Firm-level Political Risk and Credit Markets*

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Preliminary draft

Abstract:

We examine the effect of firm-level political risk on debt markets. While prior research mainly relies on economy-wide proxies for political risk, such as the economic policy uncertainty index, in a recent study, Hassan et al. [2019] suggests that substantial part of political risk plays out at the firm-level. We use their measure of political risk to show that borrower-level political risk is reflected in pricing and liquidity of public debt, in the cost of private debt, and in credit default swap spreads and recovery rates. We also document the extent to which pricing effects are stronger for persistent versus temporary variation in firm-level political risk. Further, we show that lender-level political risk influences the supply of credit and in turn has a significant effect on loan pricing. Taking advantage of the granularity of our measure, we also show that firm-specific changes in political risk propagate across firms and lenders, suggesting the importance of network effects in amplifying the effects of political uncertainty. Finally, we show that borrowers and lenders can mitigate the effect of political risk via political activism and well as changes to contractual terms.

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1. Introduction

Financial markets jittered during the recent, prolonged US government shutdown resulting from a staring contest between a recently empowered Democratic House and a Republican President, highlighting the potential impact of politicians on economic outcomes. And while the effects of economy-wide shocks emanating from the political system on markets have been studied in some detail, recent work has made it clear that these aggregate shocks might only reflect the tip of the iceberg of a given firm's exposure to political events. When President Trump criticizes Amazon for not paying a fair share of taxes or praises General Motors for expanding jobs in the US, among others, he follows in the footsteps of JF Kennedy and Harry Truman, using the bully pulpit of their office to point fingers at individual companies.[1] These examples illustrate that political risk is a firm-specific phenomenon, and possibly much more so than previously thought. So far, the closer examination of this conjecture has been significantly hampered by the lack of a validated political risk measure that quantifies the time variation in exposure to *firm*-level political risk. However, recent work by Hassan, Hollander, van Lent and Tahoun [2019] (HHLT henceforth) provides such a measure and shows that only about 1 percent of variation in measured political risk is accounted for by variation in aggregate political risk over time, whereas, in sharp contrast, firm-level variation accounts for about 90 percent.[2]

We build on this work by using the HHLT measure to examine comprehensively how firm-level political risk affects public and private credit markets. We not only examine how lenders respond to the political risk of their borrowers, but we also study the effects of political risk of the financial institution itself when it prices loans and makes lending decisions. What's more, the granularity of this political risk measure, which is available at the firm-quarter level, allows us to examine how the political risk of lenders

[1] Some historical examples are discussed in a recent Forbes article "How Trump's Tweets Impact Stocks" (January 10, 2019).
[2] The remaining variation is accounted for by sector and sector × time fixed effects.

propagates through their connections with other financial institutions, showing potential network effects of exposures to political risk. Relatedly, we show that banks are able to transmit the costs of their own political risk to relationship-borrowers in particular. We also use detailed information about the political activities of the borrowers to examine whether companies can mitigate the consequences of political risk on credit market outcomes by actively managing their exposure through lobbying and providing campaign donations to politicians. In addition to active risk management, we further examine whether financial institutions respond passively to political risk by cutting back on their lending share in syndicate loans.

Previous attempts to measure firm-level political exposure have either mobilized specific shocks to political uncertainty (e.g., by using closely-contested election campaigns) or have adapted the Baker, Bloom, and Davis (BBD) [2016] measure of economy-wide policy uncertainty (EPU) to the firm-level [Bordo, Duca and Koch 2016, Drobetz, El Ghoul, Guedhami and Janzen 2018, Francis, Hasan and Zhu 2014, Kaviani, Kryzanowski, Maleki and Savor 2017, Wang, Xu and Zhong 2018]. While important first steps, such approaches are subject to significant limitations. In particular, while elections are a salient potential source of political risk, they are just one reason why firms might be exposed to more or less uncertainty. As a consequence, these findings need not generalize to other (non-election) political events. More importantly, the above studies remain silent about the importance of firm-specific political risk as they focus on the over-time variation in the policy uncertainty with respect to *aggregate* outcomes. As documented in HHLT [2019], attempts to bring BBD measure of policy uncertainty to the firm-level are simply picking up heterogeneous exposure to aggregate political risk rather than capturing firm-level political risk. As such, BBD-based exposure measures *cannot* exploit within-firm variation in political risk or variation stemming from different firms within the same industry being differentially exposed to political risk over time. Election-based (aggregate) shocks likewise do not reflect the fact that most of a given firm's exposure appears to stem from political events that are specific to its industry or even vary within the sector over time. And indeed, Akey and Lewellen [2017] show there is little persistence in a firm's "EPU sensitivity" across election cycles.

To investigate the effects of political risk on credit markets, we use a recently developed and comprehensively validated measure of firm-level political risk, $PRisk_{it}$, which measures the share of conversation about politics in a given firm's quarterly earnings conference call with financial analysts [Hassan, et al. 2019]. Intuitively, when analysts ask more questions about political topics or management volunteers more discussion of politics in their opening statement, the firm is more likely to be exposed to political risk.

We exploit $PRisk_{it}$ to first establish the existence of firm-level political risk in credit markets. Conceptually, firm-level political risk can influence credit markets through the demand or supply side. From the demand side, we document a link between the *borrower* political risk and both bond markets outcomes, such as bid-ask spreads, yields, and trading volume, and loan market outcomes. We also consider the association between borrower political risk and CDS market outcomes, not only because these present us with another proxy for default risk, but also because we can examine how political risk and recovery rates are related. This is important because politicians might exert influence over settlement negotiations in default proceedings, with consequences for the loss experienced by creditors upon default. Our baseline results indicate that the cost of debt is significantly higher for borrowers facing higher political risk. We show that a one-standard-deviation increase in political risk increases the bond yield (total cost of private debt) by approximately 6.5 (6.9) basis points or, equivalently, by 5.2 (7.6) percent relative to the sample median. CDS spreads also show an economically meaningful association with firm-level political risk inasmuch as a one-standard deviation change in the latter, increases the former by about 5.2 basis point or 5.9 percent relative to the median. Further probing the pricing effects, we show that the cost-of-debt sensitivity to *persistent* firm-level political risk are larger, ranging from about 8.7 basis points for bond yield to 9.5 basis points for the cost of private debt in response to a one-standard deviation change in persistent firm-level political risk, measured over a 5 year window.

Turning attention to the supply side of credit market, we document that political risk of credit institutions affect loan market outcomes. Specifically, we find that the *lender-level* political risk affects the supply of credit as suggested by the association between $PRisk_{it}$ and loan growth or deposit growth. The magnitudes of these effects suggest that a one-standard-deviation increase in bank-level political risk is associated with about 16.6 (15.3) percent decrease in median loan growth (deposit growth). Further, taking advantage of the granularity of our data, we also show that lender political risk is transmitted to borrowers in the sense that it raises the latter's cost of borrowing, but only when the borrower is in a long-term relationship with the lender.

Having established that political risk affects credit market outcomes, we investigate the existence of the network effects and potential externalities as sources of political risk. Network effects are of particular interest because in their presence even unrelated idiosyncratic shocks to individual companies can cascade into sector or economy wide consequences (e.g., Acemoglu et al 2012, 2014). Conceptually, there are three ways in which political risk can be transmitted in credit markets. Political risk can emanate directly from the borrower or from the lender, as discussed above. However, political risk can also emanate through networks because (1) lenders hold portfolios of borrowers, which are differentially exposed to political shocks; and (2) lenders tend to repeatedly seek out the same set of financial institutions (business partners) to form syndicates, which exposes them to political events experienced by those related banks. We explore these two channels and find evidence in support of network effects in transmitting firm-level political risk.

Finally, we ask whether financial institutions or borrowers can mitigate the impact of political risk on market outcomes. We find that borrowers engaging actively in the political process by lobbying politicians or by giving money to their election campaigns exhibit a dampened effect of political risk on loan spreads. In addition to the active management of political risk, we also find that lenders (passively) manage their exposure to borrower's political risk by reducing their share of ownership retained in the syndicate, increasing the syndicate size as well as the likelihood that the loan is secured.

Our study relates to several recent efforts in the literature. Although we are the first comprehensive study to use a direct and validated firm-time specific measure of political risk to study a broad set of credit market outcomes[3], we build on a quickly expanding set of papers examines the effects of risk and uncertainty about shocks stemming from the political system on financial and factor markets.[4] These prior papers provide some important first evidence on how variations in exposure to aggregate sources of political risk, such as federal elections, or a given industry's dependence on government contracts, affects asset prices, investments, employment, and the business cycle [e.g., Kara and Yook 2018]. Amid a range of measures of aggregate political uncertainty in an economy,[5] the Economic Policy Uncertainty measure developed by Baker, Bloom and Davis [2016] has perhaps been the most influential in work probing the effects of aggregate sources of political risk. Related to our work are the studies that have examined the association between a firm's sensitivity to EPU and credit market outcomes [see, e.g., Berger, Guedhami, Kim and Li 2018, Bordo, et al. 2016, Drobetz, et al. 2018, Francis, et al. 2014, Kaviani, et al. 2017, Ng, Saffar and Zhang 2018, Wang, et al. 2018]. Using measures of *aggregate* political risk exposure, such as a firm's sensitivity to EPU, masks rich the variation in political risk existing within-firm (over time) as well as between firms in a given industry or sector and also puts severe limits on the possibility to study policy-relevant questions such as how political risk transmits through financial markets.

