Firm-level Political Risk and Bank Loan Contracting[*]

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Abstract

We investigate whether and how firm-level political risk affects firms' bank loan contracting. Firm-level political risk, measured by the share of earning call conversations with financial analysts that centers on risks associated with political topics, is positively associated with firms' loan cost. This impact is amplified for firms with higher degrees of information asymmetry and firms with more financial constraints. We also find that the firm-level political risk effect has a short-term persistent nature. Moreover, loan contracts for firms with higher firm-level political risk have significantly higher likelihood of collateral requirement and more covenant restrictions. Our results are robust to various model specifications.

Keywords: Firm-level political risk; Bank loan cost; Loan covenants

JEL Classification: G21, G32, P16, P26

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1. Introduction

Prior studies have shown that political uncertainty has a severe impact on real business activities. Both theoretical and empirical studies suggest that political uncertainty hampers firm investment (Julio and Yook, 2012, 2016; Gulen and Ion, 2015), lowers employment growth (Baker, Bloom, and Davis, 2016), and increases default risk (Pástor and Veronesi, 2012, 2013). These studies typically focus on aggregate political uncertainty. However, recent anecdotal evidence suggests that aggregate shocks do not fully capture a given firm's exposure to political events. For example, when president Trump tweeted that Lockheed Martin's F-35 program is too expensive, which immediately caused shares tumble. After the tweet, Lockheed Martin shares declined about 2% and shaved off $1.2 billion of its market value.[1] This is clearly an example of political risk being a firm-specific phenomenon, which leads to severe economic consequences for the firm. Moreover, firms' exposure and acquaintance of political events and risks are different, due to their specific business characteristics, different stages in the business life cycle, and diverse operating conditions in various industries. Thus, the assumption of homogenous exposure to political events is far from realistic when examining the effect of political risk or uncertainty on businesses.

A deeper investigation on firm-level exposure to political risk is highly in demand, but it has not been done until recently due to lack of a comprehensively validated political-risk measure. Hassan, Hollander, Lent, and Tahoun (2019) conduct a textual analysis of the quarterly earnings conference call transcripts of listed firms, and construct an index of firm-level political risk (hereafter $PRisk$) as the share of conversations with financial analysts that centers on risks

[1] President Trump tweeted on December 23, 2016 about Lockheed Martin as "The F-35 program and cost is out of control. Billions of dollars can and will be saved on military (and other) purchases after January 20th" (https://www.cnbc.com/2016/12/22/lockheed-martin-shares-take-another-tumble-after-trump-tweet.html).

associated with political matters in general, and with specific political topics.[2] In each earnings call conference, the more questions analysts ask on political topics in the Q&A session, or the more political speech managers give in the opening statement, the more likely this firm is exposed to political risk. Unlike the aggregate measures of political uncertainty, such as measures based on election data or the economic policy uncertainty (EPU) index constructed by Baker, Bloom, and Davis (2016), the $PRisk$ measure enables researchers to examine not only over-time variation, but also the cross-sectional variation in political risk. Indeed, the cross-sectional variation is the more relevant and important topic. Indeed, Hassan et al. (2019) stress that their measure has real economic content and that much of the economic impact of political risk is not well described by conventional models in which individual firms have relatively stable exposure to aggregate political risk. They show that the variation in aggregate political risk over time account for only 1% of the aggregate political risk, and in sharp contrast, firm-level political risk accounts for around 90% of the total variation.[3] Although Hassan et al. (2019) find that firm-level political risk has a significant effect on firms' investment activities, research on the impact of firm-level political risk on other corporate outcomes remains scarce, likely because the firm-level political risk measure has only become available recently.

This paper helps to fill this gap by considering how firm-level political risk affects financing activities. Financing is another important firm activity, and lenders respond to firm-level political risk by adjusting their lending activities in terms of loan costs and covenant restrictions. We use the political risk measure developed by Hassan et al. (2019), with a focus on firms' bank

[2] Hassan et al. (2019) stress that: "The vast majority of US listed firms hold regular earnings conference calls with their analysts and other interested parties, in which management gives its view on the firm's past and future performance and responds to questions from call participants."

[3] In the same vein, Akey and Lewellen (2017) use the loading on the EPU index to define a firm's policy sensitivity and find very fewer cases of persistent policy sensitivity across election cycles and industries.

loan contracting for several reasons. First, bank loans are the predominant sources of external financing. The bank loan market is much larger than the bond or equity market, in terms of both the total amount of financing and the total scope of borrowers (Drucker and Puri, 2008; Qian and Strahan, 2007; Bae and Goyal, 2009). Second, given the relatively complicated nature of firm-level political risk, it is reasonable to assume that many investors are unable to properly obtain or process information on political risk. In contrast, banks are much more centralized and sophisticated in assessing their clients. Banks can access private information and analyze particular situations of political risk when assessing a borrower's default risk. Also, loan contracting is multi-dimensional. It thus reflects the effects of firm-level political risk through a variety of explicit loan contract features (Dennis and Mullineaux, 2000; Dichev and Skinner, 2002; Huang et al., 2018). Both the direct costs (interest rates) and indirect costs (covenants, restrictions, and transaction fees) of bank loans can be investigated. Therefore, we feel that bank loans are an opportune setting to examine the effects of firm-level political risk.

Several studies offer predictions regarding the expected relation between firm-level political risk and bank loan costs. First, political risk can shape a firm's information environment, and firms facing greater firm-level political risk are expected to have higher levels of information risk (Kim et al., 2011; Bradley et al., 2016). Prior literature has shown that various externalities (such as a politician-shareholder's deteriorating health, sudden death and/or involvement in scandals) can lead to greater firm-level political risk (Faccio and Parsley, 2009; Fisman, 2001; Bradley et al., 2016). Moreover, political risk could form ambiguity about the possible political and legal interference with a firm's corporate decisions. Political risk could also create a possibility that managers/owners connected to politicians or lobbyists have privileged access to political information (e.g., strategic details of upcoming hearings, current policy positions, and potential amendments) and how they alter a company's prospect (Wellman, 2017).[4] Therefore, higher firm-specific political risk widens information asymmetry between managers and credit investors (Pástor and Veronesi, 2012, 2013). Firms facing radical changes in their political environments find that their value can be greatly affected by political risk, and in such situations, the loan market investors (i.e., banks) are less informative. Thus, information risk tends to increase with a firm's degree of exposure to political risk.

Borrowers facing greater information risk are charged higher loan spreads. Firm having more informative financial numbers suffer less information risk, because banks can evaluate borrower's risk profiles much easier and more accurately (Fama, 1985; Easley and O'Hara 2004). Prior studies suggest that higher information risk incurs more unfavorable loan terms. For example, Bharath et al. (2008) document that firms with lower accounting quality tend to pay more for bank loans, and they receive loans with shorter maturity. Graham et al. (2008) find that banks typically tighten loan contract terms after accounting restatements. Overall, these studies suggest that firms associated with higher firm-level political risk have higher information risk, leading to higher bank loan costs and stricter loan contracts.

Besides the information risk, higher firm-level political risk could also impact a firm's bank loan cost by increasing the firm's default risk. Hassan et al. (2019) find that firm-level political risk not only impedes a firm's investment activity and hiring but also distorts asset allocation, and thus threatening business continuity. As discussed earlier, possible political and legal interference with a firm's corporate decisions could also adversely affect investment opportunities, cash flows, and the value of collaterals. All of these increase the default risk. One example of this interference

[4] Privileged access to political information is made possible because members of Congress are legally permitted to selectively disclose such information to outside parties (Wright, 1990; Jerke, 2010; Ovtchinnikov et al., 2016).

could be modifying a firm's hiring and firing decisions in order to benefit incumbent politicians' re-election campaigns (Bertrand et al., 2018). Therefore, higher exposure to political risk and interference induce more volatile and asymmetric payoffs for firms. In periods of extremely negative performance, firms may be unable to fulfill their loan contract obligations. Thus, firm-level political risk increases a firm's exposure to default risk.

Moreover, a theoretical study by Freixas and Rochet (1997) indicates that when default risk is high, borrowers are less likely to serve their debt on time. Graham et al. (2008) and Bradley and Roberts (2015) provide empirical evidence that more profitable firms have lower default risk, and can therefore obtain loans at lower rates and with better terms. Hasan et al. (2012) also find a higher loan cost for firms with volatile earnings, which suggests that borrowers generally benefit from a stable stream of cash flows. As firms facing higher political risk are more likely to exhibit negative performance and experience more severe outcomes, they are more likely to default on their payments. To compensate for such increased default risk, banks tend to charge more for loans to such firms.

In summary, prior studies suggest that information risk and default risk are the two main channels through which firms facing greater firm-level political risk incur higher costs for loans. Using of a sample of 11,590 loan-level observations from 2002 to 2016, we find that firms facing higher firm-level political risk are charged higher loan spreads. Concerning the economic magnitude, a one-standard deviation increase in firm-level political risk leads to six basis-points increase in firms' bank loan cost. For a typical loan, this is equivalent to about US $1.4 million increase in total interest expenses. Thus, the documented effect of firm-level political risk is economically meaningful.

Our findings may not necessarily imply causality, because our results could reflect the effects of some omitted variables that drive both firm-level political risk and bank loan cost. Thus, endogeneity is a potential concern. To mitigate this concern, we apply a battery of sensitivity tests. First, our results are robust to the inclusion of industry and time fixed effects, which indicates that our findings are not driven by persistent industry-level characteristics or by unobservable time-invariant factors. Moreover, our findings are robust to controlling for loan type and purpose, and they still hold after excluding cases occurring during the 2007–2008 financial crisis. Therefore, neither the loan-level attributes nor the excess volatility during the recent financial crisis drives the observed impact of firm-level political risk on loan costs. We also alleviate concerns about potential confounding effects of other characteristics or omitted variables in a propensity score matching (PSM) framework. Although our results are not likely to suffer from the reverse causality issue, we also employ a lead-lag test, and show that only lagged firm-level political risk impacts the loan cost, but not the other way round. We also use the focal firm's political distance and neighbor firm's political risk as the instrumental variables for the focal firm's political risk. Both variables are positively related with focal firm's political risk in the first stage regression, and the predicted firm-level political risk is still positively related with firm's loan cost.

To shed further light on the information and default risk channels, we examine how the relation between firm-level political risk and loan costs varies in the cross section. This analysis not only provides insights on the channels through which the documented relation operates, but also strengthens identification, as this relation is unlikely to arise if our measure of firm-level political risk simply reflects unobserved economic forces. The positive effect of firm-level political risk on loan costs should be more pronounced in the presence of the factors that exacerbate the information and default risks. We assess the conditioning effect of two factors: information opacity and financial constraints. Prior work shows that opaque firms suffer from severe information risk, because they are "less known" in the syndicated loan market, lack enough monitoring by creditors, and thus incurring an adverse selection problem (Sufi, 2007; Dass and Massa, 2011). Moreover, financially constrained firms are more likely to default. Prior studies suggest that financial constraints impede a firm's flexibility to choose major investments and restrict their ability to tackle unexpected consequences brought by the macro event. (Fazzari, Hubbard, and Petersen, 1987; Whited and Wu, 2006). Accordingly, we expect the positive relation between firm-level political risk and loan costs to be stronger for opaque and financially constrained firms. The cross-sectional tests support our predictions. More importantly, these results strengthen support for the information and default risk views, as they are difficult to reconcile with alternative explanations.

