEX}{Lag\ of\ TA}$.

stronger negative relationships between firm-level political risk and DTD for firms with low analysts' accuracy, organizational capital, and investment growth.

Table 8 presents the test results. Panel A shows the re-estimation of Eq. 3 with the dependent variable as analysts' forecast accuracy (Column 1), organizational capital (Column 2), and investment growth (Column 3). As expected, our results indicate that firm-level political risk has significant negative relationships with analysts' forecast accuracy, organizational capital, and investment growth. These findings are consistent with the extant literature (Li and Born, 2006; Baloria and Mamo, 2017; Jens, 2017). In Panel B, DTD is the dependent variable for subsamples of firms with low versus high analysts' forecast accuracy (Columns 1 and 2), low versus high organizational capital (Columns 3 and 4), and low versus high investment growth (Columns 5 and 6). For each channel, we sort the firms into five quintiles in ascending order. We show that the negative relationship between political risk and DTD is only significant for firms that experience low analysts' forecast accuracy, organizational capital, and investment growth. Overall, the findings support our hypotheses H2a, H2b, and H2c that firm-level political risk increases default risk through information asymmetry, organizational capital, and investment growth channels.

[Insert Table 8 about here]

8. Managing firm-level political risk: The role of corporate lobbying

Thus far, we have established a negative relationship between firm political risk and DTD. We have also identified that this relationship is channeled through information asymmetry, organizational capital, and investment growth. In this section, we explore whether corporate lobbying can help mitigate the adverse impact of political risk. In section 2.3, we posit that corporate lobbying enables firms to gain systematic favors and access to strategic resources. To test this idea empirically, we manually collect lobbying expenditures data from the Center for Responsive Politics (CRP) website. The CRP is a Washington-based non-profit research organization which provides an open-access database on corporate lobbying expenditures.

We conjecture that firms exploit corporate lobbying to mitigate the adverse effect of political risk. Initially, we want to examine whether firms with high political risk spend heavily on lobbying expenditure compared to their counterparts. For this purpose, in Appendix Table A5, we divide firms based on whether they spend on lobbying or not. Then, we calculate the average of their overall political risk and compare the difference in means between firms with and without lobbying expenditures. We find that the average political risk is significantly higher for firms with lobbying expenditures.[12] This finding primarily supports our argument that firms exposed to higher political risk spend more on lobbying expenditures to mitigate their political risk.[13]

To investigate this hypothesis empirically, we then examine the following model:

$$DTD_{i,t} = \alpha + \beta_1 PRisk_{i,t} + \beta_2 LobEx_{i,t} + \beta_3 PRisk_{i,t} \times LobEx_{i,t} + \beta_4 control\ variables + \varepsilon_{i,t} \quad (8)$$

where $LobEx_{i,t}$ is the corporate lobbying expenditures. Our variable of interest is the interaction term. We include the set of control variables that we have considered in Eq. 3.

Table 9 presents the results of the regressions. Column 1 includes the regression results of lobbying expenditure on the distance to default for the full sample. The result shows a significant positive relationship, suggesting that corporate lobbying has a positive impact on reducing default risk. Concerning the effect of our variable of interest, column 2 reveals that the coefficient of the interaction term $LobEx_{i,t} \times PRisk_{i,t}$ is positive and significant, suggesting that firms which spend on corporate lobbying can mitigate the impact of political

[12] We also perform the same analysis for all the political risk categories and find qualitatively similar results (see Appendix Table A5).
[13] In our corporate lobbying sample, on average firms spend $961,081.20 on lobbying. Corporate lobbying has a positive correlation of 0.044 (*p*-value 0.00) with DTD.

risk. In columns 3 and 4, we present results based on the matched sample. To match the sample, we first divide the full sample based on zero and non-zero firm-level lobbying expenditures. We then employ the propensity score matching method to obtain the matched sample. Our results remain qualitatively similar in column 4. Overall, these results support our hypothesis H3 that corporate lobbying significantly mitigates the impact of political risk. These findings are consistent with Pham (2019), who reports political activism mitigates the negative impact of economic policy uncertainty on the cost of equity.