With EPU measures common across all financial institutions, a further probing of the effects of the considerable heterogeneity in bank political risk that we document, is out-of-reach. We tackle this issue by comprehensively analyzing the firm-specific dimension of political risk in credit markets. Indeed, using a time-varying firm-level measure of political risk allows us to address several questions that the literature has not previously been able to answer. These questions include not just examining whether and how a shock to the lender's political risk is transmitted to borrowers, but also extend to considering potential network effects, where the political risk of one agent (e.g., lender or borrower) affects other agents participating in credit markets. Firm-level approach also allows us to map out the "management" of political

[3] Saffar, Wang, and Wei [2019], in a contemporaneous working-paper, use the Hassan et al. [2019] to study bank loan contracting. Their results point in a similar direction as some of our findings reported in Table 3.
[4] See, e.g., Belo, Gala and Li [2013], Besley and Mueller [2017], Gourio, Siemer and Verdelhan [2015], Handley and Limao [2015], Kelly, Pástor and Veronesi [2016], and Koijen, Philipson and Uhlig [2016].
[5] Examples include Bachmann, Elstner and Sims [2013], Giglio, Kelly and Pruitt [2016], Jurado, Ludvigson and Ng [2015].

risk by the borrowers using their lobbying and election campaign donations to trace their respective response to exposures.

2. Firm-level political risk and credit market outcomes

Firm-level political risk is expected to affect credit markets even in the absence of (or beyond) a systematic political risk factor, such as macro-economic policy uncertainty [Pastor and Veronesi 2012]. This effect can happen via the demand side, i.e., the borrower's political risk, or the supply side, i.e., the lender's political risk. This section discusses theory relating to the role of firm-level political risk and its expected consequences.

From the demand side perspective, political risk of the borrower can affect credit market outcomes via two channels. First, political risk is expected to affect credit spreads (bond yields) because it creates uncertainty with respect to the potential for political and regulatory interference with firm's operating and investment decisions, resulting in political costs that can diminish investment opportunities, lower cash flows or adversely affect the value of collateral. Political interference can increase both the likelihood of default and the loss given default and hence is expected to be related to debt pricing and recovery rates. One admittedly extreme example of this interference could be any political actions that result in the seizure of assets owned by US companies in a foreign country, with creditors bearing significant costs of such political actions [Pagano and Volpin 2001]. Politicians could also exert influence over the resolution of court proceedings or other legal disputes between creditors and other stakeholders to the firm. Local politicians, for example, might have incentives to protect a debtor's labor force or local suppliers in an effort to mitigate the adverse consequences of a default on the local economy, and hence on the voting public. Politicians might also seize certain assets in default proceedings or they might prevent firms from going bankrupt in the first place [Faccio, Masulis and McConnell 2006, Tahoun and van Lent 2018]. All of these potential interventions, by politicians at the local, state, and federal level, directly impinge on the loss given default.

Firm-level political risk is expected to affect credit spreads even when it is “idiosyncratic” in the traditional asset pricing sense. This happens due to the nature of the creditor’s claim. To see this, consider a risk neutral economy where all uncertainty about risky debt is firm specific and all loans earn a risk free rate in expectation. Since bond investors have limited upside potential, an increase in firm-level uncertainty (and hence in default and in loss given default risk) needs to be compensated by an increase in bond yields in order to guarantee an expected return to be equal to the risk free rate. Indeed, both theoretical work [e.g., Gilchrist, Sim and Zakrajšek 2014, Merton 1974] and empirical evidence confirms the importance of idiosyncratic volatility in explaining bond yields [e.g., Campbell and Taksler 2003].

Another channel through which borrower-level political risk can influence debt markets is the information asymmetry channel, i.e., by creating a layer of informational asymmetries related to the politics of, as opposed to the economics of, the firm. In particular, the scope for political interference naturally creates a possibility that some economic agents connected to politicians, firm insiders or lobbyists will have informational advantage regarding forthcoming political events and how they impact on the company’s future [Bertrand, Bombardini and Trebbi 2014, Wellman 2017]. This possibility is consistent with the observation that analysts often use conference calls as an opportunity to ask questions related to political topics. This practice, in turn, suggests that *uninformed* market participants will generally price protect against political risk, which in turn is expected to affect both yields and liquidity in credit markets.

From the supply-side perspective, political risk can influence credit market via its effect on lenders’ decisions. A growing body of literature suggests that, in the presence of lending relationships and informational asymmetries among lenders, idiosyncratic shocks to lenders propagate to the real sector and impose costs on firms [e.g., Chodorow-Reich 2014, Chodorow-Reich and Falato 2017, Christensen, Macciocchi and Nikolaev 2018]. For example, Chodorow-Reich [2014] shows that exogenous variation in lender health affects the employment choices by these companies. This suggests that exogenous variation in political risk at the level of a lender can have a plausible effect on credit decisions and loan outcomes.

Finally, it is also possible that firm- or lender-specific political risk imposes negative externalities on other firms due to the presence of network effects in credit markets. Political shocks to one credit institution propagate to other institutions due to their interconnectedness potentially leading to significant disruptions in credit market [e.g., Acemoglu, Bimpikis and Ozdaglar 2014, Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi 2012, Blume, Easley, Kleinberg, Kleinberg and Tardos 2011]. In particular, in syndicated loan markets, lenders often engage in repeated interactions with other syndicate members which provides scope for forging relationships and developing reputations. These ongoing-relationships may expose network lenders to the political risks of their partners. Furthermore, a political shock disrupting the loan supply by a reputable lead arranger creates the need to absorb additional risk by the lending partners and can impose additional monitoring and adverse selection costs.

3. Data

In this section, we describe the methodology used by Hassan et al. [2019] to construct the firm-level political risk measure ($PRisk_{it}$) and provide summary statistics for this measure as well as for the key variables in our study. As our tests move from the borrower-level to the lender-level, we organize our discussion of the sample selection procedure, the data sources, and the pertinent descriptive statistics accordingly.

3.1 $PRisk_{it}$ measure

To arrive at a firm-specific time-varying measure of political risk, Hassan et al. [2019] exploit the practice that publicly listed firms hold quarterly earnings conference calls, in which financial analysts and other market participants discuss the current state-of-affairs with senior management. Applying a machine learning algorithm to the transcripts of these calls, the authors then determine how much of the conversation in the conference call centers on political topics. To determine what political topics are being discussed, the algorithm extracts all two-word combinations ("bigrams") from training libraries that contain comprehensive sets of political topics $\mathbb{P}$ and non-political topics $\mathbb{N}$. To identify these sets, they use (1) an undergraduate text book on American Politics, supplemented with newspaper articles from the Domestic Politics sections of major US newspapers and (2) an undergraduate financial accounting textbook together with newspaper articles on corporate events. The political risk measure is constructed by counting the number of occurrences of exclusively political bigrams in conjunction with a synonym for risk or uncertainty and then dividing it by the total number of bigrams in the transcript (to adjust for the length of the transcript):

$$PRisk_{it} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \left\{ 1[b \in \mathbb{P} \backslash \mathbb{N}] \times 1[|b - r| < 10] \times f_{b,\mathbb{P}} / B_{\mathbb{P}} \right\},$$

where r is the position of the nearest synonym of risk or uncertainty and $b = 0,1,\ldots, B_{it}$ indexes the bigrams contained in the call of firm i at time t. Each bigram is weighted with a score that reflects how strongly the bigram is associated with the discussion of politics, where $f_{b,\mathbb{P}}$ is the frequency of bigram b in the overall political training library and $B_{\mathbb{P}}$ is the total number of bigrams in the training library. Hassan et al. [2019] subject this measure to a battery of stringent validity checks: (1) a human verification of whether the algorithm correctly identifies conversations about risk associated with political topics in the transcript, (2) an inspection of how the measure aligns with political events over time and with sectors that have high versus low exposure to political risk, (3) a set of tests of the correlation between political risk and firm-level outcomes that are a priori likely to be impacted by political risk (such as (planned) investments and hiring), (4) a set of tests to ensure the measure does not reflect news about the mean, i.e., about the sentiment about political events in a firm's conference call, and (5) a set of tests to establish that $PRisk_{it}$ is different from non-political risk.

Hassan et al. [2019] also show that $PRisk_{it}$ is positively associated with implied and realized stock price volatility and that larger companies with higher $PRisk_{it}$ actively manage their exposure by donating more money to the election campaign of politicians and spend more on lobbying. Perhaps the most relevant of their findings for our study pertains to the variance decomposition of $PRisk_{it}$. In contrast with conventional wisdom that political and regulatory decisions have relatively uniform impacts across firms in a developed economy [Pastor and Veronesi 2012], the political system appears to be a major source of "idiosyncratic risk". Only 0.81 percent of the variation in $PRisk_{it}$ is explained by time fixed effects (i.e., by aggregate shocks), whereas sector fixed effects and sector-by-time fixed effects explain another 4.38

percent and 3.12 percent, respectively. The remaining 91.69 percent is firm-level variation that consists of 19.87 percent of permanent differences across firms, i.e., between firm variation, and 71.82 percent of changes over time, i.e., within firms that belong to a given the sector. This evidence suggest that a large part of political risk indeed pertains to the firm-level, justifying our attempt to examine its effects on the credit market.