In addition to the pricing terms or bank loan spreads, bank loan contracts also contain multi-dimensional information. Rajan and Winton (1995) suggest that to mitigate information risk, banks tend to monitor certain borrowers more vigilantly by demanding collateral or more extensive covenants. Graham et al. (2008) find that loan contracts made after restatement announcements tend to have significantly shorter maturity. Such contracts are more likely to require security and to impose more covenant restrictions. To facilitate monitoring and limit potential loss, banks tend to impose more customized contracts, which can feature both pricing and non-pricing terms (Gan (2007), Qian and Strahan (2007), Hasan et al. (2012), and Francis et al. (2014)). We thus predict that firm-level political risk has also real effects on a loan's non-pricing terms. We find that firms facing higher firm-level political risk are commonly subject to stricter restrictions and more covenants. Overall, our results support the intuition that firm-level political risk exerts an impact on a firm's terms of loan contracting.

Our paper contributes to the literature in several ways. First, the growing importance of political risk within a business context makes a strong case for research into whether a *firm-level* political risk is priced, specifically by lending institutions. Our study fills the gap and provides an initial evidence on the impact of firm-level political risk on firm's financing cost. This is contrast to prior studies in *aggregate* political risk literature (Bloom et al., 2007; Julio and Yook, 2012, 2016; Gulen and Ion, 2015; Çolak, Durnev, and Qian, 2017).[5] *Aggregate* political risk cannot reflect the variation in political risk that exists within-firm (over time), as well as the heterogeneity in political risk among firms. By investigating firm-specific political risk, we deepen and broaden our understanding of the effects that political risk can have on firms' operations.

Second, our paper contributes to the stream of research examining the firm-level determinants of loan contracting. Prior studies on cost of debt have mainly focused on default risk (Graham et al., 2008; Francis et al., 2012; Huang et al., 2018), and information asymmetry (Qian and Strahan, 2007; Bharath et al., 2008; Duarte et al., 2008), among other factors. Our study provides evidence that firm-specific political risk is an incrementally significant factor determining credit quality, above other loan- and firm-specific determinants known to affect the price and non-pricing terms of loan contracts.

Lastly, our study helps deepen our understanding of the nature of the firm-specific political risk. Hassan et al. (2019) argue that much of the economic impact of political risk is not well described by conventional models in which individual firms have relatively stable exposure to

[5] Our work in this area builds on the findings of a relevant paper. Francis et al. (2014) capture firm-level heterogeneity in response to political uncertainty by using the regression coefficient of the EPU index. They find a positive relation between the absolute coefficient and loan costs. In applying this approach, we realize that using the absolute value of the EPU coefficient might give questionable results, especially as the data used by Francis et al. include a large proportion of negative coefficients. Our paper uses a different approach in that we apply the firm-level political risk measure developed by Hassan et al. (2019), and we provide more plausible evidence of the effects of firm-level policy risk on loan contracting.

aggregate political risk. We find that firm-level political risk is relatively less persistent. Specifically, only the one-quarter lagged and two-quarter lagged firm-level political risk exerts impact on firm's borrowing cost. Thus, our results provide support for Hassan et al.'s (2019) argument that assuming a relatively stable exposure to aggregate political risk documented in prior literature may not be reasonable.

The rest of this paper proceeds as follows. Section 2 describes sample construction and descriptive statistics. Section 3 discusses empirical evidence linking firm-level political risk to borrowing costs. Session 4 presents results of identification strategies. Section 5 presents cross-sectional implications. Section 6 presents additional analyses. We conclude in Section 7.

2. Sample and data

2.1 The sample

Our data come from five main sources. We obtain our measure of firm-level political risk from Hassan's personal website.[6] We collect the bank loan data from the DealScan database, which is provided by the Loan Pricing Corporation (LPC). Our sample period covers 2002 to 2016, as the data relevant to firm-level political risk are available only for this period. Our firm financial information is obtained from Compustat, and our stock return information is from the CRSP. We also collect information on macroeconomic variables from the Federal Reserve Bank of St. Louis database (FRED). Consistent with prior research, we exclude financial firms (SIC codes 6000–6999) and utility industries (SIC codes 4900–4999) from our sample. We also exclude firms with missing data on firm-level political risk, missing loan pricing information, and missing financial information. Following common practice, we winsorize all of the variables (except for the dummy

[6] We thank Tarek Alexander Hassan's team for making the firm-level political risk measure available.

variables and dependent variables) at both the top and bottom 1-percentiles to mitigate the effects of outliers. Our final sample consists of 11,590 loan-level observations from 2002 to 2016.

2.2 Variables

2.2.1 Loan spreads

We use the DealScan database to obtain our bank loan information. The DealScan database covers comprehensive loan characteristics such as loan start dates, loan end dates, loan amounts, spreads, and maturities. Following the previous literature (Bharath et al., 2008; Graham et al., 2008; Kim et al., 2011), we include loans that are term loans, revolvers, and 364-day facilities, but we exclude non-fund-based facilities such as standby letters of credit, or very short-term bridge loans. To make the spreads comparable between loans, we restrict our sample to loans whose spreads are based on LIBOR. To link the loan data with the firm's accounting data, we use the link-table between LPC DealScan and Compustat, which has been provided by Professor Michael Roberts.[7] Following previous work (Chava et al., 2009; Sunder et al., 2014), we define loan spread as the natural logarithm of the all-in-spread drawn (AISD), and we denote this variable as $Log\ (Spread)$. The AISD includes the coupon spread over LIBOR on the drawn amount, plus the annual fee, which is denoted in basis points.

2.2.2 Firm-level political risk

Hassan et al. (2019) develop a novel firm-level measure of political risk from their texture analysis of the quarterly earnings conference call transcripts of U.S. corporations since 2002. First, these researchers distinguish political topics from non-political topics using the pattern-based

[7] See Chava and Roberts (2008) for further details.

sequence classification method. Specifically, they define lexical training libraries of "political" texts and "non-political" texts. The training library of political texts include an undergraduate political science textbook and texts from the political sections of newspapers. The training library for the non-political texts include an accounting textbook, texts from the non-political sections of newspapers, and transcripts of speeches on non-political topics.

Hassan et al. (2019) then use the adjacent two-word combination bigrams to represent the text classifications, and decompose the conference call transcripts into lists of bigrams. They next count the numbers of bigrams in conjunction with synonyms for "risk" or "uncertainty." Furthermore, they restrict the distance between the words surrounding a synonym for risk or uncertainty to within 10 words. Thus, the weighted number of occurrences of political bigrams, divided by the total number of bigrams, is defined as firm i's level of political risk, which is calculated as follows:

$$PRisk_{i,t} = \frac{\sum_{b}^{B_{it}} (1\ [b \epsilon P \backslash N] \times 1[\ |b-r| < 10] \times \frac{f_{b,P}}{B_P}}{B_{it}},$$

where $1\ [\ldots]$ is the indicator function; $P\backslash N$ is the set of bigrams contained in political texts; and r is the position of the nearest synonym of "risk" or "uncertainty." Also, $b = 1, \ldots, B_{it}$ is the number of bigrams contained in the transcript; $f_{b,P}$ is the frequency of bigram b in the political training library; and B_P is the total number of bigrams in the political training library. Overall, $PRisk_{i,t}$ captures the percentages of the conversations devoted to risks associated with political topics, adjusted by the total number of bigrams contained in the transcripts. Thus, a higher percentage measure of $PRisk_{i,t}$ implies a more severe degree of firm-level political risk.

2.2.3 Control variables

We select control variables based on Graham et al. (2008). For the firm-level control variables, we include the natural logarithm of firm's total assets ($Size$) to control for the lower information asymmetry and the lower loan costs of larger firms (Blackwell and Kidwell, 1988; Houston and James, 1996). We include firm profitability ($Profit$), because profitable firms have lower default risk and better reputations in the credit market, and can thus borrow at a lower cost (Diamond, 1991). We include total debt ratio (LEV), because firms with higher leverage ratios (all else being equal) have higher default risk, and thus we expect these firms to face higher costs for bank borrowing. (Faulkender and Petersen, 2005; Sufi, 2007).

In addition, we include firms' market-to-book ratios (M/B) to control for differences in firms' investment opportunities. All else being equal, a firm that is recognized as having better investment opportunities can obtain lower borrowing costs (Diamond, 1991). We also control for the tangibility of a firm's assets ($Tang$). As banks may recover tangible assets should the firm default, we expect firms with more tangible assets to have lower borrowing costs (Denis and Mihov, 2003). We include a firm's cash flow volatility (CF_Vol) to control for earnings risk relative to the firm's total debt commitments. We expect cash flow volatility to be positively correlated with the cost of debt (Bharath et al., 2008; Graham et al., 2008). We include Altman's (1968) Z-score (*Z-score*) to further control for default risk. A higher Z-score indicates better financial health, and thus lower default risk (Graham et al., 2008; Huang et al., 2018; Ma et al., 2018). Besides, we also control for stock return volatility (T_Vol), which captures the firm's overall risk. We expect that firms with higher overall risk pay higher loan borrowing costs (Bittlingmayer, 1998). All of the above-described variables are measured as of the fiscal year prior to each loan initiation date.

We further control for loan characteristics that might be correlated with loan pricing. We control for loan maturity ($Log\ (Mat)$), as lenders require a liquidity premium for longer-term debt, and this liquidity premium translates into a higher loan spread (Graham et al., 2008; Huang et al., 2018). We also include loan amount ($Log\ (Amt)$), which may capture economies of scale in bank lending, and thus we expect this variable to be negatively related to the loan rate. Alternatively, this same negative relation might occur if riskier borrowers are granted smaller loans with higher interest rates (Kim et al., 2011). We also consider a performance pricing provision in loan contracts ($Perf\_Provision$), to control for the possibility that lenders may price loans differently if they contain performance pricing clauses (Chava and Roberts, 2008; Roberts and Sufi, 2009). We also control for default risk ($Default\_Rate$), because banks require more compensation for increased default risk in times of economic downturn. Moreover, we control for the term spread ($Term\_Spread$). We expect the term spread to be positively related to loan spread (Graham et al., 2008; Huang et al., 2018).

2.3 Descriptive statistics

Panel A of Table 1 reports the annual distribution of loan amounts. During the sample period, the number of loan-taking firms per year ranges from 151 in 2002 to 639 in 2011. The number of loan issuances from 2002 to 2016 also shows dramatic shifts, ranging from 218 in 2002 to 1,011 in 2013.[8] The distribution of loans indicates some cyclicality in the number of bank loans issued over time. This finding is consistent with that of Becker and Ivashina (2014), who document that access to bank loans becomes more difficult during times of poor economic performance and tight monetary policy.

Panel B of Table 1 shows the sample distribution across different industries. As documented in Hassan et al. (2019), the distribution of $PRisk$ demonstrates some sector-level (SIC

[8] As the data on $PRisk_{i,t}$ start during 2002, any banks loans issue in 2002 Q1 are not included in the sample.

division) clustering. To illustrate this variation between industries, we calculate the mean $PRisk$ for each industry, as classified by the first two-digit SIC code. To save space, we only report the top 5 and bottom 5 $PRisk$ industries with at least 30 observations in our final sample. The *Engineering and Management Services* industry has the highest $PRisk$, with a mean of 0.90. In contrast, the *Food Stores* industry has the lowest rank, with 0.25 $PRisk$. Moreover, Firms in top 5 $PRisk$ industry have an average loan spread of 232 bps, which is about 43 bps higher than that for the bottom 5 $PRisk$ industry. This provides the first intuitive evidence that higher $PRisk$ firms are associated with a higher loan cost.