[Insert Table 9 about here]

9. Conclusion

A body of empirical literature indicates that national political factors such as elections and regime stability significantly affect sovereign debt and bank default rates. However, Hassan *et al.* (2019) argue that national political events have a trivial effect on firm-level political risk, concluding that firm-level political risks are largely due to industry-level policy and regulatory changes, local political and policy uncertainty, and idiosyncratic circumstances. This novel firm-level political risk measure motivates us to examine the effect of firm-level political risk on distance-to-default.

On the basis of our investigation, we report the following findings. First, our empirical evidence reveals a negative association between firm political risk and DTD, suggesting that firm-level political risk is a significant determinant of corporate default risk. This finding is robust following the consideration of an exogenous policy shock (i.e., redrawing of federal electoral district boundaries), a possible omitted variable bias, and systematic differences between high and low politically risky firms. Moreover, our results are not sensitive to sample compositions, firm-specific variables, time-invariant unobservable industry characteristics, lagged effect of firm characteristics, and the dynamic effect of political risk.

Second, we show that the negative effect of firm political risk on DTD propagates through information asymmetry, organizational capital, and investment growth. More specifically, we find that firm political risk decreases analysts' forecast accuracy, organizational capital, and investment growth. While we find these channels exacerbate a firm's default risk, however, there may be some other factors that could also have a similar impact, which provides direction for future research. Finally, our results highlight that the adverse impact of firm political risk on DTD can be mitigated by systematic favors garnered through corporate lobbying.

Our findings have important policy implications for policymakers, regulators, and corporate managers. Since firm-level political risk is a crucial driver of corporate default, policymakers and regulators could minimize political uncertainty and limit rapid policy changes to ensure sustainable growth. Our results also highlight the importance of corporate lobbying that significantly mitigates default risk.

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Table 1: Summary statistics.

The table reports summary statistics for the sample firm-quarter observations. The variables are defined in Appendix A1. Our sample contains 107,886 firm-quarter observations between 2002 and 2019.

Variable	N	Mean	Std. Dev.	Minimum	Median	Maximum
DTD	107,886	5.062	2.905	0.098	4.592	14.026
PRisk	107,886	1.054	1.534	0.000	0.549	9.446
Equity	107,886	6329.892	17157.990	13.555	1049.727	122891.700
Debt	107,886	922.262	2333.876	0.000	114.289	15606.500
Excess return	107,338	0.002	0.115	-0.322	-0.002	0.410
σ_E	107,354	0.119	0.069	0.031	0.101	0.403
Income/Assets	107,886	-0.002	0.054	-0.299	0.010	0.092
Tobin's q	107,886	2.046	1.368	0.694	1.594	8.509

Table 2: Regressions of distance-to-default on political risk.

The table presents ordinary least squares (OLS) regressions of default risk on political risk. The dependent variable is the distance-to-default (*DTD*). Column 1 presents the results of the regression with only the political risk measure. Column 2 presents the results of the regression without the political risk measure. Columns 3 to 5 report the results of regressions with different variations of industry and year fixed effects. Column 6 presents Fama-Macbeth regression results. Column 7 uses firm fixed effects. Column 8 uses the natural logarithm of firm-level political risk. We use *Ln(Equity), Ln(Debt),* $1/\sigma_E$, *Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRisk	-0.033***		-0.022***	-0.038***	-0.023***	-0.019***	-0.010**	
	(0.009)		(0.000)	(0.000)	(0.001)	(0.000)	(0.023)	
Ln(PRisk)								-0.038***
								(0.000)
Ln(Equity)		0.732***	0.732***	0.739***	0.735***	0.746***	0.992***	0.729***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Debt)		-0.387***	-0.387***	-0.369***	-0.381***	-0.399***	-0.330***	-0.381***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$1/\sigma_E$		0.207***	0.206***	0.222***	0.206***	0.204***	0.121***	0.207***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Excess return		-0.476***	-0.477***	-0.773***	-0.472***	-0.496***	-0.564***	-0.439***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income/Assets		6.232***	6.189***	6.121***	6.367***	6.713***	1.158***	6.387***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's q		0.323***	0.323***	0.349***	0.298***	0.279***	0.282***	0.290***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	2.134***	-2.004***	-1.984***	-1.883***	-2.067***	-1.496***	-3.231***	-2.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	107,886	90,619	90,619	90,619	90,619	90,619	90,613	77,024
Adjusted R-squared	0.164	0.640	0.640	0.607	0.643	0.623	0.484	0.644
Industry effects	Yes	No	No	Yes	Yes	Yes	No	Yes
Year effects	Yes	Yes	Yes	No	Yes	No	Yes	Yes
Firm fixed effects	No	No	No	No	No	No	Yes	No

Table 3: Redistricting, political risk and distance-to-default.