In our sample, summarized in Table 1, Panel A, the average $PRisk_{it}$ measured at borrower level is equal to 130, and the median is 67, indicating a significant right skew. Table 1, Panel D shows that $PRisk_{it}$ measured at the lead arranger level (lender-level) is more than two times higher as compared to the borrower measure, with an average of 246 and median of 245. The finding that financial institutions are generally subject to high levels of political risk underlines the idea that, given the concentration in financial sector, political risks can propagate to the real sector via their effect on credit supply and on contracting with the borrowers.

Figure 1 depicts how the average $PRisk_{it}$ evolves over time both for borrowers and for lenders. In addition to higher levels of political risk for financial institutions observed before, the other immediate takeaway from the figure is that the time series begins to diverge noticeably in the run-up to the 2008 financial crisis and exhibits only slow convergence in the aftermath of the crisis.

Using a very similar methodology, Hassan et al. [2019] construct a measure of the firm's overall sentiment ($Sentiment_{it}$), which is also derived from the conference calls. Sentiment is constructed by assigning a value of +1 if a bigram *b* is associated with a positive sentiment (using Loughran and McDonald [2011]'s sentiment dictionary), a value of –1 if bigram *b* is associated with negative sentiment, and 0 otherwise. Overall sentiment is then simply calculated by summing across all bigrams in a given transcript and scaling by the total number of bigrams in the transcript. To ease the interpretation of our regression results, we standardize $PRisk_{it}$ and $Sentiment_{it}$ in all subsequent analyses to have zero mean and a standard deviation of unity, and refer to the standardized variables as $zPRisk_{it}$ and $zSentiment_{it}$, respectively.

3.2 Other data sources

To examine the effect of firm-level political risks on credit markets, we use data from a number of sources. Data on public debt yields and liquidity is from the TRACE database and is measured on a quarterly basis. Data on private debt is taken from Thomson Reuters' Dealscan database and is at the deal level. Credit default swaps data is provided by the Markit CDS Pricing database. Financial data on borrowers is from Compustat, whereas financial data for lenders comes from the quarterly bank holding company reports (FR Y-9C) submitted to the Federal Reserve. Finally, data on lobbying (lobby expenses and PAC donations) is from the Center for Responsive Politics (CRP), a nonpartisan not-for-profit research group that gathers the reports filed by lobbying firms and lobbyists with the Clerk of the House of Representatives and the Secretary of the Senate.[6] We also obtain data on campaign contributions by the Political Action Committees associated with our sample firms from the CRP. We use intersections of these datasets to perform the analysis and examine the role of $PRisk_{it}$ in credit markets, as discussed next.

We begin by analyzing the intersection of non-financial companies from Compustat and the Trade Reporting and Compliance Engine (TRACE) data provided via WRDS Bond Returns database. In addition, we use bond data from the Mergent's Fixed Income Securities Database (FISD). Because bond-level data is trade-by-trade, we measure the median yield, bid-ask spread, and trading volume in a given quarter. Following prior studies [e.g., Amiraslani, Lins, Servaes and Tamayo 2017, Weston and Yimfor 2018], we exclude bonds that are variable, perpetual, foreign currency, preferred, puttable, convertible and exchangeable or that have credit enhancements as well as private placements. The bond market sample consists of approximately 150,000 firm-quarter observations by 1,515 firms. We then turn attention to private loan markets and use the intersection of Dealscan and Compustat, merged using the link constructed by Chava and Roberts [2008]. Our loan market sample for this analysis contains 11,039 observations from 2,576 firms. Table 1, Panel A provides summary statistics for all variables used in the firm-level analyses. Finally, our CDS market sample consists of the U.S. nonfinancial firms and includes spreads and recovery rates for 5-year contracts. After merging with Compustat and political data, the final sample consists of 546 firms and 36,611 monthly observations.

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[6] Lobbying firms are required (based on the Lobbying Disclosure Act of 1995) to provide a good-faith estimate, rounded to the nearest USD 10,000 of all lobbying related income from each of their clients.

Our *bank-level* analysis focuses on the sample of lead arrangers, consistent with prior research [e.g., Bharath, Dahiya, Saunders and Srinivasan 2007, Giannetti and Saidi 2018, Ivashina and Scharfstein 2010]. We further follow prior research [e.g., Gopalan, Nanda and Yerramilli 2011] and use the Dealscan variable "LeadArrangerCredit" to identify lead arrangers. We use a manually constructed link to merge the lead arranger's CompanyID in Dealscan with the identifier in the Compustat and the HHLT datasets, to obtain a lender-level quarterly measure of political risk for each lead arranger. The link file includes 70 unique banks covering about 75 percent of the loans arranged by US banks in Dealscan. Our final sample for this analysis after merging with political risk data consists of 8,958 loans arranged by 50 unique banks. For loans with more than one arranger, we have one observation for each arranger and, thus, we have a total 17,715 observations. Table 1, Panel B shows various political and non-political risk measures at the arranger-level, which we use to examine questions of how political risk is transmitted through the syndicate networks and the loan portfolios of financial institutions.

To analyze the effect of political risk on loan supply, we use information from the quarterly bank holding company reports (FR Y-9C reports) submitted to the Federal Reserve. We use the PERMCO-RSSD links from the website of the Federal Reserve Bank of New York to identify each bank's GVKEY and then further link it to the political risk data in HHLT. This procedure yields a final sample of 4,479 quarterly observations.

4. Borrower political risk

Our first set of analyses examines the relation between firm-level (i.e., borrower) political risk and credit market outcomes. We ask three related questions, namely whether firm-level political risk is priced by investors in the public bond market, by lenders in the private debt market, as well as whether firm-level political risk is associated with credit default swap spreads. We start our investigation in the public bond market and examine the relation between the firm-level political risk measure and bond yield, bid-ask spreads and liquidity. Next, we turn to the private debt market and consider how firm-level political risk affects loan pricing, as measured by the total-cost-of-borrowing and the all-in-spread-drawn. Finally, we examine the market for credit default swaps and consider the association between firm level political risk and CDS spreads as well as recovery rates.

4.1 Empirical strategy

To test our prediction that firm-level political risk increases required yields and reduces credit liquidity in bond market, we estimate variations of a panel regression, which in all cases includes sector × time fixed effects ($\delta_s \times \delta_t$) to isolate the firm-level variation in $zPRisk_{it}$ from aggregate or sector-level variation:

$$DepVar_{it+1} = \alpha_0 + \beta_1 zPRisk_{it} + \gamma X_{it} + \delta_s \times \delta_t + \varepsilon_{it} \quad (1)$$

where *DepVar* stands for different credit market outcomes. For public debt market, we examine bond pricing and liquidity whereas for the private debt market we focus on pricing as we do not observe information on liquidity (many private debt contracts are not traded), for CDS, we consider the five-year spread and the recovery rate; *X* is a vector of control variables that includes standardized overall sentiment ($zSentiment_{it}$), the natural logarithm of the borrower's market capitalization (*lnMCAP*), the borrower's return-on-assets (*ROA*), leverage (*LEV*), market-to-book value (*MTB*), stock price volatility (*ReturnVol*), and financial distress (*Zscore*). As our main interest is in isolating the effect of political risk, controlling for "generic" risk is paramount, which we do by including stock return volatility and financial distress. In addition, it is important to control for news about firm performance, which is captured by ROA as well as by our sentiment measure. Control variables as measured as of period *t*. To further probe whether the firm-level political risk that matters most for credit pricing is fixed vs. varies over time within the same borrower, we report a specification that also includes firm fixed effects. In all regressions, to account for interdependence among observations, we cluster standard errors at the firm level.

4.2 Results

Table 2 presents the results for the public debt market analysis. We examine three outcome variables, the quarterly median trade weighted bid-ask spread (*Bid-ask spread*), the difference between the quarterly median yield-to-maturity and the yield of a treasury bill with matched maturity (*Bond yield*), and liquidity (*Liquidity*), defined as the natural logarithm of quarterly median total dollar volume traded divided by total par value and for each outcome variable present two sets of results. In columns (1), (3), and (5), we show the specification that exploits variation in $PRisk_{it}$ at the firm-level, by controlling for sector×time-fixed-effects, i.e., the identifying variation is across firms within a sector and within a firm over time. We also report a further specification in columns (2), (4), and (6) that controls for permanent differences across firms in a given sector (by including firm fixed effects), which implies that the identifying variation in these regressions stems from changes over time in the assignment of political risk within a firm. We do so as Hassan et al. [2019] report that in their sample, about 71 percent of the variance in $PRisk_{it}$ derives from the variation across firms within a given sector.

We find a strong positive association between $zPRisk_{it}$ and bid-ask spreads in columns (1) and (2). A one standard deviation increase in firm-level political risk increases the bid-ask spread by 0.96 (*t-value* = 2.55) basis points, which is about 2.3 percent relative to the sample median. After controlling for permanent differences across firm (i.e., firm fixed effects), the estimate is about 40 percent smaller, but still significant at the ten percent level, consistent with the idea that non-permanent changes in firm-level political risk are priced.

This pattern is repeated when we consider the yields in columns (3) and (4). Again, we find a strong positive association between bond yields and political risk, with coefficient estimates 2.5 times larger for the specification that considers both permanent and changing firm-level political risk than for the case in which permanent differences are controlled. In economic terms, for a one standard deviation change in firm-level political risk, bond yields increase by 6.5 basis points (*t-value* = 3.02), which is equivalent to about 5.3 percent increase relative to the sample median.

Finally, we consider *Liquidity* in columns (5) and (6). We find a coefficient estimate of -0.001, which is significant at the ten percent level, on $zPRisk_{it}$ in column (5), implying that trading volumes are negatively associated with firm-level political risk. Column (6) shows that the estimate is about the same (albeit now significant at the one percent level) when considering within-firm changes in firm-level political risk.