[Insert Table 1 here]

Panel A of Table 2 presents the summary statistics on the variables. The sample includes 11,590 loan issuances during the sample period. The mean (median) $PRisk$ is 0.47 (0.24), with a wide range: between 0.07 at the 25th percentile to 0.53 at the 75th percentile. Concerning loan characteristics, the average interest spread is 211 bps above LIBOR. Moreover, a typical (i.e., average) loan issuance has an amount of US $520 million and a maturity of 4.47 years. In terms of the fundamental characteristics, the profitability of the average loan borrower is 0.14 with a cash flow volatility of 0.1. These descriptive characteristics are comparable with prior literature (Bharath et al., 2008; Graham et al., 2008; Kim et al., 2011).

Panel B of Table 2 shows the correlation matrix of the different variables. The results suggest that $Log(Spread)$ is positively correlated with $PRisk$. Furthermore, many firm characteristics such as large firms, profitable firms, firms associated with more investment opportunities, and firms with higher Z-scores show lower private debt costs, which is consistent with prior studies (Graham et al., 2008; Kim et al., 2011; Huang et al., 2018).

[Insert Table 2 here]

3. Empirical findings

3.1 Regression analysis

Loan pricing is the most critical contract term in a loan contract. We investigate the impact of a firm's exposure to political risk on the loan cost by using the following regression model:

$$Log(Spread_{t+1}) = \alpha + \beta_1 \times PRisk_{i,t} + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}, \tag{1}$$

where i denotes the firm and t the time; $X_{i,t}$ contains the sets of control variables. We estimate the above regression model using ordinary least squares (OLS). The t-statistics are computed by using standard errors that are robust to heteroscedasticity and clustered at the firm level. Prior studies suggest that business loans are classified into different categories. Furthermore, borrowers may take out loans for various usages, such as corporate initiatives, debt repayments, working capital, and takeovers (Graham et al., 2008; Huang et al., 2018). As various types and purposes of loans are associated with different levels of risk, these loans may be priced differently. To address this issue, we estimate our model regressions by incorporating a loan type fixed effect and a loan purpose fixed effect. In addition, we use the 2-digit SIC codes to control for potential differences in firm-level political risk and loan prices across industries. This analysis alleviates the concern that the loan cost is driven by unobserved industrial characteristics. Furthermore, we take account of the unobserved time invariant characteristics, and include the quarter fixed effect.

Table 3 reports the empirical results with different model specifications. Column (1) presents the estimates of the loan cost by incorporating only the firm-level control variables. The coefficient of $PRisk$ is significantly positive on loan spreads at the 1% significance level (coefficient = 0.036; t-statistic = 3.43), which suggests that firms with higher $PRisk$ are, on average, charged higher interest rates. Economically, a one-standard deviation increase in firm-level political risk leads to a six bps increase in a firm's bank loan cost. For a typical loan, this cost is equivalent to US $1.4 million increase in total interest expense. Thus, the documented effect of firm-level political risk is economically meaningful. Moreover, this estimation of the coefficient of $PRisk$ is conservative, because firms with extremely high $PRisk$ may delay their financing activities to mitigate the expensive financing costs.

Table 3 column (2) includes both firm-level and loan-level control variables, such as loan amount ($Log\ (Amt)$), loan maturity ($Log\ (Mat)$), and performance provision ($Perf\_Provision$). We also observe a positive relation between $PRisk$ and $Log(Spread)$. Column (3) is our *Baseline Model*. After controlling for loan-, firm-, macro-level control variables and different fixed effects, $PRisk$ *is still* positively related with $Log(Spread)$ at the 1% significance level (coefficient = 0.022; *t*-statistic = 2.77). As none of the fixed effects have a discernable impact on our findings, this analysis mitigates the concern that our findings represent spurious results from omitted, correlated variables. Collectively, the results shown in Table 3 provide evidence that banks do indeed charge different prices for credit to firms with different degrees of firm-level political risk. Firms associated with greater firm-level political risk are charged higher loan spreads.

In addition to the key explanatory variables, the coefficients of the control variables in the regression are also significant, and consistent with the findings in prior literature (Graham et al., 2008; Kim et al., 2011; Huang et al., 2018). For example, loan spreads are negatively associated with firm size (coefficient = -0.059; *t*-statistic = -6.89), profitability (coefficient = -0.791; *t*-statistic = -6.85), and the inverse measure of financial distress (Z-score) (coefficient = -0.031; *t*-statistic = -9.27). Loan spreads are positively associated with maturity (coefficient = 0.063; *t*-statistic = 3.25), and return volatility (coefficient = 10.311; *t*-statistic = 13.74).

[Insert Table 3 here]

3.2 Robustness checks

To assess the robustness of our main findings, we conduct several sensitivity tests and present the results in Table 4. First, there is a concern that our sample period includes the recent financial crisis period. As the financing behavior of firms may have been unusual during this crisis period, we exclude the years 2007–2008 from the full sample. Column (1) shows that the coefficient of $PRisk$ remains at the same magnitude with similar significance (coefficient = 0.022; t-statistics = 2.75), suggesting that the financial crisis period has no substantial effect on our findings.

Second, in the baseline analysis, we apply the 2-digit SIC code to control for the industry fixed effect. To further test how our results are sensitive to the unobserved industry factors, we control for the industry fixed effect by using the 4-digit SIC code. Column (2) indicates that the effect of $PRisk$ on $Log(Spread)$ is still significant after controlling for the 4-digit SIC code (coefficient = 0.023; t-statistic = 2.81). Thus, our results are robust under different industry fixed effect.

Next, we test whether our result is driven by the standardized process of firm-level political risk. Following Hassan et al. (2019), we use the standardized firm-level political risk as the key variable in previous tests. If the borrowers with higher firm-level political risk would be charged more debt cost, the empirical evidence should not suffer too much when using the raw measure. In column (3) we use the raw firm-level political risk measure to conduct the analysis and still find a significant relation.[9] Thus, the variable standardization does not affect the main result.

Lastly, we examine the sensitivity of our results to alternative measures of loan spread. To alleviate the concern that our findings are driven by the distributions of loan interest, we follow

[9] To facilitate the comparison on the effect of firm-level political risk among different tests, we divide the raw measure of firm-level political risk over 100.

Francis et al. (2014), and use the loan spread instead of the natural logarithm of loan spread to re-examine the relation between firm-level political risk and credit costs. Table 4 column (4) shows that the coefficient of $PRisk$ on the raw loan spread (rather than the natural logarithm) is statistically significant (coefficient = 4.318; t-statistic = 2.43). Thus, the results suggest that our main findings are robust to alternative measures of loan costs.

[Insert Table 4 here]

4. Identification issues

In the previous analysis, we have shown the robust positive relation between firm-level political risk and loan cost. We further deal with identification issues to establish the causality. We address three aspects of possible endogeneity issues: omitted variables, confounding effects, and reverse causality. Our results hold after incorporating more control variables or using a propensity score matching sub-sample. To further alleviate the reverse causality concern, we first use an instrumental variable and conduct the two-stage OLS regression. Then through a lead-lag time test, we find that only lagged firm-level political risk could predict future loan spreads, and not the other direction. These findings help us establish the causal relation between firm-level political risk and firm's borrowing costs.

4.1 Additional control variables

To rule out the potential omitted variables concern, we include additional control variables in Equation (1). First, prior studies find that aggregate political uncertainty generally affects a firm's financing decisions.[10] It might be that the aggregate political uncertainty affect the firm-

[10] See for example, Bradley et al., 2016; Francis et al., 2014; Waisman, Ye, and Zhu, 2015; Çolak, Durnev, and Qian, 2017).

level political risk and the loan spread at the same time. So we control for the impact of aggregate political uncertainty (PU_a), and present the finding in Table 5 column (1).[11] We find that $PRisk$ positively and significantly affects the borrowing cost after controlling for PU_a. Because our model includes the quarter fixed effect, most of the impact from PU_a is subsumed into the time fixed effect, which explains the insignificant coefficient on the EPU index.

Second, the firm-specific political risk measure only captures the number of positive bigrams and negative bigrams, but ignores the direction, which is a kind of second moment measure. Hassan et al. (2019) also address this issue and construct a measure of political sentiment by incorporating directions of the political bigrams. Following them, we include the political sentiment in our model specification. Table 5 column (2) indicates that the political sentiment does not affect the impact of $PRisk$ on loan spreads. We continue to find a significantly positive relation between $PRisk$ and loan spreads (coefficient = 0.021; t-statistics = 2.68). We also find a negative relation between political sentiment and loan costs (coefficient = -0.011; t-statistics = -1.74).

Third, macroeconomic conditions can also affect loan pricing. We therefore include additional variables to control for macroeconomic cycles. Following Belo et al. (2013), we include the inflation rate ($Inflation$), the industrial production rate ($Production$), and a recession dummy ($Recession$) in our model. We measure the macroeconomic factors one month before the loan initiation date. Detailed definitions of all above variables are shown in the Appendix. Column (3) shows the result. The coefficient on $PRisk$ remains positive and significant at the 1% level. In column (4), we add all additional control variables in Equation (1) and find that $PRisk$ is positively

[11] We thank Baker, Bloom, and Davis for making the EPU index available at http://www.policyuncertainty.com/. To make the coefficients comparable, PU_a is measured as the EPU index divided by 100.

and significantly associated with the borrowing cost, which helps mitigate the omitted variables concern.

[Insert Table 5 here]

4.2 Propensity score matching approach

To discern the impact of firm-level political risk, it is most appropriate to compare firms that have different degrees of firm-level political risk but are as similar as possible in terms of their other characteristics. In this subsection we present an alternative to the standard multivariate regression approach. We apply propensity score matching (PSM), which is specifically designed to create a platform for comparison of firms that are facing high and low degrees of firm-level political risk, but are similar in their other features. In particular, we first define $DPRisk$ as an indicator that equals one if a firm's $PRisk$ falls in the top 5% at that quarter (treatment group), and zero if a firm's $PRisk$ falls in the bottom 30% (control group). To find matching firms for the treatment group, we then run logit regression of $DPRisk$ on all variables. As there are no sound predictors of firm-level political risk, we include all firm-related characteristics in the first-step logit regression. The fitted value of $DPRisk$ captures the probability (i.e., propensity score) of being in the treatment group. We then select a matching sample for each treatment sample based on the closest estimated probability (without replacement). We also require the matching sample to come from the same 2-digit SIC industry and same quarter. After applying the above-described PSM process, we obtain a matched sample of 800 loan facilities, consisting of 400 facilities for borrowing firms in the treatment group, and 400 facilities for borrowing firms in the control group.

Table 6 reports the estimated results using the PSM sample. The coefficient for $PRisk$ in the PSM sample is 0.098 (t-statistic = 2.64), indicating that the loan spread of the treatment group is about 9.8% higher than the matched sample. Using a typical loan spread of 211 bps, the loan spread difference in the treatment group and matched group is about 21 bps. Overall, the positive relation between firm-level political risk and bank loan cost is not likely to be driven by potential omitted variable or unobservable confounding effects.