The table presents the coefficient estimates for difference-in-difference regressions using Congressional redistricting as an exogenous shock. The dependent variable is the distance-to-default (*DTD*). *Treated* is a categorical variable that takes the value of +1 if political risk has increased due to Congressional redistricting, -1 if the political risk has decreased due to redistricting, and zero if the political risk has remained unchanged. *Post event* is an indicator variable that equals to 1 after 2011, and 0 otherwise. We use *Ln(Equity), Ln(Debt),* $1/\sigma_E$, *Excess Return*, *Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at the firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Treated × Post event	-0.166**	-0.169**
	(0.044)	(0.033)
Treated	0.003	-0.004
	(0.961)	(0.920)
Post event	0.872***	0.943***
	(0.000)	(0.000)
PRisk	-0.076*	-0.071**
	(0.098)	(0.038)
Ln(Equity)	0.758***	0.868***
	(0.000)	(0.000)
Ln(Debt)	-0.439***	-0.453***
	(0.000)	(0.000)
$1/\sigma_E$	0.280***	0.226***
	(0.000)	(0.000)
Excess return	-0.923***	-0.748***
	(0.001)	(0.003)
Income/Assets	15.826***	11.622***
	(0.000)	(0.000)
Tobin's q	0.701***	0.672***
	(0.000)	(0.000)
Intercept	-3.471***	-3.514***
	(0.000)	(0.000)
Observations	6,372	6,372
Adjusted R-squared	0.641	0.467
Industry fixed effects	Yes	No
Year fixed effects	Yes	Yes
Firm fixed effects	No	Yes

Table 4: Propensity score matching.

The table presents results from propensity score-matched samples. First, we divide the full sample into above and below the median political risk. Columns 1 and 2 present results of pre- and post-match regressions. Column 3 shows the results of the regression of distance-to-default on political risk based on the matched sample. Second, we divide the full sample based on zero and non-zero firm-level political risk. Columns 4 and 5 present results of pre- and post-match regressions. Column 6 shows the results of the regression of distance-to-default on political risk based on the matched sample. We use *Ln(Equity), Ln(Debt),* $1/\sigma_E$, *Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at the firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Pre-match	Post-match		Pre-match	Post-match	
	Above and below median political risk dummy		*DTD*	Zero and non-zero political risk dummy		*DTD*
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk			-0.025***			-0.032***
			(0.000)			(0.000)
Ln(Equity)	0.073***	0.006	0.721***	0.218***	0.008	0.736***
	(0.000)	(0.710)	(0.000)	(0.000)	(0.702)	(0.000)
Ln(Debt)	-0.019**	0.001	-0.377***	-0.002	-0.002	-0.386***
	(0.036)	(0.909)	(0.000)	(0.886)	(0.878)	(0.000)
$1/\sigma_E$	-0.005*	-0.000	0.207***	-0.014***	-0.001	0.204***
	(0.053)	(0.891)	(0.000)	(0.000)	(0.743)	(0.000)
Excess return	-0.128**	0.040	-0.438***	-0.348***	-0.061	-0.603***
	(0.033)	(0.613)	(0.000)	(0.000)	(0.585)	(0.000)
Income/Assets	-1.862***	-0.195	6.138***	-2.187***	0.053	6.599***
	(0.000)	(0.506)	(0.000)	(0.000)	(0.890)	(0.000)
Tobin's q	-0.012	-0.001	0.279***	-0.024	0.006	0.326***
	(0.445)	(0.967)	(0.000)	(0.177)	(0.754)	(0.000)
Intercept	-0.087	-0.014	-1.981***	0.763***	-0.026	-1.946***
	(0.340)	(0.891)	(0.000)	(0.000)	(0.850)	(0.000)
Observations	90,677	69,523	69,523	90,683	89,259	89,253
Pseudo R-squared	0.025	0.000	0.644	0.03	0.001	0.642
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Regression estimates using two-stage least squares.