Together these findings provide support for the idea that firm-level political risk is priced on bond markets. An economically meaningful part of the effect of measured political risk on bond prices derives from changes in firm-level political risk over time, whereas the remainder is based on permanent differences in political risk across firms.

Table 3 presents the results for the loan market analysis. As previously, we use a standard specification with sector×time-fixed-effects and an alternative specification that includes firm fixed effects. In this analysis, we use an average $PRisk_{it}$ over four quarters preceding loan initiation. We also use year fixed effects as the dependent variable is available at a relatively low frequency. As previously, we use these regressions to understand the effect of permanent differences in firm-level political risk from within firm variation in political risk. We consider two outcome variables in this table, namely the total cost of borrowing (*Total cost*) as defined in Berg et al. [2016] and the *All-in-Drawn*, i.e., the all-in-spread-drawn, defined as the spread over LIBOR.

We find strong associations in all four columns of Table 3. Specifically, in column (1), the coefficient estimate on $zPRisk_{it}$ equals 6.869 (*t-value* = 2.88), which implies that a one-standard deviation increase in firm-level political risk is associated with a 6.9 basis point increase in total cost-of-borrowing, which is about a 7.5 percent increase relative to the sample median. After controlling for firm-fixed effects in column (2), the estimated coefficient drops to 4.45, which is still significant at the 5% level), implying that approximately two-thirds of the association is due to within-firm variation. Similarly, when we consider the all-in spread in column (3), we find that it has a positive association with $zPRisk_{it}$. The drop in coefficient estimate after controlling for firm-fixed effects is similar in magnitude to the attenuation we observed for total-cost-of-borrowing. Economically speaking, increasing firm-level political risk by one standard deviation raises the all-in spread by 5.56 points, which is about a 3.2 percent increase relative to the sample median.

Our next set of results is presented in Table 4. Returning to our standard specification, we now consider the market for credit default swaps. The spread on CDS provides an alternative measure of default risk and our expectation is that a higher exposure to political risk should be reflected in higher spreads. In addition to CDS spreads, we also have data on the recovery rate, which represents the value of a security when it emerges from default—and as such, enables an estimate to be made of the loss that would occur in the event of default.

We find that firm-level political risk is positively associated with credit default swap spreads. We estimate that a one-standard deviation change in firm-level political risk, increases the five-year spread by 5.2 basis points (*t-value* = 1.54), if we consider overall firm-level political risk. The response to the within firm variation in political risk (in column 2) is in the same order of magnitude, with a coefficient estimate of 6.2 (*t-value* -1.96), which is statistically significant at 10 percent level. Turning to the recovery rate, we find a negative effect of firm-level political risk, consistent with the idea that a higher exposure to political risk increases the loss given default. Once again, the estimate does not change much upon the inclusion of firm fixed effects, but the precision of the estimate increases, inasmuch that we now find an effect significant at the five percent level. These findings are consistent with the idea that the recovery rate responds to over-time changes in firm-level political risk.

Throughout our discussion we have presented results with and without firm fixed effects, to accommodate the idea that part of the variation in firm-level political risk is persistent and part is time varying. We now further examine whether the persistent component in firm-level political risk has a more pronounced effect on debt market outcomes. The pricing response of long-term debt to transitory fluctuations in political risk should be weaker as these ups-and-downs over time should revert to the mean in the near future. To isolate the persistent component in firm-level political risk, we measure the average *PRisk* over five years preceding the measurement of our outcome variables and examine whether it has an effect on the cost of debt as captured by bond yields, loan interest rates, and CDS spreads. We use the same regression model as in equation (1) and cluster the standard errors at firm-level. The sample used in this analysis is smaller as we require data on political risk going back for five years. We also do not include firm-fixed effects as the 5-year averages are by construction highly persistent.

Table 5 presents the results of this analysis. The evidence in the table indicate that a one unit change in the standard deviation of persistent component of firm-level political risk leads to a significant increase in the cost of debt financing measured across three different markets. In particular, the coefficient of interest associated with bond yield is 8.7 (*t-value* = 2.25) which is considerably higher than the corresponding estimate of 6.47 in Table 2. Similarly, the effects of political risk on private debt market's total cost of borrowing and all-in-drawn spread are 9.5 (*t-value* = 2.79) and 9.1 (*t-value* = 3.43), respectively. As is expected, these magnitudes are also considerably higher than the corresponding coefficients estimates based on the *PRisk* measured in the most recent year (quarter) in Table 3. In contrast, the magnitude of the coefficient on *PRisk* associated with CDS spread remains largely the same as that in Table 4, indicating the lack of evidence of persistent component being more important relative to political risk in the most recent quarter. With the exception of CDS market, the findings line up with the economic intuition that the persistent component of firm-level political risk is priced by the credit markets rather than temporary fluctuations of the same.

In sum, we find consistent evidence supporting the hypothesis that firm-level political risk is reflected in credit default swap spreads and recovery rates as well as that it is priced on loan and bond markets. We also find that across private loan and public bond markets, the pricing response to the permanent component of firm-level political risk is stronger than to transitory changes at the firm-level. Together, a picture starts to take shape that the firm-level (*borrower*) political risk has an economically meaningful effect on credit markets. In what follows next, we probe the role of firm-level political risk further by examining how the firm-level political risk of *bank holding companies* is associated with credit supply and deposit growth.

5. Lender firm-level political risk and credit supply

Having documented that the firm-level political risk of borrowers is priced on the demand side of bond and loan markets, the question naturally arises whether firm-level political risk affects the supply side as well. Our conjecture is that financial institutions experiencing higher levels of political risk will reduce their credit supply—and thus will exhibit slower loan growth. One source behind such slow-down is likely to be a reduced growth in deposits, as banks depositors are likely to shy away from banks exposed to elevated level of political risks. We address these possibilities using the following empirical specification estimated at the *lender* level:

$$DepVar_{it} = \alpha_i + \beta_1 zPRisk_{it} + \gamma X_{it} + \delta_t + \varepsilon_{it}, \quad (2)$$

where *DepVar* is either *Loan Growth*, defined as the change in loans scaled by lagged loans, or *Deposit Growth*, defined as the change in deposits scaled by lagged deposits, *zPRisk* is defined as earlier, and *X* is a vector of control variables that include *zSentiment* as well as salient bank characteristics such as the *Tier 1 Capital Ratio* and *Asset Risk*, in addition to *lnAssets* and profitability (*ROA*); α_i denotes bank fixed effects and δ_t are quarterly time fixed effects. In these analyses, contrary to before, lender-level political risk, in the absence of within-sector variation (as we concentrate on financial institutions), is simply $PRisk_{it}$ after controlling for time fixed effects. Standard errors are clustered at the bank level.

Table 6 reports the results of these regressions. In column (1), we document a negative association between $zPRisk_{it}$ and loan growth in the standard specification that controls for changes in aggregate political risk (by including quarter fixed effects). Unlike the case of borrower-level political risk, it is within-lender variation in $PRisk_{it}$ that is mainly responsible for this result as adding bank fixed effects in column (2) doubles the coefficient estimate on $zPRisk_{it}$ (which now equals -0.002 in column 2, as compared with -0.001 in column 1). In column 2 (1), the coefficient estimate is significant at the one (ten) percent level. In columns (4), we also find a significant negative association, here at the five percent level, between lender-level political risk and deposit growth. The coefficient is reduced by a factor 2 (and no longer significant at conventional levels) when we consider the specification without bank fixed effects in column 3. In terms of economic significance, focusing on the specification that controls for persistent differences in political risk between banks, we find that a one-standard deviation increase in $zPRisk_{it}$ is associated with 0.002 (0.002) percent decrease in loan (deposit) growth, which equals to about 16.6 (15.3) percent decrease relative to the sample median.

In sum, across both the loan growth and deposit growth regressions, we find evidence in support of *lender*-level political risk being a determinant of the supply of credit.

6. Lender political risk, loan pricing and relationship lending

Having established that lender-level political risk affects the credit supply, the question arises whether *lender-level* political risk affects loan pricing directly. Theoretically, such an effect is likely to materialize because in the absence of perfect competition in credit markets, lenders have the power to pass on political risks to their borrowers, in particular when borrowers have a strong relationship with their lender of choice.

To investigate this issue, we return to the specification of Equation (1), in which we relate the borrower's firm-level political risk to the total cost of borrowing (*Total cost*) and to the all-in-spread-drawn (*All-in-Drawn*) of individual loans. To estimate this equation, we now add the lender-level political risk defined as the standardized political risk of the lead arranger of the loan syndicate (*zPRisk_arranger*). As previously, we rely on the annualized versions of $PRisk_{it}$. The analysis is performed at the loan level to avoid a loss of information via aggregation. However, to account for interdependencies of loans originated by the same arranger, we cluster standard errors at the arranger level.