[Insert Table 6 here]

4.3 Instrumental variable regression

We next address the reverse causality concern. Although our results are less likely to suffer from the reverse causality problem, there might exist some unknown mechanisms for which higher borrowing cost will increase the firm-level political risk. We use two instrument variables to mitigate this concern: the firm's political distance and its neighbor firm's political risk.

We define firm's political distance as the geographic distance between firm's headquarter and its corresponding state capital city. Ades and Glaeser (1995) state that political instability and lack of democracy give households in the capital city obtain more political information than households in other regions. Besides, Kerr et al. (2014), faraway firms are less likely to initiate lobbying (one kind of political actions), because of the lower lobbying return than firms near political capital. Based on the insights from prior studies, we propose the distance between the firms' headquarters and the capitals in their states ($Political\_distance$) as the instrumental variable. When the firm's headquarter is far away the state capitals, it is more difficult for them to communicate and access information from policymakers. Remote firms are exposed more to the political uncertainty because of not only the direct consequence of policy change but also lacking channels to mitigate the untended consequences. Thus, managers in such firms would be asked more questions on firms' action to alleviate the adverse political influence during the earnings conference, implying a higher firm-level political risk. So our instrument satisfies the relevance criterion based on the intuition. Moreover, no literature documents political distance impacts on firm's loan cost, and thus the instrument satisfies the exclusion criterion.

Since firms are less likely to relocate their headquarters, one concern is that our instrument variable captures the cross-section variation in various states only. We address this concern by introducing our second instrument variables $PRisk\_nei$. On one hand, firm headquartered in the same state are shocked by the local policy and exposed to similar level of political risk with their neighbors. Mizruchi (1989) documents that the geographical proximity between two firms in terms of corporate headquarters and plant locations leads to the similarity of political behavior. Pirinsky and Wang (2010) find that when operating in an uncertain environment, managers would look to their peers for ideas about appropriate strategies. Thus, the firm's political risk should be highly correlated with its neighbor firm's political risk. While we do not see any reason that the neighbor firm's political risk could affect the focal firm's bank loan cost.

We construct two instruments as follows. Following Alam et al. (2014), we construct *Political_distance* using zip codes to measure the geographic distance between a firm's headquarters and the state capital. A higher value of the *Political_distance* instrument indicates that the borrower is exposed to higher $PRisk$. To construct the $PRisk\_nei$ instrument, we first select each borrowing firm's neighbors based on the headquarters in the same state one quarter before borrowing. We then extract the neighbor's firm level political risks and calculate the average of them. This variable is used as our second instrument. The higher neighbors' political risks, the higher firm-level political risk the borrower has.

The results of two-stage OLS regression using the instrumental variable are reported in Table 7. In the first stage, we regress $PRisk$ on $Political\_distance$ and $PRisk\_nei$ (i.e., the instruments), as well as all other control variables in the second stage. The column (1) presents the results of the first stage regression, with $PRisk$ as dependent variable. The results show that both instruments $Political\_distance$ and $PRisk\_nei$ are positively and significantly associated with $PRisk$. In the second stage, we repeat our baseline analysis but replace the variable of interest with instrumented $PRisk$. Columns (2) reports that the coefficient of instrumented $PRisk$ still significantly positive in the loan spread regression at 5% level (coefficient=0.205, t-statistic=2.17). Therefore, the instrumental variable estimation confirms the causal effect of firm-level political uncertainty on firm's loan cost, suggesting that a higher firm-level political risk increases firm's cost to borrow loan from banks.

[Insert Table 7 here]

4.4 Lead-lag placebo tests

Then we address the reverse causality issue using placebo test. If our main results suffer from reverse causality issue, statistically, we should observe a significant relation between the lagged loan cost and lead firm-level political risk. To examine this concern, we conduct a lead-lag test. We present the results in Table 8. We consider a loan contract in quarter t+1, and the depended variable is the $Log(Spread)_{i,t+1}$. Column (4) presents the benchmark one-quarter lagged $PRisk$ for comparison. The columns (5) to (7) serve as placebo tests, where we model borrowing costs at quarter t+1 as a function of future (columns (6) and (7)) exposures of firm-level political risk. These regressions provide falsification to a causal relation between $PRisk$ and loan spread: the risk that has not yet been exposed cannot be evaluated from lenders. We observe that none of columns (5) to (7) shows a statistically significant coefficient, and the magnitudes are much smaller than that observed in the column (4). This evidence provides support for a causal interpretation: lenders evaluate and respond to the political risk that firms are exposed to, while it is impossible to respond to a political event which has not yet been exposed.

Besides the falsification test, we also find some interesting results on the persistence of the firm-level political risk. In the first three columns of Table 8, we use the four, three and two-periods lagged firm-level political risk as the explanatory variable. The results show that the one-quarter lagged and two-quarter lagged firm-level political risks exert significant impacts on firm's bank loan costs, while much earlier firm-level political risk (columns (1) and (2)) has no significant influence. This finding suggests that the effect of the firm-level political risk has a short-term persistence (two quarters in our results).

[Insert Table 8 here]

To further explore whether there is a persistent nature of firm-level political risk, we conduct additional tests. If the firm-level political risk is persistent, the average value over a longer horizon should cancel out the noise component in the empirical measure and reflect nature more closely. Empirically, we construct the one-year average and five-year average firm-level political risk, and test whether these two measures could better predict the loan spread. Given that we find only that the one-quarter lagged and two-quarter lagged firm-level political risks are significant in Table 9, we construct four different average firm-level political risk measures. $PRisk\_1yr1$ is the one-year average firm-level political risk preceding the loan issuance. $PRisk\_1yr2$ is an alternative one-year average firm-level political risk preceding the loan issuance, but we keep a two-quarter window, so the one-quarter lagged and two-quarter lagged firm-level political risks are not included. $PRisk\_5yr1$ and $PRisk\_5yr2$ are constructed analogously but with the five-year averages. If the persistent component of firm-level political risk predicts loan cost well, we should get the similar result using different constructions. We conduct the regression test using the same regression model as in Equation (1).

Table 9 reports the results of persistence analysis. The first two columns indicate that the result of the one-year averaged $PRisk$ and the last two columns show the impact the five-year averaged $PRisk$. Comparing columns (1) and (3), we find that although the coefficient on $PRisk\_5yr1$ is larger than the one-year averaged version $PRisk\_1yr1$, the economic magnitude is almost the same. A one-standard-deviation increase in $PRisk\_5yr1$ leads to a four-bps increase in the loan cost. Meanwhile, the corresponding magnitude for $PRisk\_1yr1$ is 3.5 bps.[12] These magnitudes remain largely the same as that in Table 3 using one-quarter $PRisk$ preceding the loan issuance, which indicates that using a long-horizon averaged firm-level political risk does not improve the results. Besides, when using the alternative five-year average skipping a two-quarter window, we find that the significance and magnitude of the firm-level political risk coefficient decreases dramatically, even smaller than those of the one-year average effect. The evidence suggests that the loan pricing is mainly affected by $PRisk$ of the recent two quarters, which is in line with the economic intuition that the credit market is efficient. Investors in credit market utilize the most recent information to evaluate and price the borrower's political risk exposure.

[Insert Table 9 here]

5. Cross-sectional analysis

The results described in the prior section show that on average, firms associated with higher degrees of firm-level political risk are charged higher interest rates on loans. We interpret this

[12] The standard deviations of $PRisk\_5yr1$, $PRisk\_5yr2$, $PRisk\_1yr1$, and $PRisk\_1yr2$ are 0.529, 0.460, 0.615 and 0.537, respectively.

positive relation as resulting from an increase in information risk and/or default risk caused by $PRisk$. In this section, we test the validity of our interpretation by investigating the cross-sectional differences in the impact of firm-level political risk on bank loan costs. In particular, we want to check the prediction that the positive relation between a particular firm's exposure to political risk and its price of bank loan is accentuated in the presence of factors that increase the volatility of accounting numbers, and factors that heighten downside risk. Based on insights from prior studies, we consider the following factors: (1) financial information opacity and (2) the degree of financial constraints. We develop and test our conjectures regarding the moderating effects of each of these two factors on the relation between $PRisk$ and loan cost.

5.1 The role of financial information opacity

Banks assess loan borrowers' financial health based on their financial statements (Watts and Zimmerman, 1990; Chaney et al., 2011). We expect that for opaque firm financial information, banks will ask for more compensation from borrowers that are exposed to greater firm-level political risk. Specifically, a firm's financial numbers in an opaque environment could lack of credibility. Banks are more likely to impose unfavorable terms on firms with less predictable accounting numbers (Fama, 1985; Easley and O'Hara, 2004; Hassan, Park, and Wu, 2012). When considering also greater firm-level political risk in such environment, financial reports could become more volatile and less precise to predict the firms' future performance, and thus are charged more by banks. Therefore, we predict that the documented effect of firm-level political risk on loan costs will be stronger in firms with more opaque financial information.

Following prior research (Francis et al., 2005; Livingston and Zhou, 2011; Haggard, Howe, and Lynch, 2015; Jiang et al., 2016; Ma et al., 2018), we consider three measures of a firm's financial information opacity. Our first measure is firm size, which is measured as the natural logarithm of each firm's total assets. Larger firms, on average, are less subject to information opacity (Blackwell and Kidwell, 1988; Houston and James, 1996; Ma et al., 2019). The second proxy for firm's information environment is tangibility ($Tang$). Tangible assets are easier to collateralize. Moreover, tangible assets reduce the likelihood for shareholders to substitute high risk assets for low risk ones, which decrease the information asymmetry. Higher tangibility is therefore expected to result in lower borrowing costs (Denis and Mihov, 2003; Bae and Goyal, 2009). Our third measure is the level of analyst coverage ($AnalystCov$), which is an important characteristic of a firm's information environment (Das et al., 1998; Frankel and Li, 2004; Piotroski and Roulstone, 2004). Das et al. (2008) find that firms covered by more analysts have better information environment. That is, the greater the analyst following a borrower, the less opaque its financial information tends to be. To examine the impact of financial information opacity on the $PRisk$-loan cost relation, we modify our baseline regressions by including the interaction term between $PRisk$ and each of the three information opacity measures discussed above.

Table 10 presents the results for the three measures in columns (1) to (3), respectively. The coefficient on the interaction term $PRisk \times Size$ exhibits a negative and significant coefficient (coefficient = -0.011; t-statistic = -2.13), which suggests that the impact of firm-level political risk on loan cost is accentuated for smaller firms. The coefficient on the interaction term $PRisk \times Tang$ is positive and significant (coefficient = -0.050; t-statistic = -2.13), suggesting the $PRisk$-loan cost relation is weaker among firms with more tangible assets. Furthermore, the coefficient on the interaction term $PRisk \times AnalystCov$ is negative and significant, which indicates that analyst coverage helps to reduce additional borrowing costs due to higher $PRisk$. Collectively, these results support the notion that the impact of firm-level political risk is amplified (mitigated) for firms with more (less) opaque financial information. These cross-sectional investigations provide additional support for our baseline results.