The table presents the results of the 2SLS regressions. Column 1 shows the first-stage regression where *PRisk* is the dependent variable, and the model fits the instrumental variable. The instrumental variable is the partisan conflict index used by D'Mello and Toscano (2020). Column 2 shows the second-stage regression where the dependent variable is the distance-to-default (*DTD*). We use *Ln(Equity)*, *Ln(Debt)*, $1/\sigma_E$, *Excess Return*, *Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at the firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	First Stage (1)	Second Stage (2)
Variable	*PRisk*	*DTD*
Partisan conflict	0.048**	
	(0.041)	
PRisk fitted		-7.710***
		(0.000)
Ln(Equity)	-0.006	0.689***
	(0.515)	(0.000)
Ln(Debt)	-0.014**	-0.501***
	(0.010)	(0.000)
$1/\sigma_E$	-0.003*	0.216***
	(0.061)	(0.000)
Excess return	-0.015	-0.830***
	(0.677)	(0.005)
Income/Assets	-0.814***	-0.008
	(0.000)	(0.997)
Tobin's q	-0.012	0.266***
	(0.209)	(0.001)
Intercept	-0.323***	-3.527***
	(0.005)	(0.000)
Observations	77,024	77,024
Industry effects	Yes	Yes
Year effects	Yes	Yes
Endogeneity test:		
Wu-Hausman F-statistic	283.320***	
Underidentification test:		
Kleibergen-Paap LM statistic	16.478***	
Weak identification test:		
Kleibergen-Paap rk Wald F-statistic	16.695***	
Weak instrument robust inference:		
Anderson-Rubin Wald Chi-square	633.220***	

Table 6: Robustness checks.

The table presents ordinary least squares (OLS) regressions of different variations of default risk on firm-level political risk with a dynamic effect, and across different sub-samples. We use two different dependent variables – distance-to-default (*DTD*) and 3-month probability of default (*PTD*). In Panel A, we control for the lag of political risk. In Panel B, we exclude firms belonging to sin industries – alcohol, tobacco, gambling, and weapon. In Panel C, we exclude periods when political risk reached its peaks, such as the Iraq war and Trump winning the presidential election. We control for other standard controls and industry and year fixed effects. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Variable	*DTD*	*PTD*	*DTD*	*PTD*
	(1)	(2)	(3)	(4)
Panel A: Dynamic effect using lag of political risk				
PRisk	-0.019***	0.003**		
	(0.001)	(0.011)		
Ln(PRisk)			-0.030***	0.007***
			(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Panel B: Excluding sin industry				
PRisk	-0.015**	0.004***		
	(0.027)	(0.010)		
Ln(PRisk)			-0.029***	0.007***
			(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Panel C: Excluding peak political risk quarters				
PRisk	-0.022***	0.003**		
	(0.002)	(0.021)		
Ln(PRisk)			-0.035***	0.006***
			(0.001)	(0.003)
Controls	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Table 7: Political risk and alternative measures of bankruptcy risk.