We present the results of this augmented specification in Table 7. Columns (1) and (3) report the coefficient estimates without including arranger (bank) fixed effects, whereas columns (2) and (4) include fixed effects as additional controls. The estimates without arranger fixed effects capture both persistent and time-varying effects of arranger-level political risk, while the inclusion of these fixed effects yields coefficient estimates of the time-varying component in lender-level political risk. We find economically large effects of arranger-level political risk on both *Total cost* and on *All-in-Drawn*. The coefficient estimate on the former is 15.99 (*t-value* = 4.24), implying that a one-standard deviation change in arranger-level political risk increases the total cost-of-borrowing by almost 16 basis points. Likewise, the coefficient estimate for *All-in-Drawn* equals 9.62 (*t-value* = 4.02), which is also an economically considerable effect. Both of these effects are partly explained, however, by the cross-sectional variation of political risk across lenders, as can be seen from columns (2) and (4). The difference between the estimated effects on arranger and lender political risk is significantly reduced once we control for persistent arranger-level differences in political risk (by including arranger fixed effects). The importance of arranger-level political risk can be appreciated even more by comparing the coefficient estimates to those on the political risk of the *borrower* (i.e., to $zPRisk_{it}$), which is also an independent variable in the regression. In particular, the effect of borrower $zPRisk_{it}$ is considerably lower as compared to the effect of *zPRisk_arranger* in columns (1) and (3). This can be explained by the fact that lenders cannot diversify their *own* exposure to political risk whereas they can diversify at least some of the exposure across borrowers.

It is also worthwhile to highlight the finding that lead arrangers in loan syndicates that experience higher political risk, have higher credit spread on the loans offered to their borrowers, *holding the borrower's political risk constant*. This finding begs the questions under what circumstances lead arrangers are able to push their own political risk to the borrowers by increasing loan prices. We address that question in Table 8.

The banking literature has argued that some borrowers can benefit from developing long-term relationships with their lenders [e.g.,Berger and Udell 1995, Petersen and Rajan 1994, Rajan 1992]. Once such a relationship is established, borrowers are vulnerable to rent extraction by the lender [Rajan 1992, Sharpe 1990]. We therefore examine whether the effect of arranger-level political risk on loan pricing is stronger for borrowers in a relationship-lending arrangement. To this effect, we return to our augmented version of Equation (1), which includes the arranger-level political and non-political risk, but now add an indicator variable that takes the value of unity if the borrower is in relationship lending and zero otherwise. We then interact this indicator variable with *zPRisk_arranger*, the arranger-level political risk. If borrowers are in relationship lending then we predict that the political risk of lead arrangers will be reflected in loan prices more strongly and hence we predict a positive coefficient estimate on the interaction term.

In Table 8, we provide evidence consistent with this prediction. We report three specifications that each use a different definition to identify when a borrower engages in relationship lending. In column 1 (2), the indicator variable for relationship lending equals one when the total number of lenders that have lent to the borrower over the past four transactions (years) is below the median [see,Murfin 2012]; in column (3), the indicator equals one if the syndicate size is below the median. Of interest in these regressions is the coefficient estimate of the interaction of this indicator variable (*Relation*) and *zPRisk_arranger*. In all three columns, we find a significant, positive coefficient estimate on the interaction. Note also that the coefficient estimate on the simple effect *zPRisk_arranger* is now no longer significant in two out of three specifications (in columns 2 and 3). This coefficient estimate represents the association between the arranger-level political risk and total-cost-of-borrowing for borrowers that are *not* considered to be in relationship lending. Thus, almost the entire effect documented in Table 7 of arranger-level political risk on loan pricing derives from those borrowers that have long-term relationships with their banks.

7. Network and portfolio effects of firm-level political risk

In this section, we explore how firm-level political risk (of given borrowers and lenders) can be propagated across market participants that share economic ties. We investigate two mechanisms how "network" effects can explain the loan pricing of individual loans. Specifically, we construct two variables, *zPRisk_portfolio*, which intends to capture the political risk originating from the arranger's portfolio of borrowers, and *zPRisk_network*, which reflects, for a given arranger, the political risk associated with all co-lenders with whom the lead arranger has co-syndicated loans in the past three years (i.e., the arranger's *network*). In the same vein, we define the arranger's portfolio of borrowers to consist of all loans originated by the arranger over the past three years. Once the portfolio of loans and the associated borrowers are identified, we weigh each borrower's annualized $PRisk_{it}$ (measured as of the end of the quarter preceding the current loan) by the count of loans the borrower had in the arranger's portfolio. The political risk associated with the lead arranger's network is computed by weighing the annualized $PRisk_{it}$ of each co-lender (measured as of the end of the quarter preceding the current loan) by the count of co-syndicated loans with each co-lender. We include both of these proxies into Equation (1) and also control for borrower- and arranger-level political risk proxies.

We present the corresponding regressions in Table 9 using the total cost of borrowing as the dependent variable and clustering standard errors at the arranger level. We find a significant positive association between the political risk originating from the lender's portfolio of borrowers on the cost of borrowing. The effect is incremental to those of the borrower-level and of the lender-level political risk.

The magnitude of the effect is in the same order as we find for the arranger-level political risk when we account for persistent differences between arrangers in their loan portfolio in column 2. However, in column 1, we find a coefficient on *zPRisk_portfolio* equal to 10.92 (t = 3.21), which is about 30 percent smaller, which suggests that the political risk emanating from the portfolio of borrowers has a smaller effect on loan pricing than the arranger-level political risk (but a larger effect as compared to the borrower-level political risk).

The effects of the political risk that originates from the co-lenders of the lead arranger in his syndicate network are even larger. We find (without controlling for persistent differences between arrangers) in column (3), that the coefficient estimate on *zPRisk_network* is 20.89 (*t-value* = 3.88), implying that a one-standard deviation change in the political risk of the arranger's syndicate loan network is associated with about 21 basis point increase in the total cost of borrowing. This effect size is attenuated when focusing on changes over time in the lead-arranger's network risk, but the estimated coefficient remains larger than the effect stemming directly from *zPRisk_borrower* and *zPRisk_arranger*, respectively.

Together these findings document the importance of network mechanisms through which increases in political risk can propagate from one firm to another and hence cascade into sector wide effects [e.g., Acemoglu 2012]. Specifically, an increase in the political risk of an arranger's loan portfolio is associated with higher loan pricing for other borrowers in their portfolio. Similarly, if one co-lender in an arranger's preferred network of syndicate partners comes under closer regulatory or political scrutiny, such an arranger appears to pass on the risk to his own borrowers. Hassan et al. [2019] discuss a theoretical explanation for how firm-level political risk, through network effects, can have macroeconomic consequences. In particular, these authors highlight supply-relations and the effect on total factor productivity as a possible mechanism; our results open the possibility that another channel operates through credit markets. We caution, however, that these results should be interpreted bearing in mind the possibility that they are partly explained and reinforced by matching between borrowers and lenders. Even this this is the case, the evidence still highlights the potentially far reaching effects of firm-level political risk on credit markets.

8. Managing firm-level political risk

A natural question that arises at this point, given the pervasive effects of borrower and lender level political risk on credit markets, is whether both firms and financial institutions have means at their disposal to reduce or "manage" the adverse impact of political risk (see also, Hassan et al. [2019]). In this regard, we explore two avenues how firm-level political risk can potentially be managed. First, we hypothesize that *borrowers* manage their political risk via direct participation in the political process, either by lobbying or by donating money to the election campaigns of politicians (through their Political Action Committees or PACs) [Cooper, Gulen and Ovtchinnikov 2010, Olson 1965, Peltzman 1976, Tahoun 2014, Tullock 1967]. While political activism can take many shapes, research in the political sciences tends to use lobbying and PAC donations as a *pars-pro-toto* of the same [Ansolabehere, De Figueiredo and Snyder Jr 2003, Milyo, Primo and Groseclose 2000]. Second, we explore whether *lenders* manage political risk by lowering their exposure to borrowers with elevated levels of $PRisk_{it}$ by retaining a lower portion of the loan (*Lead share*) and increasing the number of lenders in a syndicate (*Syndicate size*), or by ensuring that the loan is secured by collateral (*Secured*).

We begin our analysis by examining the borrower's management of political risk via political activism. We use two proxies for political activism: *lnLobby* is the natural logarithm of the borrower's lobbying expense, and *lnDonation* is the natural logarithm of the borrower's total Political Action Committee donations. We return to Equation (1), estimated in the borrowers' panel, and interact each of these two measures of active political risk management with the borrower's annualized political risk $zPRisk_{it}$. This interaction term addresses the question whether borrowers who engage in political activity have lower loan pricing than those who refrain from lobbying and campaign donations. Standard errors in this panel are clustered at the borrower level.

In Table 10, column (1) we show that lobbying is associated with a weaker relation between borrowers' political risk and loan pricing. The estimated coefficient on the interaction term is -1.17 (*t-value* = -2.34). We find a similar result when we use borrower donations to election campaigns as a proxy for political activism in column (3). Again, the interaction term has a negative and significant coefficient (-

0.80, *t-value* = -1.68), implying that donating borrowers have a weaker relation between their political risk and loan pricing than non-donating borrowers. In column (3), we explore a third active political risk management strategy, suggested by Hassan et al. [2019], namely that borrowers "hedge" their connections to both political parties by giving donations to Republicans and Democrats in roughly equal amounts. Interacting *Hedge* with $zPRisk_{it}$ in column (5) reveals that doing so weakens the relation between political risk and loan pricing even further, although the coefficient is estimated less precisely than before (*t-value* = -1.73). In all of these regressions, we focus on the effect of changes in borrower-level political risk over time, as we control for persistent differences by adding firm fixed effects. However, our conclusions remain qualitatively the same if we include such persistent differences.