[Insert Table 10 here]

5.2 The role of financial constraints

Financial constraints are market frictions that may prevent a firm from funding all of its desired investment (i.e., positive net present value). This inability to obtain capital may be "due to credit constraints or inability to borrow, inability to issue equity, dependence on bank loans, or illiquidity of assets" (Lamont et al., 2001). Prior literature finds that financial constraints directly affect a firm's ability to undertake major investment decisions and capital structure choices (Hennessy and Whited, 2007). When firms with financial constraints also have high firm-level political risk, then the possibility that they will delay or even give up profitable projects increases dramatically. Thus, banks are more likely to charge high interest to such loan seekers. In other words, we expect a firm's financial constraints to accentuate the relation between $PRisk$ and loan interest rates.

To examine this, we follow prior literature and consider several measures of financial constraints (Rajan and Zingales, 1998; Khwaja and Mian, 2005; Duchin et al., 2010). Our first measure is the external financing dependency (Exf). In general, when a firm is highly dependent on external financing, the cost of external financing increases and the firm's growth will be hindered (Duchin et al., 2010). The second measure is cash flow volatility (CF_Vol). Higher cash flow volatility shows a larger degree of uncertainty regarding firm's future performance, and higher likelihood to default on loans (Bharath et al., 2008; Graham et al., 2008; Ma et al., 2019). Hadlock and Pierce (2010) use size and age of firms to estimate firm financial constraints, and construct the Hadlock and Pierce index (HP_Index). This index serves as our last measure, with a higher score indicating a higher degree of financial constraint (Chang et al., 2014). We provide the detailed construction of these measures in the Appendix. To examine the impact of financial constraints on the $PRisk$-loan spread relation, we modify our baseline regressions to include the interaction term between $PRisk$ and each of the three above-discussed measures of firms' financial constraints.

Table 11 presents the results, with the first three columns showing the results for the three above-described measures. First, the coefficient on the interaction term $PRisk \times Exf$ is positively significant, which indicates that the effect of firm-level political risk is more pronounced for firms that are highly dependent on external financing. The coefficient on the interaction term $PRisk \times CF\_Vol$ is also positive and significant at the 1% level, which indicates that the influence of firm-level political risk on a firm's loan cost is exacerbated for firms with greater uncertainty about their future performance. Lastly, we observe a positively significant coefficient on the interaction term $PRisk \times HP\_Index$, suggesting that creditors charge a higher cost when borrowers exhibit large political risk, especially when the borrowers suffer from greater financial constraints. Overall, these results support our notion that the impact of firm-level political risk on loan interest rates is more pronounced (mitigated) in firms with greater (lesser) financial constraints. The cross-sectional findings echo those results presented in the previous section.

[Insert Table 11 here]

6. Additional analyses

In addition to their pricing terms or loan spreads, bank loan contracts contain multi-dimensional information on the risks affecting borrowers (Dennis et al., 2000; Graham et al., 2008; Huang et al., 2018). Rajan and Winton (1995) suggest that banks seek to mitigate information risk by monitoring certain borrowers more vigilantly, which commonly involves demanding more collateral and more covenants. Prior studies (Gan, 2007; Qian and Strahan, 2007; Li, 2010; Francis et al., 2013) have documented that banks tend to set more customized contracts, which may involve both pricing and non-pricing terms, to facilitate monitoring and limit potential loss. We measure the relation between covenant restrictions and firm-specific political uncertainty by using the following regression:

$$Restrictions_{i,t+1} = \alpha + \beta_1 \times PRisk_{i,t} + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}, \quad (2)$$

where the dependent variable $Restrictions$ represents the various restrictive covenants used in the loan contracts. In this analysis, all of the firm-, loan- and macro-level control variables are the same as those in Equation (1).

6.1 Number of loan covenants

To test the effect of $PRisk$ on the intensity of restrictive covenants, we manually count the number of financial and general covenants included in each loan deal. Consistent with Bradley and Roberts (2015) and Kim et al. (2011), we find 30 different covenants in the DealScan database, including 18 kinds of financial covenant and 12 kinds of general covenant. We construct three covenant variables. $TotCovIndex$ represents the total number of loan covenants (including both financial covenants and general covenants) that are required for bank loan issuance. $GenCovIndex$ represents the number of general covenants, which are related to restrictions on prepayments, dividends, voting rights, or other business activities. $FinCovIndex$ represents the number of financial covenants. Following prior literature (Graham et al., 2008; Huang et al., 2018), we conduct an OLS regression on the number of loan covenants. As in our previous analyses, we expect that $PRisk$ has a positive relation with loan contracting restrictions. That is, higher $PRisk$ leads to more total, general, and financial covenants.

Table 12 presents the findings regarding covenant restrictions in loan contracts. Column 1 shows that $PRisk$ is positively related to the number of total covenants at a the 1% significance level (coefficient = 0.121; t-statistic = 3.30), which indicates that high $PRisk$ firms are subjected to tighter contracts, in terms of the total number of covenants. The other two columns show that not only the number of total covenants but also general covenants and financial covenants impose greater contract tightness to firms with higher exposure to political risk. Overall, Table11 supports the notion that borrowers with higher $PRisk$ are subjected to more total, general, and financial covenants.

6.2 Strength of loan restrictions

Loan tightness is reflected not only from the increasing number of covenants, but also from more contract strength. Graham et al. (2008) state that loan contracts after restatement announcements have significantly higher likelihood of charging secure and more transaction fees due to the increasing complexity and riskiness of the bank loans. Next we examine how $PRisk$ affects the strength of tightness requirements, including the collateral requirement, debt issuance sweep restriction, and transaction fees.

We conduct the regressions based on Equation (2) with alternative dependent variables. First, we consider two specific requirements. We define $DDebt$ as an indicator variable that equals one if the loan facility has a debt issuance sweep restriction, and zero otherwise. $DSecured$ is an indicator variable that equals one if the loan facility is secured with collateral, and zero otherwise. $Annual\_fee$ is defined as the annual charge against the entire loan commitment amount, whether it is used or unused. This kind of fee is also called a facility fee. Following prior literature (e.g. Graham et al. (2008), Huang et al. (2018)), we conduct the Probit regressions for indicator variables and OLS regression for annual fee.[13] The last three columns of Table 12 presents the results. We observe that $PRisk$ is positively and significantly associated with each of the three measures of restrictions. Therefore, lenders are more likely to impose collateral requirement and debt issuance sweep restriction, and charge higher annual fees to compensate for increased firm-level political risk.

[Insert Table 12 Here]

6.3 *Topic-specific political risk*

Till now, we have comprehensively examined how firm-specific political risk affects the borrowing cost. Hassan et al. (2019) find that firms lobby more on political topics they are most concerned about. One may be concerned that creditors evaluate the risks associated with these specific political topics, rather than politics in general. To examine this, we test the effect of eight political topics, such as economic policy & budget, environment, trade, institutions & political process, health care, security & defense, tax policy, and technology & infrastructure. We regress the loan financing cost using Equation (1) by replacing $PRisk$ with topic-specific political risk. We use suffix of $PRisk$ to indicate the specific topic. For example, $PRisk\_env$ is standardized firm-level political risk corresponding to environment topic. The detailed definitions of other topic-specific political risk are provided in the Appendix. To ease the interpretation, we follow Hassan et al. (2019) and use the standardized topic-specific political risk.

We present the results in Table 13. We find that banks consider $PRisk$ on some individual topics to evaluate borrower's profile. Firms' loan cost is positively associated with the political risks associate with institutions & political process topic, security & defense topic, and

[13] Due to limited data availability, our regressions of annual fees are based on only 1,935 observations for annual fees. The number of observations involving such fees accounts for 17% of the full sample, which is consistent with the 19% in Graham et al. (2008).

environment topic. Thus, our result suggests that topic-specific political risk also draw attention from investors in the credit market, especially institutions, security, and environment topics.

[Insert Table 13 Here]

7. Conclusions

Political uncertainty has attracted a great deal of academic attention, especially since the 2008 financial crisis. When facing extreme policy changes or political revolutions, firms are influenced in diverse ways and can react quite differently. However, except for the study by Hassan, Hollander, Lent, and Tahoun (2019), most academic papers have only considered the effects of political uncertainty at the aggregate level, or its general effects on the whole market. In this paper, we conduct an empirical investigation of the relation between firm-level political risk and bank loan contracting. Specifically, we explore the effects of firm-level political risk on bank loan costs and other non-price-related loan terms. On the basis of insights from prior research, we predict that firms facing greater firm-level political risk will be subjected to more unfavorable pricing and non-pricing terms.

Using a large sample of U.S. firms spanning the 2002–2016 period, we find that firms with greater firm-level political risk are charged higher loan spreads. The positive relation is significant at the 1% level, after controlling for other determinants of loan costs. The documented effect is robust and economically meaningful. Moreover, we conduct further tests to determine how firm-level political risk influences loan costs. We find that the impact of firm-level political risk is amplified for firms with high information opacity, such as smaller firms, firms with less tangible assets, and lower analyst following. In addition, the relation between firm-level political risk and the cost of credit is more pronounced for firms facing greater financial constraints. In addition to affecting the cost of loan, we also find that firms with greater firm-level political risk are subjected to tighter terms, i.e., more covenants, more requirements to provide collateral, and higher transaction fees. In summary, our evidence supports the notion that banks indeed distinguish between loan seekers, and ask for more compensation from firms facing greater firm-level political risk.

Prior studies have also considered firm profitability, credit quality, investment opportunity, information disclosure, corporate misreporting, and ownership structure as the determinants of bank loan contracting (Qian and Strahan, 2007; Bharath et al., 2008; Graham et al., 2008; Li, 2010; Francis et al., 2012; Hasan et al., 2012; Huang et al., 2018). In addition, a rapidly growing stream of research has examined the importance of macroeconomic characteristics such as GDP growth, financial crises, and business cycles (Peek and Rosengren, 2000; Leary, 2009; Ivashina and Scharfstein, 2010; Chava and Purnanandam, 2011). However, little attention has been given to the effects of firm-level political risk on bank loan contracting.

We examine this special firm-level characteristic by connecting the measures of particular firms' balance sheets and income statement with the measures of large macroeconomic characteristics. By examining the effects of firm-level political risk on the terms of bank loans, we distinguish between the effects of aggregate, sector-level, and firm-level uncertainties. To the best of our knowledge, our paper is the first to address this important gap in the literature.