The table presents ordinary least squares (OLS) regressions of different variations of default risk on firm-level political risk. Columns 1 to 8 present the results of the regressions of 3-month probability of default, actuarial spread, Altman Z-score, and Whited-Wu financial constraints index on political risk measure (*PRisk*), respectively. We use *Ln(Equity), Ln(Debt),* $1/\sigma_E$*, Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	3-month probability of default		Actuarial spread		Altman Z-score		Whited-Wu Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRisk	0.004**	0.004**	0.025***	0.011**	-0.157**	-0.001*	0.079**	0.019**
	(0.044)	(0.047)	(0.001)	(0.016)	(0.018)	(0.054)	(0.019)	(0.038)
Ln(Equity)	-0.119***	-0.329***	-0.701***	-1.093***	6.843***	0.030***	1.332***	0.266***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Debt)	0.077***	0.076***	0.424***	0.375***	-6.994***	-0.096***	0.146***	0.055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$1/\sigma_E$	-0.004***	-0.002***	-0.213***	-0.116***	-0.155***	-0.001***	0.024	-0.000
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.153)	(0.887)
Excess return	-0.048	-0.057	0.181***	0.438***	-2.054*	-0.009***	-0.752***	-0.145***
	(0.348)	(0.205)	(0.001)	(0.000)	(0.056)	(0.002)	(0.000)	(0.004)
Income/Assets	-0.683***	-0.534***	-8.067***	-1.814***	-7.609***	0.133***	-2.274***	-0.105
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.308)
Tobin's q	0.039***	0.109***	-0.357***	-0.332***	-1.419***	0.020***	-0.375***	-0.046**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)
Intercept	0.769**	1.926***	7.802***	9.748***	-5.464	0.587	-9.287***	-1.612***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.324)	(0.000)	(0.000)	(0.000)
Observations	74,235	74,178	74,235	74,178	75,258	75,258	78,670	78,670
Adjusted R-squared	0.056	0.065	0.621	0.454	0.053	0.605	0.112	0.008
Industry effects	Yes	No	Yes	No	Yes	No	Yes	No
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm effects	No	Yes	No	Yes	No	Yes	No	Yes

Table 8: Channel analysis.

The table reports test results for different channels through which political risk affects distant-to-default. Panel A presents regression results of different channels – analysts' forecast accuracy (*Accuracy*), organizational capital (OCA), and investment growth – on the firm-level political risk (*PRisk*). Panel B reports regression results of distance-to-default on firm-level political risk for subsamples of firms sorted quarterly into quintiles on the degree of analysts' forecast accuracy (*Accuracy*), organizational capital (OCA), and investment growth. We use *Ln(Equity), Ln(Debt), $1/\sigma_E$, Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Political risk and analysts' forecast accuracy, organizational capital, and investment growth.

	Analysts' forecast accuracy	Organizational capital	Investment growth
	(1)	(2)	(3)
PRisk	-0.0004***	-0.001**	-0.008**
	(0.002)	(0.026)	(0.036)
Firm controls	Yes	Yes	Yes
Adjusted R-squared	0.222	0.330	0.013
Observations	77,141	90,677	72,365
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes

Panel B: Political risk and distance-to-default via – analysts' forecast accuracy, organizational capital, and investment growth.

	DTD		DTD		DTD	
	Low *Accuracy* (Q1)	High *Accuracy* (Q5)	Low OCA (Q1)	High OCA (Q5)	Low investment growth (Q1)	High investment growth (Q5)
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk	-0.022**	-0.034	-0.017**	-0.002	-0.037***	-0.015
	(0.042)	(0.107)	(0.026)	(0.775)	(0.010)	(0.306)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.528	0.559	0.582	0.697	0.609	0.634
Observations	15,460	15,402	18,163	18,108	14,499	14,444
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes

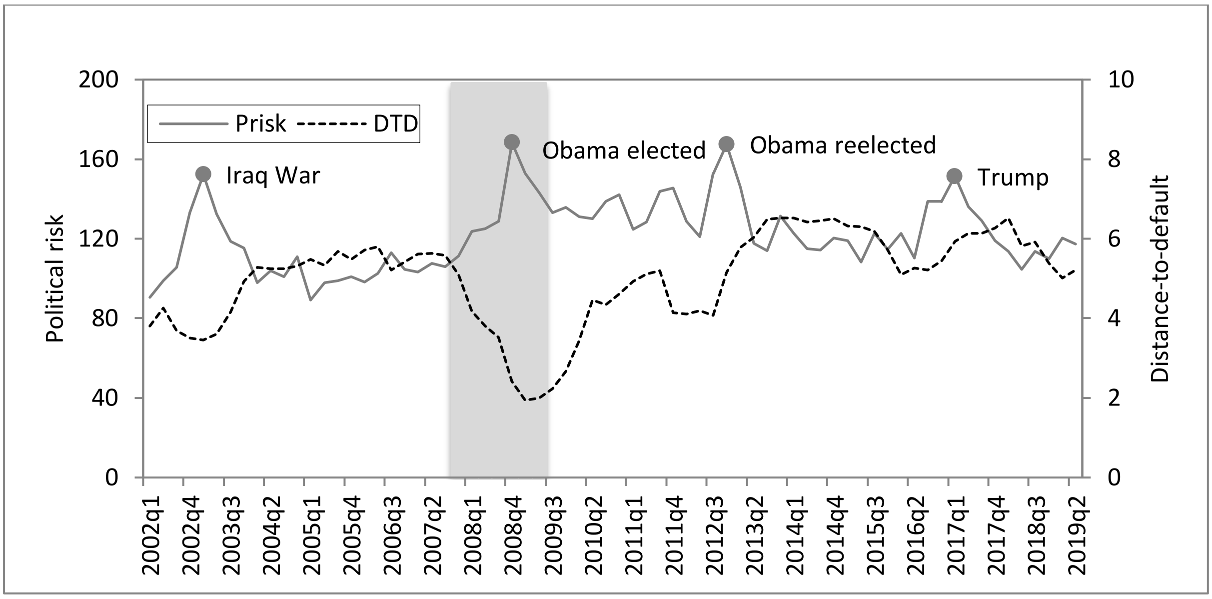
Table 9: Mitigating the impact of political risk.

The table presents results on how firms try to mitigate the impact of political risk. Specifically, we interact political risk with corporate lobbying expenditure (*LobEx*). The dependent variable is the distance-to-default (*DTD*). In the first and second columns, we report full sample results. In the third and fourth columns, we present results based on matched sample. To match sample, we first divide the full sample based on zero and non-zero firm-level lobbying expenditure. We then employ propensity score matching method to obtain the matched sample. We use *Ln(Equity)*, *Ln(Debt)*, $1/\sigma_E$, *Excess Return*, *Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
LobEx×PRisk		0.006**		0.006**
		(0.050)		(0.035)
PRisk		-0.044***		-0.060***
		(0.000)		(0.001)
LobEx	0.057**	0.048*	0.089***	0.082***
	(0.025)	(0.078)	(0.001)	(0.005)
Ln(Equity)	1.479***	1.478***	1.593***	1.587***
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Debt)	-0.344***	-0.345***	-0.396***	-0.397***
	(0.000)	(0.000)	(0.000)	(0.000)
$1/\sigma_E$	0.168***	0.168***	0.160***	0.160***
	(0.000)	(0.000)	(0.000)	(0.000)
Excess return	-0.961***	-0.962***	-0.769***	-0.782***
	(0.000)	(0.000)	(0.000)	(0.000)
Income/Assets	1.041***	1.046***	1.060	1.247
	(0.009)	(0.009)	(0.277)	(0.200)
Tobin's q	0.415***	0.412***	0.380***	0.375***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	-7.171***	-7.104***	-8.067***	-7.931***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	58,588	58,588	10,253	10,253
Adjusted R-squared	0.406	0.406	0.346	0.347
Year effects	Yes	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes	Yes

Figure 1: Political risk and distance-to-default.

The figure shows the relationship between aggregate political risk and distance-to-default. The solid and dotted line represent political risk and distance-to-default, respectively. The shaded region indicates the NBER recession periods.



Appendix

Appendix A. Alternative measures of default risk

Probability of Default

Probability of Default (PTD) is built on the forward intensity model of Duan *et al.* (2012). For each forward period τ, $\rho_{i,t}$ (τ) is constructed on a forward intensity function, and its inputs include the state of the economy (macro-financial risk factors, X_t) and the vulnerability of individual obligors (firm-specific attributes, $Y_{i,t}$):

$$\rho_{i,t}(\tau) = P_\tau(X_{t,} Y_{i,t})$$

with $\rho_{i,t}$ (τ) in place, the multi-period default probabilities with different term structures can be obtained through the typical survival-exit formula.