We next turn to the examination of the management of political risk by lenders. We examine how lenders manage their exposure to such risks by retaining a lower than average share of the loan and requiring the use of collateral. We present our findings in Table 11, where, as previously, we remove variation in aggregate political risk over time (time fixed effects), to isolate lender-level variation (in columns (1), (3), and (5)). We also control for persistent differences between lenders in firm-level political risk by adding lender fixed effects in columns (2), (4), and (6). In all regressions, standard errors are clustered at the arranger level. Across specifications, we observe that the firm-level political risk of the arranger is associated with stronger "passive" political risk management. For example, a one-standard deviation in arranger political risk, increases the number of lenders in a given syndicate by 0.15 (column 1) and also increases the probability of having a secured loan with 2.6 percent (column 5).

Together, these analyses suggest that both lenders and borrowers have means to reduce the effect of firm-level political risk on economic outcomes. Bear in mind that the potential benefits of political participation of borrowers is unlikely to be restricted to mitigating the pricing effects of political risk in credit markets, but rather extend beyond these consequences to other favorable outcomes. Financial institutions too appear to respond to political risk; in their case, by managing their exposures via changes to "contract design".

9. Conclusions

While the effects of economy-wide shocks emanating from the political system on markets have been studied in the past, recent work makes it clear that aggregate shocks only reflect the tip of the iceberg of a given firm's exposure to political events. There are multiple examples that illustrate that political risk is largely a firm-specific phenomenon. We build on recent work by using the Hassan et al. [2019] and use their a granular measure of political risk to comprehensively examine how firm-level political risk affects private and public credit markets. Based on this measure, we document that borrower-level political risk is priced when analyzing both pricing and liquidity in public debt markets, and also when analyzing the cost of private debt and credit default spreads. The effects are of moderate magnitudes but are economically important. What's more, further bolstering our confidence in the empirical credibility of our findings, we show that increasing firm-level political risk by one standard deviation yields a pricing response of essentially the same magnitude in both bond and loan markets.

Further, we show that lender-level political risk influences the supply of credit and in turn has a significant effect on loan pricing. We also take advantage of the granularity of our measure and show that firm-specific shocks to political risk propagate across firms and lenders, suggesting the importance of network effects in amplifying the effects of political uncertainty. Finally, we show that borrowers can mitigate the effect of political risk via political activism whereas lenders respond by limiting their exposure via changes to contractual terms.

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Table A1: Variable definitions

Variables	Description
Total cost of borrowing	Total cost of borrowing, as defined in Berg et al. [2016].
All-in-Drawn	All-in-spread-drawn, defined as the sum of the spread over LIBOR plus the facility fee. (Dealscan)
Loan growth	Change in loans scaled by lagged loans: ΔTotal loans$_q$/Total loans$_{q-1}$. (FR Y-9C)
Deposit growth	Change in deposits scaled by lagged deposits: ΔDeposits$_q$/Deposits$_{q-1}$. (FR Y-9C)
Syndicate size	Number of lenders in a syndicate. (Dealscan)
Lead share	The percentage of total loan retained by the lead arranger. (Dealscan)
Secured	Indicator variable equal to one if the loan is secured with collateral, 0 otherwise. (Dealscan)
Bid-ask spread	Quarterly median trade-weighted bid-ask spread. (WRDS Bond Database)
Bond Yield	The difference between the quarterly median yield-to-maturity and the yield of a treasury bill with matched maturity. (WRDS Bond Database)
Liquidity	Log of the total dollar volume traded divided by total par volume. (WRDS Bond Database)
CDS spread	The cost a protection buyer has to pay the protection seller
Recovery rate	The percentage of par value that bondholders will receive after a credit event.
zPRisk	Standardized firm-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured as the average firm-level political risk over the past four quarters preceding loan origination. *PRisk* is standardized to have a mean equal to zero and a standard deviation equal to 1.
zSentiment	The overall sentiment in the conference call as defined in Hassan et al. [2019] constructed by assigning a value of +1 if bigram is associated with positive sentiment (using Loughran and McDonald [2011]'s sentiment dictionary), a value of −1 if bigram is associated with negative sentiment, and 0 otherwise.
zPRisk_bond	Standardized firm-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured as the lagged quarter firm-level political risk.
zPRisk_bhc	Standardized bhc-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured as the lagged quarter bank holding company-level political risk.
zPRisk_Arranger	Standardized arranger-level political risk as defined in Hassan et al. [2019]. PRisk_*Arranger* is measured as the average arranger-level political risk over the past four quarters preceding loan origination.
zPRisk_Portfolio	Standardized political risk originating from the arranger's portfolio of borrowers where an arranger's portfolio includes all borrowers with outstanding loans originated by the current arranger. Once the portfolio of borrowers is identified, four-quarter-average *PRisk* of each borrower as of the quarter before the current loan date, along with the count of loans with

	each of borrowers over the past three years are used to compute the weighted average portfolio *PRisk*
zPRisk_Network	Standardized political risk originating from the arranger's network where the network for a particular lead arranger constitutes all co-lenders with whom the lead arranger has co-syndicated loans in the past 3 years starting from the quarter before current loan date. Once the network is identified, four-quarter-average *PRisk* of each co-lender as of the quarter before the current loan date, along with the count of joint-loans with each co-lender are used to compute the weighted average network *PRisk*.
lnLobby	Log of one plus average lobby expense over the past 4 quarters. (CRP)
lnDonation	Log of one plus the sum of average political action committee contributions paid to federal election candidates over the past 4 quarters. (CRP)
Hedge	Indicator variable equal to one if the average political action committee donations to Republicans over average donations to Democrats are between the 25th and 75th percentile of the sample. (CRP)
RelationI	Indicator variable equal to one if total number of lenders that have lent to the borrower over the past 4 transactions is below median, zero otherwise.
RelationII	Indicator variable equal to one if total number of lenders that have lent to the borrower over the past 4 years is below median, zero otherwise
RelationIII	Indicator variable equal to one if the syndicate size is below median, zero otherwise
ROA	Operating income before depreciation (oibdp) minus depreciation and amortization (dp) divided by total assets (at). (Compustat)
MTB	Market to book value of assets (at - ceq + mkvalt)/at. (Compustat)
lnMCAP	Log of market value of equity (csho multiplied by prcc_f). (Compustat)
LEV	Long-term debt (dltt) plus debt in current liabilities (dlc) divided by total assets (at). (Compustat)
ReturnVol	Standard deviation of monthly stock returns (ret) using the past 2 years. (CRSP)
Zscore	Altman's (1968) Z-score = (1.2*(act-lct)/at + 1.4*re/at + 3.3*(pi)/at+0.6*mkvalt/lt + 0.999*revt/at). (Compustat)

Figure 1: Fluctuations in political risk (*PRisk*) of borrowers and lenders over time.