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Appendix: Variable definition

Variable	Definition and description	Source
$PRisk$	Firm i's political uncertainty measure at time t, which is standardized by its standard deviation.	Hassan et al. (2019)
Loan variables		
$Log\ (Spread)$	Natural logarithm of loan spread (over LIBOR) for each individual loan contract.	Deal Scan
$Log\ (Amt)$	Natural logarithm of the US$ loan amount of the facility, in millions.	Deal Scan
$Log\ (Mat)$	Natural logarithm of the number of months to loan maturity.	Deal Scan
$TotCovIndex$	Total covenant index, constructed by counting the number of financial and general covenants in the bank loan issuance sample.	Deal Scan
$GenCovIndex$	General covenant index, constructed by counting the number of general covenants included in a loan contract.	Deal Scan
$FinCovIndex$	Financial covenant index, constructed by counting the number of financial covenants included in a loan contract.	Deal Scan
$Perf\_Provision$	Binary dummy that equals one if the loan includes performance pricing provisions, and zero otherwise.	Deal Scan
$Loan\ Type\ dummies$	Dummy variable for loan types, including term loans, revolvers greater than 1 year, revolvers less than 1 year, and 364-day facilities.	Deal Scan
$Loan\ Purpose\ dummies$	Dummy variable for loan purposes, including corporate initiatives, debt repayment, working capital, or takeovers.	Deal Scan
Firm-level variables		
$Size$	Firm size, measured by the natural logarithm of total assets.	Compustat
$Tang$	Measured by total property, plant, and equipment, scaled by total assets.	Compustat
LEV	Tangibility, measured by the total debt, scaled by the market value of equity.	Compustat
M/B	Market-to-book ratio.	Compustat
$Profit$	Profitability, measured by operating income before depreciation, scaled by total assets.	Compustat
$Z-score$	Modified Altman's (1968) Z-score, calculated as (1.2×(ACT – LCT) + 1.4×RE + 3.3×EBIT + 0.999×SALE)/AT + 0.6×CSHO × PRCC_C/(DLTT + DLC).	Compustat
CF_Vol	Cash flow volatility, defined as the standard deviation of quarterly cash flows from operations over the previous four fiscal years, scaled by total debt.	Compustat
T_Vol	Return volatility, defined The standard deviation of a firm's daily stock return over the fiscal year.	Compustat

HP_Index	Hadlock and Pierce index (2010), calculated as (−0.737×Assets + 0.043×Assets^2 − 0.040×Age).	Compustat
Exf	External financing dependency, measured by (Capital expenditures (CAPX) – funds from operations (FOPT / capital expenditures (CAPX). When FOPT is missing, funds from operations is defined as the sum of the following variables: Income before extraordinary items (IBC), depreciation and amortization (DPC), deferred taxes (TXDC), equity in net loss/ earnings (ESUBC), sale of property, plant, equipment and investments gain / loss (SPPIV), and funds from operations – other (FOPO).	Compustat
$AnalystCov$	Analyst coverage, measured by the number of analysts covering the firm.	I/B/E/S
Macro-level variables		
PU_a	Aggregate political uncertainty, measured by EPU divided by 100.	Baker, Bloom, and Davis (2016)
$Inflation$	Inflation rate, defined as monthly growth rate of the Consumer Price Index for all urban consumers.	FRED
$Recession$	Binary dummy that equals one if an observation's time falls in an NBER business cycle, and zero otherwise.	NBER
$Production$	Production rate, defined as the growth rate as shown by the monthly Industrial Production Index.	FRED
$Term\_Spread$	The difference between the 10-year and the 1-year government bond yield.	FRED
$Default\_Rate$	The yield spread between Moody's seasoned Baa and Aaa corporate bonds.	FRED

Table 1. Sample distributions

Panel A. Sample year distribution

Year	Firms	Loans
2002	151	218
2003	444	648
2004	611	934
2005	586	944
2006	562	892
2007	556	891
2008	378	530
2009	278	381
2010	421	617
2011	639	995
2012	547	844
2013	590	1011
2014	588	976
2015	542	878
2016	469	787
2017	31	44
Total	7,393	11,590

Panel B. Sample distribution by industry

Industry	SIC code (2 digit)	Number of Obs.	$PRisk\_mean$	Loan Spread
Engineering and Management	87	274	0.90	225.32
Agricultural Production – Crops	1	36	0.79	249.58
Health Services	80	297	0.78	269.91
Metal, Mining	10	32	0.73	206.41
Heavy Construction, Except Building	16	86	0.71	207.66
	…	…	…	…
Textile Mill Products	22	58	0.30	220.17
Paper and Allied Products	26	223	0.29	179.14
Petroleum & Coal Products	29	121	0.27	189.64
Apparel & Accessory Stores	56	143	0.25	184.55
Food Stores	54	69	0.25	170.47

This table reports the sample's distribution of bank loan issuances for period of 2002:Q2 – 2017:Q1. This time period has been selected to match the availability of $PRisk$. Panel A reports the year distribution. Panel B reports the mean firm-level political risk and loan cost in different industries. The industry classification is based on the first two digits of the Standard Industrial Classification (SIC) code. The number of observations is the number of bank loans in that industry. We require the number of observations no less than 30. $PRisk\_mean$ is the mean firm-level political risk.

Table 2. Summary statistics and correlation matrix

Panel A. Summary statistics

Variable (Obs. = 11,590)	Mean	StdDev	25%	Median	75%
$PRisk$	0.47	0.79	0.07	0.24	0.53
$Spread\ (bps)$	211	144	125	175	275
$Loan\ Amount\ (million)$	520	928	100	250	600
$Maturity\ (month)$	53.68	17.55	48.00	60.00	60.00
$Log(Amt)$	19.25	1.34	18.42	19.34	20.21
$Log(Mat)$	3.90	0.47	3.87	4.09	4.09
$Perf\_Provision$	0.45	0.50	0.00	0.00	1.00
$Size$	7.64	1.54	6.55	7.56	8.60
$Profit$	0.14	0.08	0.09	0.13	0.17
M/B	3.38	7.19	1.37	2.14	3.40
CF_Vol	0.10	0.31	0.03	0.05	0.10
T_Vol	0.02	0.01	0.02	0.02	0.03

Panel B. Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	$Log(Spread)$	1.00														
2	$PRisk$	0.01	1.00													
3	$Size$	**-0.31**	0.01	1.00												
4	M/B	**-0.03**	0.00	0.00	1.00											
5	LEV	**0.14**	-0.01	**0.07**	**-0.02**	1.00										
6	$Profit$	**-0.24**	0.00	**-0.02**	**0.16**	**-0.11**	1.00									
7	$Tang$	**-0.02**	**-0.03**	**0.03**	-0.01	**0.04**	**0.13**	1.00								
8	Z-$score$	**-0.19**	**0.03**	**-0.25**	**0.09**	**-0.16**	**0.44**	**-0.17**	1.00							
9	CF_Vol	**0.06**	0.00	**-0.12**	0.00	-0.01	**-0.02**	**-0.05**	**0.09**	1.00						
10	T_Vol	**0.40**	**-0.03**	**-0.32**	-0.01	**0.27**	**-0.20**	**0.09**	**-0.09**	**0.07**	1.00					
11	$Log(Mat)$	**0.21**	0.00	**-0.07**	0.00	**-0.03**	**0.02**	**-0.05**	**-0.02**	0.01	**-0.16**	1.00				
12	$Log(Amt)$	**-0.35**	0.02	**0.60**	**0.04**	0.01	**0.07**	**0.06**	**-0.12**	**-0.06**	**-0.28**	**0.08**	1.00			
13	$Perf\_Provision$	**-0.21**	0.00	**-0.07**	0.00	**-0.05**	**0.07**	-0.01	**0.08**	0.01	**-0.04**	0.01	**0.09**	1.00		
14	$Default\_Rate$	**0.17**	-0.01	**-0.05**	0.01	0.00	**-0.02**	**0.02**	0.01	**0.03**	**0.45**	**-0.18**	**-0.08**	**0.03**	1.00	
15	$Term\_Spread$	**0.24**	0.00	0.01	**-0.03**	**0.08**	**-0.04**	**0.05**	**-0.07**	0.00	**0.20**	**-0.15**	-0.02	**-0.07**	**0.09**	1.00

This table presents descriptive statistics and correlations for the variables used in the regressions. Correlations shown in bold face are significant at 5%. See the appendix for variable definitions.

Table 3. Firm-level political risk and loan pricing

	Dependent variable: Log(Spread)		
	(1)	(2)	(3)
	Firm-Control	Loan-Control	Baseline
$PRisk$	0.036***	0.026***	0.022***
	(3.426)	(2.787)	(2.771)
$Size$	-0.152***	-0.071***	-0.059***
	(-14.740)	(-6.800)	(-6.885)
M/B	0.000	0.001	0.001
	(0.055)	(1.099)	(0.965)
LEV	0.009*	0.008**	0.005*
	(1.909)	(1.976)	(1.759)
$Profit$	-0.821***	-0.734***	-0.791***
	(-5.563)	(-5.430)	(-6.848)
$Tang$	-0.093***	-0.101***	-0.028
	(-3.233)	(-2.998)	(-1.010)
$Z\text{-}score$	-0.047***	-0.037***	-0.031***
	(-9.994)	(-9.038)	(-9.269)
CF_Vol	0.025*	0.030**	0.016
	(1.784)	(2.137)	(1.122)
T_Vol	13.347***	12.561***	10.311***
	(13.632)	(13.559)	(13.740)
$Log(Mat)$		0.367***	0.063***
		(17.811)	(3.248)
$Log(Amt)$		-0.143***	-0.130***
		(-12.687)	(-13.781)
$Perf\_Provision$		-0.154***	-0.055***
		(-9.503)	(-3.989)
$Default\_Rate$			0.036
			(0.526)
$Term\_Spread$			0.098**
			(2.551)
Intercept	6.257***	7.000***	8.251***
	(67.844)	(37.981)	(42.564)
Loan Purpose FE	No	No	Yes
Loan Type FE	No	No	Yes
Industry FE	No	Yes	Yes
Year Quarter FE	Yes	Yes	Yes
Obs.	11,590	11,590	11,590
Adj. R^2	0.389	0.503	0.639

This table reports the regression results for the effect of firm-level political risk on loan pricing using $\text{Log (Spread)}_{i,t+1} = \alpha + \beta_1 \times PRisk_{i,t} + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}$, where the dependent variable $Log(Spread)$ is the natural logarithm of loan spread (over LIBOR) of each individual loan contract. $PRisk$ is firm i's firm-level political risk measure at year quarter t (standardized). Column (1) only control for firm-level control variables, and Column (2) adds the loan-level control variables, and Column (3) reports the baseline results. The sample period is 2003 to 2016. Financial firms (SIC 6000-6999) and utilities firms (SIC 4900-4999) are excluded from this sample. The industry fixed effects are controlled by 2-digit SIC codes. All variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Robustness tests

Dependent variable	(1) Log(Spread) Excluding Financial Crisis Period (2007-2008)	(2) Log(Spread) 4-digit Industry FE	(3) Log(Spread) Raw PRisk/100	(4) Spread
$PRisk$	0.022***	0.023***	0.008**	4.318**
	(2.747)	(2.805)	(2.391)	(2.428)
$Size$	-0.061***	-0.065***	-0.059***	-2.822
	(-6.713)	(-7.500)	(-6.884)	(-1.584)
M/B	0.001	0.001**	0.001	0.271*
	(0.953)	(1.963)	(0.971)	(1.696)
LEV	0.010*	0.006**	0.005*	1.480
	(1.898)	(1.997)	(1.755)	(1.459)
$Profit$	-0.937***	-0.695***	-0.792***	-116.592***
	(-8.001)	(-5.931)	(-6.854)	(-4.316)
$Tang$	-0.024	-0.088**	-0.028	-8.405
	(-0.807)	(-2.574)	(-1.017)	(-1.309)
$Z\text{-}score$	-0.029***	-0.031***	-0.031***	-4.242***
	(-8.202)	(-9.234)	(-9.237)	(-5.881)
CF_Vol	0.016	0.023	0.016	1.338
	(1.238)	(1.374)	(1.107)	(0.421)
T_Vol	12.273***	9.009***	10.312***	2,873.557***
	(12.451)	(12.108)	(13.739)	(13.499)
$Log(Mat)$	0.067***	0.068***	0.063***	14.312***
	(3.188)	(3.324)	(3.254)	(2.954)
$Log(Amt)$	-0.134***	-0.139***	-0.130***	-23.844***
	(-13.700)	(-17.163)	(-13.776)	(-12.313)
$Perf\_Provision$	-0.060***	-0.054***	-0.055***	-26.531***
	(-4.225)	(-4.184)	(-3.989)	(-10.376)
$Default\_Rate$	0.050	-0.004	0.037	9.885
	(0.522)	(-0.061)	(0.530)	(0.566)
$Term\_Spread$	0.120***	0.090**	0.098**	14.289*
	(3.056)	(2.442)	(2.547)	(1.731)
Intercept	8.234***	8.543***	8.252***	708.464***
	(39.248)	(46.317)	(42.579)	(17.035)
Loan Purpose	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Obs.	10,707	11,590	11,590	11,590
Adj. R^2	0.643	0.662	0.639	0.547