Actuarial Spread

Actuarial Spread (AS) is an alternative credit risk measure to the CRI PD. Constructed on the design of conventional Credit Default Swaps (CDS) excluding the upfront fee, the AS reflects the credit risk of a firm by summarizing the information embedded in the term structure of the physical (real-world) CRI PD and the risk-free discount rate. Therefore, it is equivalent to computing the CDS spreads based on their '*actuarial*' values by using the CRI PD. In other words, the CRI PD can be interpreted as an equivalent to pricing CDS purely based on their actuarial values. This rate therefore is referred to as '*actuarial spread*'. A simple lagged regression of the log ratio of the CDS spread over its corresponding AS yields a high R^2 of 85% with the predictive equation:

$$\ln\left(\frac{S_t}{S_t^{(a)}}\right) \approx 0.1487 + 0.9296 \times \ln\left(\frac{S_{t-1}}{S_{t-1}^{(a)}}\right)$$

Where S_t refers to the CDS spread at time *t* and $S_t^{(a)}$ refers to the AS at time *t*.

Altman Z-score

Altman (1968) developed a Z-score formula to measure the financial health of a firm and predict bankruptcy by using multiple corporate incomes and balance sheet values. We compute Altman Z-score as follows:

$$Z = 0.012 \times \frac{Working\ Capital}{Total\ Assets} + 0.014 \times \frac{Retained\ Earnings}{Total\ Assets}$$
$$+ 0.033 \times \frac{Earnings\ Before\ Interest\ and\ Taxes}{Total\ Assets}$$
$$+ 0.006 \times \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Debt} + 0.999 \times \frac{Sales}{Total\ Assets}$$

Whited-Wu Financial Constraints Index

We construct Whited-Wu financial constraints index as follows:

$$Whited - Wu$$
$$= -0.091 \times \frac{Cash\ Flow}{Book\ Value\ of\ Assets} - 0.062 \times Dividend\ Dummy$$
$$+ 0.021 \times \frac{Long - term\ Debt}{Book\ Value\ of\ Assets}$$
$$- 0.044 \times Natutal\ Log\ of\ Book\ Value\ of\ Assets$$
$$+ 0.102 \times Industry\ Sales\ Growth - 0.035 \times Sales\ Growth$$

Table A1: Variable definitions

Variables	Definitions
Political risk (PRisk)	Firm-level quarterly political risk developed by Hassan, Hollander, Lent, and Tahoun (2019). We scale *PRisk* by 100.
Distance-to-default (DTD)	Distance-to-default, calculated following Merton (1974) and Bharath and Shumway (2008).
Equity	Market value of equity (in millions of dollars) calculated as the product of the number of shares outstanding and stock price at the end of the quarter.
Debt	Face value of debt (in millions of dollars) computed as the sum of debt in current liabilities and one-half of long-term debt.
Income/Assets	Ratio of net income to total asset.
Excess return	Annual excess return, calculated as the difference between firm stock return and market return over the same period.
σ_E	Annualized stock return volatility computed as the standard deviation of monthly stock returns over the prior year.
Tobin's q	Market value of assets over book value of assets calculated using data from COMPUSTAT: (ATQ-CEQQ+CSHOQ×PRCCQ)/ATQ where ATQ is total asset, CEQQ is total common equity, CSHOQ is common shares outstanding, and PRCCQ is stock price at the end of the quarter.
Accuracy	Analysts' forecast accuracy is the negative of the absolute value of the consensus forecast error at time *t* scaled by the stock price at time *t*. $\text{Accuracy} = (-1)\frac{\lvert \text{Forecast}_{t-1}\text{-EPS}_t \rvert}{\text{PRICE}_t}$ where Forecast is the average of forecasts issued during fiscal months 4 to 6 (270 to 180 days prior to the fiscal year-end) for period *t* earnings. Price is the stock price at time *t*. Multiplying the absolute forecast error by (-1) gives a measure that increases with greater forecast accuracy.
Altman Z-score	Bankruptcy score of Altman (1968).
Whited-Wu financial constraints index	Financial constraints index of Whited and Wu (2006).
Institutional owners	Number of institutional owners.
Board size	The total number of directors on the board.
Female directors	The number of women directors on the board expressed as a percentage of total board size.
Board independence	The number of independent directors on the board expressed as a percentage of total board size.

Table A2: Distribution of distance-to-default by political risk groups.