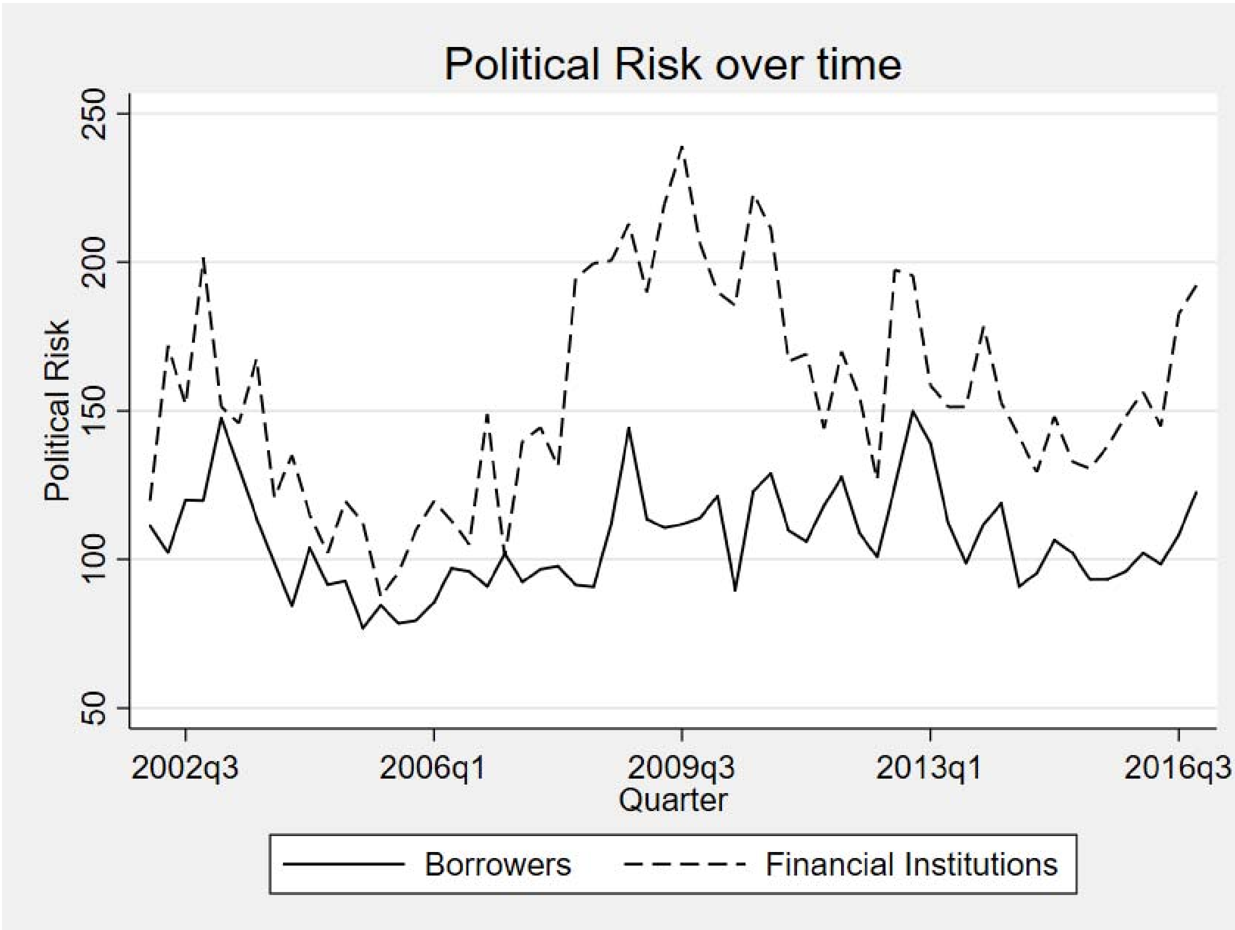

Table 1: Summary statistics

	N	Mean	St. Dev.	p25	Median	p75
Panel A: Bond market						
Bid-ask spread spread (bps)	122,388	61.929	82.924	21.813	42.283	77.259
Bond_Yield (bps)	115,463	196.182	348.85	70.383	123.046	216.621
Liquidity	150,696	0.054	0.132	0.001	0.043	0.111
lnMCAP	150,696	9.708	1.452	8.8	9.778	10.658
ROA %	150,696	9.029	5.959	5.404	7.795	11.962
LEV %	150,696	33.224	13.599	23.779	32.155	40.953
MTB	150,696	1.643	.741	1.154	1.38	1.877
ReturnVol	150,696	7.519	4.187	4.781	6.316	8.895
Zscore	150,696	2.278	1.578	1.013	1.914	3.25
PRisk	150,696	130.257	201.562	23.045	67.07	152.636
Sentiment	150,696	821.571	534.648	455.52	800.641	1172.17
Panel B: Loan market (Borrowers)						
Total cost of borrowing (bps)	8,543	155.019	157.034	51.395	91.489	209.749
All-in-Drawn (bps)	11,039	201.038	150.457	100	175	250
lnMCAP	11,039	7.713	1.786	6.495	7.674	8.949
ROA %	11,039	8.475	7.781	4.962	8.066	12.211
LEV %	11,039	29.477	20.175	15.4	27.486	40.397
MTB	11,039	1.724	0.881	1.166	1.455	1.97
ReturnVol	11,039	11.283	6.967	6.796	9.565	13.659
Zscore	11,039	3.103	3.39	1.368	2.553	4.078
PRisk	11,039	107.779	138.338	35.89	70.476	129.151
Sentiment	11,039	791.028	451.516	490.811	763.652	1082.713
Lobby expense ($thousands)	3,602	295.698	706.498	0	45	248.661
Donation expense ($thousands)	3,246	28.047	57.706	0.875	8.146	28.5
Hedge	3,246	0.29	0.454	0	0	1
Panel C: CDS market						
CDS Spread (bps)	36,611	185.467	410.658	46	88.542	200.369
Recovery rate	36,542	39.055	3.746	39.329	40	40
lnMCAP	36,611	8.965	1.433	7.993	9	9.889
ROA %	36,611	9.807	6.429	5.953	9.186	13.123
LEV %	36,611	30.152	15.789	19.069	27.777	38.281
MTB	36,611	1.722	.757	1.207	1.506	1.987
ReturnVol	36,611	9.289	5.949	5.692	7.811	10.843
Zscore	36,611	2.798	2.092	1.489	2.528	3.762
PRisk	36,611	107.294	176.348	18.338	56.129	126.247
Sentiment	36,611	838.251	535.491	479.91	824.057	1185.771
Panel D: Loan market (Lenders)						
TCB	13,870	143.451	136.166	51.421	85.497	200.5
All-in-Drawn	17,715	183.491	126.679	100	150	250
lnMCAP	17,715	8.367	1.701	7.204	8.343	9.563
ROA %	17,715	8.948	7.044	5.325	8.241	12.082
LEV %	17,715	31.472	19.503	18.241	29.302	42.283
MTB	17,715	1.724	0.855	1.184	1.456	1.96
ReturnVol	17,715	9.905	5.9	6.141	8.445	11.93
Zscore	17,715	2.887	3.004	1.269	2.331	3.79
PRisk_Arranger	17,715	245.878	162.752	134.23	208.046	313.99
Sentiment	17,715	428.09	470.25	164.426	463.111	725.006
PRisk_Network	13,401	246.153	65.763	200.036	244.846	288.659
PRisk_Portfolio	13,397	126.982	27.649	109.753	124.249	140.14
Panel E: Bank Holding Companies						
Deposit Growth	4,479	0.024	0.07	-0.009	0.012	0.04
Loan Growth	4,479	0.021	0.055	-0.005	0.013	0.034

PRisk	4,479	158.265	231	41.702	99.637	191.199
Sentiment	4,479	425.588	587.878	70.089	480.596	815.144
lnASSETS	4,479	16.312	1.766	15.095	15.958	17.065
ROA %	4,479	0.487	0.816	0.232	0.497	0.854
Tier1 Capital Ratio	4,479	12.851	6.071	9.96	11.67	13.81
Asset Risk	4,479	0.741	0.131	0.663	0.75	0.824

This table provides descriptive statistics on loan market, bond market, CDS market, and *PRisk* measures used in the paper. Data in panel A is at the firm level, data in panel B is at the arranger level and variables are defined in Appendix Table A1.

Table 2: Political risk in public debt markets

	(1) Bid-ask spread	(2) Bid-ask spread	(3) Bond Yield	(4) Bond Yield	(5) Liquidity	(6) Liquidity
zPRisk	0.955**	0.558*	6.474***	2.550*	-0.001*	-0.001***
	(2.55)	(2.00)	(3.02)	(1.72)	(-1.68)	(-2.64)
zSentiment	0.049	-1.400**	-8.352**	-9.427***	0.007***	0.006***
	(0.07)	(-2.64)	(-2.50)	(-3.60)	(3.50)	(6.14)
lnMCAP	-3.933***	-10.935***	-48.493***	-134.475***	0.013***	0.040***
	(-4.88)	(-3.97)	(-10.72)	(-7.05)	(5.77)	(7.08)
ROA	-0.002	-0.268	-3.895***	-3.525***	0.002***	0.001**
	(-0.01)	(-1.36)	(-3.52)	(-3.14)	(3.89)	(2.57)
LEV	-0.103	0.320***	1.554***	1.282*	-0.001***	-0.001***
	(-1.13)	(3.14)	(3.33)	(1.92)	(-2.68)	(-3.04)
MTB	-0.257	1.953	30.232**	78.059***	-0.011*	-0.020***
	(-0.14)	(0.81)	(2.38)	(4.23)	(-1.81)	(-4.10)
ReturnVol	1.798***	1.057***	20.914***	5.364***	-0.005***	-0.002***
	(5.93)	(3.46)	(10.29)	(3.12)	(-8.24)	(-3.33)
Zscore	-2.575**	0.709	-14.930**	-7.749	-0.004	0.002
	(-2.31)	(0.58)	(-2.11)	(-0.88)	(-1.12)	(0.55)
Observations	122,388	122,334	115,463	115,399	150,696	150,664
R-squared	0.194	0.288	0.344	0.517	0.291	0.478
Industry x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

The table presents the effect of firm-level political risk on bid-ask spread, bond yield, and a volume-based measure of liquidity. The dependent variable in column 1 and 2 (*Bid-ask spread*) is the quarterly median trade-weighted bid-ask spread. The dependent variable in column 3 and 4 (*Bond yield*) is the difference between the quarterly median yield-to-maturity and the yield of a treasury bill with matched maturity. The dependent variable in column 5 and 6 (*Liquidity*) is the log of the total dollar volume traded divided by total par volume. The main independent variable is the standardized firm-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured in the firm-quarter preceding the bond trading date and prefix '*z*' indicates that the measure is standardized. For each bond feature, we estimate a specification with industry-quarter fixed effects and a specification with issuer fixed effects. Data is at the issuer level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the issuer level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Political risk and loan markets

VARIABLES	(1) Total Cost	(2) Total Cost	(3) All-in-Drawn Spread	(4) All-in-Drawn Spread
zPRisk	6.869***	4.450**	5.558***	3.385*
	(2.88)	(1.97)	(2.94)	(1.81)
zSentiment	-5.386**	-3.938	-5.872***	-6.706***
	(-2.50)	(-1.48)	(-3.47)	(-3.25)
lnMCAP	-18.580***	-46.450***	-24.303***	-40.750***
	(-11.42)	(-9.95)	(-18.50)	(-11.48)
ROA	-3.828***	-1.655***	-2.931***	-1.325***
	(-7.84)	(-2.77)	(-9.08)	(-3.49)
LEV	1.806***	0.849***	1.086***	0.458**
	(11.99)	(3.81)	(9.57)	(2.58)
MTB	17.572***	10.169**	10.656***	7.431**
	(4.37)	(2.09)	(3.37)	(1.98)
ReturnVol	3.071***	1.132**	3.478***	1.354***
	(6.81)	(2.41)	(8.76)	(2.93)
Zscore	-0.377	0.741	-1.148	-0.041
	(-0.34)	(0.51)	(-1.55)	(-0.05)
Observations	8,543	7,962	11,039	10,405
R-squared	0.345	0.637	0.408	0.645
Firm FE	No	Yes	No	Yes
Industry x Year FE	Yes	Yes	Yes	Yes