This table presents the results of additional tests for the impact of firm-level political risk on loan pricing. Column (1) presents the effect of $PRisk_{i,t}$ on $Log(Spread)$ after excluding the financial crisis period. Column (2) presents the effect of $PRisk_{i,t}$ on $Log(Spread)$ after controlling for 4 digit SIC code. Column (3) uses the raw firm-level political risk (divided by 100 to make it comparable). Column (4) shows the effect of $PRisk_{i,t}$ on loan spread. All regressions are performed by OLS, with the t-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. All variables are winsorized at the 1% level. See the appendix for control variable definitions. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5. Additional controls

	Dependent variable: Log(Spread)			
	(1)	(2)	(3)	(4)
	Add PU_a	Add Sentiment	More Macro	Add All
$PRisk$	0.022***	0.021***	0.022***	0.021***
	(2.767)	(2.678)	(2.775)	(2.678)
PU_a	0.039			0.036
	(1.329)			(1.236)
$PSentiment$		-0.011*		-0.011*
		(-1.735)		(-1.737)
$Production$			0.001	-0.007
			(0.009)	(-0.077)
$Inflation$			0.013	0.014
			(0.764)	(0.808)
$Recession$			-0.028**	-0.027**
			(-2.193)	(-2.134)
$Size$	-0.059***	-0.059***	-0.059***	-0.059***
	(-6.885)	(-6.879)	(-6.886)	(-6.879)
M/B	0.001	0.001	0.001	0.001
	(0.969)	(0.997)	(0.970)	(1.005)
LEV	0.005*	0.005*	0.005*	0.005*
	(1.761)	(1.766)	(1.748)	(1.757)
$Profit$	-0.792***	-0.793***	-0.792***	-0.795***
	(-6.858)	(-6.857)	(-6.861)	(-6.880)
$Tang$	-0.028	-0.029	-0.028	-0.029
	(-1.007)	(-1.044)	(-0.992)	(-1.023)
$Z\text{-}score$	-0.031***	-0.031***	-0.031***	-0.031***
	(-9.263)	(-9.246)	(-9.288)	(-9.259)
CF_Vol	0.016	0.016	0.016	0.016
	(1.100)	(1.123)	(1.095)	(1.077)
T_Vol	10.319***	10.268***	10.316***	10.284***
	(13.763)	(13.658)	(13.675)	(13.617)
$Log(Mat)$	0.063***	0.064***	0.064***	0.064***
	(3.247)	(3.295)	(3.264)	(3.311)
$Log(Amt)$	-0.130***	-0.130***	-0.130***	-0.130***
	(-13.801)	(-13.791)	(-13.783)	(-13.810)
$Perf\_Provision$	-0.055***	-0.055***	-0.055***	-0.055***
	(-3.973)	(-4.000)	(-4.013)	(-4.008)
$Default\_Rate$	0.039	0.039	0.013	0.023
	(0.569)	(0.558)	(0.176)	(0.303)
$Term\_Spread$	0.101***	0.098**	0.108***	0.112***
	(2.614)	(2.567)	(2.800)	(2.867)
Intercept	8.198***	8.256***	8.229***	8.178***
	(41.104)	(42.575)	(40.615)	(38.926)
Loan Purpose FE	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes
Obs.	11,590	11,590	11,590	11,590
Adj. R^2	0.639	0.639	0.639	0.639

This table reports the results of predicting bank loan cost with firm-level political risk as Log $(\text{Spread})_{i,t+1} = \alpha + \beta_1 \times PRisk_{i,t} + \beta_2 \times Z_t + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}$, where Z_t is one of controlling variables. All variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6. The effect of firm-level political risk on loan spreads: The PSM sample

Dependent variable: Log(Spread)	
$DPRisk$	0.098***
	(2.640)
$Size$	-0.077***
	(-3.318)
M/B	0.003
	(0.421)
LEV	0.064***
	(3.091)
$Profit$	-1.095***
	(-3.026)
$Tang$	-0.034
	(-0.379)
$Z\text{-}score$	-0.017**
	(-2.253)
CF_Vol	0.193*
	(1.713)
T_Vol	6.528**
	(2.379)
$Log(Mat)$	0.063
	(0.773)
$Log(Amt)$	-0.127***
	(-5.872)
$Perf\_Provision$	-0.107**
	(-2.279)
$Default\_Rate$	0.030
	(0.101)
$Term\_Spread$	-0.222
	(-1.584)
Intercept	9.009***
	(14.801)
Loan Purpose FE	Yes
Loan Type FE	Yes
Industry FE	Yes
Year Quarter FE	Yes
Obs.	800
Adj. R^2	0.669

This table presents the results concerning the effects of firm-level political risk on loan cost, using the PSM sample. The industry fixed effects, time fixed effects, loan purpose fixed effects, and loan type fixed effects are included in all regressions. All of the regressions are performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. All of the variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Instrumental variable regression

	First Stage: Firm-level political risk	Second Stage: Log(Spread)
	(1)	(2)
PRisk_nei	0.458***	
	(3.298)	
Political_distance	0.019*	
	(1.698)	
PRisk(Instrumented)		0.205**
		(2.166)
Size	0.016	-0.061***
	(1.529)	(-6.813)
M/B	-0.000	0.001
	(-0.235)	(1.089)
LEV	-0.000	0.005*
	(-0.046)	(1.706)
Profit	-0.285*	-0.718***
	(-1.663)	(-6.064)
Tang	0.007	-0.017
	(0.181)	(-0.590)
Z-score	0.012**	-0.033***
	(2.071)	(-9.176)
CF_Vol	0.093	0.066
	(0.948)	(1.641)
T_Vol	-2.080**	10.637***
	(-2.032)	(14.016)
Log(Mat)	0.017	0.065***
	(0.680)	(3.219)
Log(Amt)	0.006	-0.129***
	(0.706)	(-13.204)
Perf_Provision	-0.024	-0.056***
	(-1.168)	(-3.889)
Default_Rate	-0.059	0.047
	(-0.525)	(0.667)
Term_Spread	-0.168**	0.137***
	(-2.569)	(3.186)
Intercept	0.580**	7.411***
	(2.457)	(34.470)
Loan Purpose FE	Yes	Yes
Loan Type FE	Yes	Yes
Industry FE	Yes	Yes
Year Quarter FE	Yes	Yes
Obs.	10,660	10,660
Adj. R^2	0.067	0.612

This table reports the results of two-stage least squares regressions. Our instrumental variable are *Prisk_nei* and *political_distance*. *Prisk_nei* is defined as the firm-level political risks of the other firms, which are in the same state with the borrower. *Political_distance* is defined as the distance between the borrower's headquarter and its state capital. The industry fixed effects, time fixed effects, loan purpose fixed effects, and loan type fixed effects are included in all regressions. All the regressions are performed by OLS, with the t-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. All the variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. The effect of leads and lags of firm-level political risk on loan costs

	Dependent variable: $\text{Log(Spread)}_{i,t+1}$						
	(1) PRisk in Qtr t-3	(2) PRisk in Qtr t-2	(3) PRisk in Qtr t-1	(4) PRisk in Qtr t	(5) PRisk in Qtr t+1	(6) PRisk in Qtr t+2	(7) PRisk in Qtr t+3
$PRisk_{i,t-3}$	0.005						
	(0.656)						
$PRisk_{i,t-2}$		0.004					
		(0.657)					
$PRisk_{i,t-1}$			0.015**				
			(2.003)				
$PRisk_{i,t}$				0.022***			
				(2.771)			
$PRisk_{i,t+1}$					0.002		
					(0.269)		
$PRisk_{i,t+2}$						0.002	
						(0.308)	
$PRisk_{i,t+3}$							0.007
							(0.930)
Intercept	8.356***	8.248***	8.258***	8.251***	8.315***	8.351***	8.408***
	(41.238)	(40.958)	(41.452)	(42.564)	(41.473)	(41.820)	(41.578)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10,387	10,738	11,002	11,590	10,756	10,470	10,158
Adj. R^2	0.642	0.639	0.639	0.639	0.636	0.635	0.635

This table reports the impact of leads and lags of the firm-level political risk measure on the firm's loan spread. Column (4) repeat the baseline results ($PRisk$ in quarter t) and serve as benchmark. In column (1) and (3), we replace the 1-period lag $PRisk_{i,t}$ with 2-period-lag, 3-period-lag and 4-period-lag firm-level political risks as the key variables. In column (5) and (7), we replace the 1-period lag $PRisk_{i,t}$ with contemporary, 1-period-lead and 2-period-lead firm-level political risks as the key variables. Column (5) to (7) serve as placebo tests. All regressions include industry fixed effect and year quarter fixed effect. We also control loan type and loan purpose fixed effect. The t-statistics (in parentheses) are computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 9. The persistence of firm-level political risk

	Dependent variable: Log(Spread)			
	(1)	(2)	(3)	(4)
$PRisk\_1yr1$	0.027***			
	(2.743)			
$PRisk\_1yr2$		0.020*		
		(1.809)		
$PRisk\_5yr1$			0.036***	
			(3.171)	
$PRisk\_5yr2$				0.027*
				(1.783)
$Size$	-0.059***	-0.059***	-0.059***	-0.059***
	(-6.893)	(-6.752)	(-6.874)	(-6.797)
M/B	0.001	0.001	0.001	0.001
	(0.962)	(0.958)	(0.971)	(0.994)
LEV	0.005*	0.005	0.005*	0.005*
	(1.748)	(1.600)	(1.731)	(1.665)
$Profit$	-0.795***	-0.775***	-0.792***	-0.785***
	(-6.874)	(-6.559)	(-6.859)	(-6.616)
$Tang$	-0.027	-0.019	-0.026	-0.022
	(-0.970)	(-0.676)	(-0.945)	(-0.763)
$Z\text{-}score$	-0.031***	-0.032***	-0.031***	-0.032***
	(-9.224)	(-9.004)	(-9.245)	(-9.083)
CF_Vol	0.016	0.018	0.016	0.017
	(1.128)	(1.198)	(1.152)	(1.197)
T_Vol	10.296***	10.276***	10.344***	10.332***
	(13.720)	(12.841)	(13.772)	(13.211)
$Log(Mat)$	0.064***	0.059***	0.065***	0.060***
	(3.283)	(2.944)	(3.322)	(3.001)
$Log(Amt)$	-0.129***	-0.129***	-0.130***	-0.129***
	(-13.754)	(-13.442)	(-13.744)	(-13.420)
$Perf\_Provision$	-0.055***	-0.058***	-0.056***	-0.059***
	(-3.994)	(-4.135)	(-4.036)	(-4.243)
$Default\_Rate$	0.035	0.012	0.035	0.012
	(0.502)	(0.175)	(0.506)	(0.165)
$Term\_Spread$	0.096**	0.100**	0.095**	0.103***
	(2.514)	(2.536)	(2.491)	(2.615)
Intercept	8.248***	8.286***	8.239***	8.273***
	(42.486)	(41.570)	(42.335)	(41.408)
Loan Purpose FE	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Obs.	11,590	11,020	11,590	11,061
Adj. R^2	0.639	0.637	0.639	0.636