The table reports the distribution of *DTD* across five groups of stocks formed on the political risk measure during the sample period between 2002 and 2019. For each quarter, stocks are assigned into one of the five groups based on their political risk measure. Group 1 consists of stocks with the lowest *PRisk*, and stocks in group 5 have the highest *PRisk*. For each group, we report the average *DTD*. Table A1 defines the variables. The High-Low row reports the average *DTD* difference between the highest and lowest political risk portfolio of stocks. Below in parentheses is the *t*-statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Political risk (*PRisk*) portfolios	Average *DTD*
Low	5.22
2	5.17
3	5.11
4	5.07
High	4.94
High-Low	-0.28^{***} [-5.98]

Table A3: Within-industry regressions.

The table reports the coefficients for the political risk measures from OLS regressions with *DTD* as the dependent variable for each of the Fama and French 10 industry classifications. We control for both firm and quarter fixed effects in all regressions. For brevity, we only report coefficients of *PRisk*. We use *Ln(Equity), Ln(Debt),* $1/\sigma_E$*, Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at the firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Industry	Description	*DTD*	N
NoDur	Consumer nondurables	-0.021 (0.445)	5,478
Durbl	Consumer durables	-0.062* (0.095)	3,517
Manuf	Manufacturing	-0.043*** (0.002)	16,535
Enrgy	Oil, gas, and coal extraction and products	-0.053** (0.022)	5,255
HiTec	Business equipment	-0.039*** (0.000)	17,195
Telcm	Telephone and television transmission	0.029 (0.188)	3,230
Shops	Wholesale, retail, and some services	-0.059*** (0.001)	13,379
Hlth	Healthcare, medical equipment, and drugs	-0.038*** (0.004)	10,421
Utils	Utilities	-0.001 (0.939)	4,316
Other	Other	-0.037*** (0.000)	14,456

Table A4: Political risk and distance-to-default controlling economic policy uncertainty.

The table presents ordinary least squares (OLS) regressions of default risk on firm-level political risk controlling for the economic policy uncertainty index of Baker *et al.* (2016). We use *Ln(Equity), Ln(Debt), 1/σ_E, Excess Return, Income/Assets, and Tobin's q* as control variables. Appendix A1 presents variable definitions. We cluster standard errors at the firm level and present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
PRisk	-0.022***	-0.009**
	(0.001)	(0.028)
EPU	-0.105***	-0.083***
	(0.001)	(0.006)
Ln(Equity)	0.735***	0.992***
	(0.000)	(0.000)
Ln(Debt)	-0.381***	-0.330***
	(0.000)	(0.000)
1/σ_E	0.206***	0.121***
	(0.000)	(0.000)
Excess return	-0.474***	-0.564***
	(0.000)	(0.000)
Income/Assets	6.359***	1.146***
	(0.000)	(0.000)
Tobin's q	0.298***	0.281***
	(0.000)	(0.000)
Intercept	-1.961***	-3.146***
	(0.000)	(0.000)
Observations	90,613	90,613
Adjusted R-squared	0.643	0.484
Industry effects	Yes	No
Year effects	Yes	Yes
Firm effects	No	Yes

Table A5: Difference in means between firms with and without lobbying expenditure.

The table reports sample means of political risk and their differences across firm-level political risk and its other dimensions. We divide our full sample based on whether a firm makes lobbying expenditures or not. The last column shows the difference in means. We present *p*-values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Firms with lobbying expenditure (N = 5,798)	Firms without lobbying expenditure (N = 62,657)	Difference
$PRisk$	1.078	1.004	0.074***
			(0.000)
$PRisk_{Economy}$	34.048	32.123	1.925***
			(0.035)
$PRisk_{Environment}$	40.448	35.421	5.026***
			(0.000)
$PRisk_{Health}$	36.098	31.418	4.680***
			(0.005)
$PRisk_{Security}$	35.830	30.123	5.707***
			(0.000)
$PRisk_{Tax}$	36.974	32.055	4.918***
			(0.000)
$PRisk_{Technology}$	24.345	23.588	0.757
			(0.361)
$PRisk_{Trade}$	27.774	23.939	3.835***
			(0.005)