The table reports the testing result of the persistent component of firm-level political risk on loan cost. $PRisk\_1yr1$ is measured as the average firm-level political risk over the 1 years preceding loan origination, counted from quarter t. $PRisk\_1yr2$ is measured as the average firm-level political risk over the 1 years preceding loan origination, counted from quarter t-2. $PRisk\_5yr1$ is measured as the average firm-level political risk over the 5 years preceding loan origination, counted from quarter t. $PRisk\_5yr2$ is measured as the average firm-level political risk over the 5 years preceding loan origination, counted from quarter t-2. All variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Cross-sectional analysis: Information opacity

	Dependent variable: Log(Spread)		
	(1)	(2)	(3)
$PRisk$	0.105***	0.044***	0.044***
	(2.797)	(4.358)	(3.828)
$PRisk \times Size$	-0.011**		
	(-2.128)		
$PRisk \times Tang$		-0.050**	
		(-2.134)	
$PRisk \times\ AnalystCov$			-0.012*
			(-1.888)
$AnalystCov$			-0.049***
			(-4.462)
$Size$	-0.054***	-0.059***	-0.040***
	(-6.023)	(-6.869)	(-4.377)
M/B	0.001	0.001	0.001
	(0.978)	(0.920)	(1.336)
LEV	0.005*	0.005*	0.004
	(1.748)	(1.761)	(1.509)
$Profit$	-0.783***	-0.793***	-0.738***
	(-6.827)	(-6.869)	(-6.528)
$Tang$	-0.028	-0.006	-0.034
	(-1.012)	(-0.200)	(-1.193)
$Z\text{-}score$	-0.031***	-0.031***	-0.028***
	(-9.456)	(-9.276)	(-8.558)
CF_Vol	0.016	0.016	0.016
	(1.102)	(1.133)	(1.129)
T_Vol	10.323***	10.296***	10.249***
	(13.761)	(13.714)	(13.596)
$Log(Mat)$	0.063***	0.062***	0.065***
	(3.203)	(3.205)	(3.373)
$Log(Amt)$	-0.129***	-0.130***	-0.129***
	(-13.757)	(-13.773)	(-13.854)
$Perf\_Provision$	-0.055***	-0.055***	-0.054***
	(-3.988)	(-3.965)	(-3.899)
$Default\_Rate$	0.036	0.031	0.043
	(0.521)	(0.454)	(0.620)
$Term\_Spread$	0.097**	0.097**	0.098**
	(2.548)	(2.527)	(2.560)
Intercept	8.211***	8.247***	8.165***
	(42.449)	(42.508)	(42.126)
Loan Purpose FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes
Obs.	11,590	11,590	11,590
Adj. R^2	0.639	0.639	0.641

This table presents the regression results concerning the effects of financial information opacity on the relation between firm-level political risk and bank loan cost. The industry fixed effects, time fixed effects, loan purpose fixed effects, and loan type fixed effects are included in all of the columns. All of the regressions are performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. All variables are winsorized at the 1% level. See the appendix for control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Cross-sectional analysis: Financial constraints

	Dependent variable: Log(Spread)		
	(1)	(2)	(3)
$PRisk$	0.018**	0.003	0.135**
	(2.217)	(0.338)	(2.269)
$PRisk \times Exf$	0.027***		
	(3.826)		
$PRisk \times CF\_Vol$		0.155***	
		(3.924)	
$PRisk \times HP\_Index$			0.029*
			(1.775)
Exf	0.000		
	(0.100)		
HP_Index			0.117***
			(5.919)
$Size$	-0.059***	-0.058***	-0.033***
	(-6.785)	(-6.765)	(-3.672)
M/B	0.001	0.001	0.000
	(0.865)	(0.961)	(0.545)
LEV	0.005*	0.005*	0.006*
	(1.762)	(1.745)	(1.902)
$Profit$	-0.743***	-0.778***	-0.781***
	(-6.431)	(-6.776)	(-6.972)
$Tang$	-0.027	-0.028	-0.002
	(-0.981)	(-0.991)	(-0.060)
$Z\text{-}score$	-0.031***	-0.032***	-0.031***
	(-9.338)	(-9.718)	(-9.544)
CF_Vol	0.017	-0.020	0.002
	(1.137)	(-1.624)	(0.270)
T_Vol	10.214***	10.261***	9.707***
	(13.694)	(13.682)	(13.196)
$Log(Mat)$	0.067***	0.063***	0.065***
	(3.445)	(3.220)	(3.329)
$Log(Amt)$	-0.130***	-0.129***	-0.131***
	(-13.759)	(-13.764)	(-14.278)
$Perf\_Provision$	-0.055***	-0.054***	-0.055***
	(-3.943)	(-3.944)	(-4.012)
$Default\_Rate$	0.044	0.035	0.035
	(0.630)	(0.503)	(0.501)
$Term\_Spread$	0.100***	0.098**	0.104***
	(2.626)	(2.563)	(2.720)
Intercept	8.218***	8.250***	8.508***
	(42.382)	(42.524)	(43.730)
Loan Purpose FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes
Obs.	11,564	11,590	11,590
Adj. R^2	0.640	0.640	0.644

This table presents regression results concerning the effects of financial constraints on the relation between firm-level political risk and bank loan cost. All of the regressions are performed by OLS, with the *t*-statistics (in parentheses) computed using standard errors robust to both clustering at the firm level and to heteroscedasticity. All variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Firm-level political risk and loan tightness

Dependent variable	$TotCovIndex$ (1)	$GenCovIndex$ (2)	$FinCovIndex$ (3)	$DDebt$ (4)	$DSecured$ (5)	$Annual\_fee$ (6)
$PRisk$	0.121***	0.073***	0.048***	0.108***	0.117**	0.610*
	(3.303)	(3.158)	(2.611)	(2.779)	(2.521)	(1.702)
$Size$	-0.471***	-0.292***	-0.179***	-0.401***	-0.384***	-2.620***
	(-16.209)	(-14.965)	(-11.558)	(-9.534)	(-8.490)	(-5.720)
M/B	0.000	0.000	-0.000	0.002	0.011*	0.013
	(0.024)	(0.072)	(-0.038)	(0.548)	(1.754)	(0.354)
LEV	0.009	0.004	0.005	0.008	0.094	3.316***
	(0.952)	(0.586)	(1.413)	(0.740)	(1.157)	(6.664)
$Profit$	-0.112	-0.454	0.342	0.882	-2.597***	-10.155
	(-0.224)	(-1.398)	(1.373)	(1.289)	(-3.851)	(-1.432)
$Tang$	-0.315***	-0.195**	-0.120**	-0.398***	-0.339**	-1.707
	(-2.700)	(-2.444)	(-2.159)	(-2.666)	(-2.146)	(-1.236)
$Z\text{-}score$	-0.082***	-0.067***	-0.015**	-0.141***	-0.117***	-0.840***
	(-6.261)	(-7.631)	(-2.449)	(-6.114)	(-5.787)	(-3.795)
CF_Vol	0.070	0.114***	-0.044	0.302	0.440*	11.819
	(1.262)	(3.869)	(-1.307)	(1.468)	(1.674)	(1.513)
T_Vol	22.276***	18.921***	3.356*	20.895***	50.349***	321.446***
	(6.052)	(7.858)	(1.758)	(4.974)	(8.499)	(4.143)
$Log(Mat)$	0.120	0.118*	0.002	0.109	0.527***	-5.217**
	(1.309)	(1.955)	(0.048)	(0.879)	(4.990)	(-2.462)
$Log(Amt)$	0.052**	-0.005	0.057***	0.071**	-0.197***	0.025
	(2.047)	(-0.292)	(3.225)	(1.963)	(-4.745)	(0.065)
$Perf\_Provision$	1.965***	0.958***	1.008***	1.260***	0.738***	-0.333
	(30.293)	(21.905)	(33.062)	(14.534)	(10.158)	(-0.477)
$Default\_Rate$	0.636*	0.335	0.302*	0.493	0.687	-4.381
	(1.725)	(1.309)	(1.774)	(1.007)	(1.600)	(-0.615)
$Term\_Spread$	0.188	0.089	0.099	0.300	-0.141	-2.842
	(0.989)	(0.704)	(1.099)	(1.151)	(-0.685)	(-1.571)
Intercept	4.282***	3.543***	0.739*	-0.560	8.841***	65.877***
	(5.022)	(6.217)	(1.685)	(-0.316)	(5.138)	(4.517)
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	11,590	11,590	11,590	11,510	11,590	1,935
Adj. R^2	0.386	0.349	0.338	0.222	0.328	0.491

This table reports the regression results concerning the effects of non-pricing loan terms on firm-level political risk. $TotCovIndex$ is total covenant index, constructed by counting the number of financial and general covenants in the bank loan issuance sample. $GenCovIndex$ is general covenant index, constructed by counting the number of general covenants included in a loan contract. $FinCovIndex$ is financial covenant index, constructed by counting the number of financial covenants included in a loan contract. $DDebt$ is an indicator variable that equals one if the loan facility has the debt issuance sweep restriction, and zero otherwise. $DSecured$ is an indicator variable that equals one if the loan facility is secured with collateral, and zero otherwise. $Annual\_fee$ is the annual charge against the entire loan commitment amount, whether it is used or unused. Regressions in column (4) and (5) are performed by Logit. Regressions in other columns are performed by OLS, with the t-statistics (in parentheses) computed by using standard errors robust to both clustering at the firm level and to heteroscedasticity. See the appendix for control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13. Topic-specific political risk and loan spreads

	Dependent variable: Log(Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PRisk\_ior$	0.015**							
	(2.398)							
$PRisk\_sec$		0.010**						
		(2.296)						
$PRisk\_env$			0.008*					
			(1.762)					
$PRisk\_tech$				0.005				
				(0.763)				
$PRisk\_hel$					0.011			
					(1.558)			
$PRisk\_tra$						0.008		
						(0.382)		
$PRisk\_eco$							0.009	
							(1.546)	
$PRisk\_tax$								-0.006
								(-0.786)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	11,590	11,590	11,590	11,590	11,590	11,590	11,590	11,590
Adj. R^2	0.639	0.639	0.639	0.639	0.639	0.639	0.639	0.639

This table reports the results of the impacts of different types of firm-level political risk on loan pricing. $PRisk_{i,t}^{T}$ is the average for a firm and quarter of the transcript-based scores of topic T, where T = {Economic Policy & Budget, Environment, Trade, Institutions & Political Process, Health, Security & Defense, Tax policy, Technology & Infrastructure}, are the separate topic scores and standardized by their respective standard deviation. All variables are winsorized at the 1% level. See the appendix for the control variable definitions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.