The table reports the effect of firm level political risk on loan pricing. The dependent variable in columns 1 and 2 (*Total cost*) is the total cost of borrowing. The dependent variable in columns 3 and 4 (*All-in-Drawn*) is all-in spread drawn. The main independent variable is the standardized firm-level political risk (PRisk) as defined in Hassan et al. [2019]. *PRisk* is measured as the average firm-level political risk over the past four quarters preceding loan origination and prefix '*z*' indicates that the measure is standardized. For each dependent variable, we estimate a specification with industry-year fixed effects and a specification with industry-year and firm fixed effects. Data is at the borrower level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the borrower level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Political risk in CDS markets

VARIABLES	(1) CDS Spread	(2) CDS Spread	(3) Recovery rate	(4) Recovery rate
zPRisk	5.153	6.117*	-0.053	-0.052**
	(1.54)	(1.96)	(-1.49)	(-2.27)
zSentiment	-28.721***	-33.180***	0.140*	-0.031
	(-4.23)	(-5.02)	(1.76)	(-0.73)
lnMCAP	-56.689***	-339.294***	0.201**	1.540***
	(-5.90)	(-5.20)	(2.40)	(5.90)
ROA	-9.101***	-3.501*	0.025	-0.013
	(-4.53)	(-1.89)	(1.21)	(-0.91)
LEV	3.844***	3.577**	-0.014	-0.013
	(5.47)	(2.57)	(-1.22)	(-1.29)
MTB	23.092	124.959***	-0.215	-0.577***
	(1.27)	(3.30)	(-0.98)	(-2.60)
ReturnVol	14.246***	-1.891	-0.104***	-0.034
	(8.66)	(-0.88)	(-2.78)	(-1.51)
Zscore	2.659	11.764	-0.096	-0.018
	(0.38)	(1.13)	(-0.67)	(-0.19)
Observations	36,611	36,602	36,542	36,533
R-squared	0.314	0.497	0.218	0.597
Firm FE	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes

The table reports the effect of firm level political risk on CDS markets. The dependent variable in columns 1 and 2 (*CDS Spread*) is the cost a protection buyer has to pay the protection seller. The dependent variable in columns 3 and 4 (*Recovery rate*) is an estimate of the percentage of par value that bondholders will receive in case of a credit event. The main independent variable is the standardized firm-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured in firm-quarter preceding the CDS spread date and prefix '*z*' indicates that the measure is standardized. For each dependent variable, we estimate a specification with industry-year fixed effects and a specification with firm fixed effects. Data is at the firm level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the firm level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Persistent political risk and credit markets

VARIABLES	(1) Total cost	(2) All-in-Drawn spread	(3) Bond Yield	(4) CDS spread
zPRisk_5Y	9.456***	9.063***	8.713**	6.102
	(2.79)	(3.43)	(2.25)	(1.62)
zSentiment_5Y	-1.431	-0.878	-8.271**	-28.793***
	(-0.58)	(-0.45)	(-2.41)	(-3.89)
lnMCAP	-14.043***	-21.03***	-45.824***	-59.378***
	(-7.53)	(-14.95)	(-10.63)	(-5.64)
ROA	-3.566***	-2.917***	-2.803***	-9.036***
	(-6.86)	(-8.69)	(-2.84)	(-4.10)
LEV	2.007***	1.206***	1.440***	3.856***
	(12.06)	(9.99)	(3.07)	(5.56)
MTB	12.614***	8.295***	16.141	22.665
	(2.97)	(2.69)	(1.39)	(1.13)
ReturnVol	2.966***	3.034***	19.765***	14.363***
	(5.40)	(7.81)	(9.67)	(7.55)
Zscore	0.941	-0.470	-14.253**	2.712
	(0.89)	(-0.66)	(-2.21)	(0.36)
Observations	6,466	8,586	98,475	31,999
R-squared	0.322	0.391	0.338	0.301
Industry x Year/Quarter FE	Yes	Yes	Yes	Yes

The table reports the effect of persistent component in firm level political risk on debt market outcomes. The dependent variable in columns 1 (*Total cost*) is the total cost of borrowing. The dependent variable in columns 2 (*All-in-drawn spread*) is all-in spread drawn. The dependent variable in columns 3 (*Bond yield*) is bond yield measured as the difference between the quarterly median yield-to-maturity and the yield of a treasury bill with matched maturity. The dependent variable in column 4 (*CDS Spread*) is the cost a protection buyer has to pay the protection seller. The main independent variable is standardized firm-level political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured as the average firm-level political risk over the past 5 years preceding loan origination/trading date and prefix '*z*' indicates that the measure is standardized. Data is at the borrower level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the borrower level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The effect of political risk on credit supply and deposit growth

VARIABLES	(1) Loan growth	(2) Loan growth	(3) Deposit growth	(4) Deposit growth
zPRisk	-0.001*	-0.002***	-0.001	-0.002**
	(-1.86)	(-2.74)	(-1.39)	(-1.98)
zSentiment	0.007***	0.006***	0.006***	0.004**
	(5.04)	(4.12)	(3.75)	(2.58)
lnASSETS	-0.001	0.016***	0.000	0.012*
	(-1.00)	(2.84)	(0.14)	(1.66)
ROA	0.008***	0.007***	0.003	0.003
	(4.98)	(3.64)	(1.09)	(0.90)
Tier1 Capital Ratio	-0.001***	-0.003***	-0.000	-0.001
	(-3.69)	(-4.88)	(-0.32)	(-1.22)
Asset Risk	-0.034***	-0.038	-0.017	-0.037
	(-2.90)	(-1.59)	(-1.09)	(-1.23)
Observations	4,479	4,469	4,479	4,469
R-squared	0.110	0.229	0.032	0.135
Quarter FE	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes

The table reports the effect of bank political risk on loan and deposit growth. The dependent variable in columns 1 and 2 is quarterly loan growth (*Loan growth*), which is defined as $\Delta \text{Total loans}_q / \text{Total loans}_{q-1}$. The dependent variable in columns 3 and 4 is quarterly deposit growth (*Deposit growth*), which is defined as $\Delta \text{Deposits}_q / \text{Deposits}_{q-1}$. The main independent variable is the standardized political risk (*PRisk*) as defined in Hassan et al. [2019]. *PRisk* is measured at the level of bank-holding company and is lagged by one quarter. Prefix '*z*' indicates that the measure is standardized. We estimate the relationship with year and bank fixed effects. Data is at the bank holding company level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the institution level, are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Lender's political risk and loan pricing

VARIABLES	(1) Total cost	(2) Total cost	(3) All-in-Drawn spread	(4) All-in-Drawn spread
zPRisk_arranger	15.993***	4.066***	9.616***	3.043***
	(4.24)	(2.74)	(4.02)	(3.01)
zPRisk	2.958*	3.045**	2.845**	2.897**
	(1.82)	(2.03)	(2.20)	(2.36)
zSentiment_arranger	5.951	-0.334	0.511	-5.007***
	(1.11)	(-0.12)	(0.15)	(-2.77)
zSentiment_borrower	-0.475	-0.242	-0.886	-0.650
	(-0.36)	(-0.20)	(-0.84)	(-0.61)
lnMCAP	-19.235***	-21.352***	-23.879***	-24.853***
	(-9.18)	(-8.36)	(-15.09)	(-12.91)
ROA	-3.170***	-2.851***	-2.176***	-2.060***
	(-7.82)	(-6.91)	(-9.58)	(-9.30)
LEV	1.813***	1.584***	1.264***	1.114***
	(18.95)	(11.30)	(20.77)	(13.91)
MTB	7.909***	8.768***	1.833	2.518
	(3.30)	(3.75)	(0.95)	(1.30)
ReturnVol	3.426***	3.126***	3.731***	3.582***
	(7.82)	(6.76)	(10.17)	(9.51)
Zscore	1.138	0.818	0.121	-0.059
	(1.56)	(1.15)	(0.26)	(-0.12)
Observations	13,870	13,870	17,715	17,715
R-squared	0.411	0.457	0.481	0.506
Bank FE	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes

The table reports the effect of lender's political risk on loan pricing. The dependent variable (*Total cost*) in column 1 and 2 is the total cost of borrowing. The dependent variable in column 3 and 4 (*All-in-Drawn*) is all-in drawn spread. The main independent variable is the standardized arranger-level political risk as defined in Hassan et al. (2017). *PRisk_Arranger* is measured as the average arranger-level political risk over the past four quarters preceding loan origination. Prefix '*z*' indicates that the measure is standardized. For each dependent variable, we estimate a specification with industry-year fixed effects and a specification with industry-year and bank fixed effects. Data is at the arranger level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the arranger level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Lender's political risk and loan pricing

VARIABLES	(1) Total cost	(2) Total cost	(3) Total cost
zPRisk_arranger	2.239*	-0.482	-1.809
	(1.80)	(-0.35)	(-1.04)
RelationI	43.766***		
	(4.66)		
ZPRisk_Arranger x RelationI	13.392***		
	(2.75)		
RelationII		6.872**	
		(2.16)	
ZPRisk_Arranger x RelationII		10.311***	
		(2.94)	
RelationIII			41.524***
			(7.13)
ZPRisk_Arranger x RelationIII			11.902***
			(3.15)
ZPRisk_borrower	2.849*	1.165	3.310**
	(1.93)	(1.27)	(2.21)
zSentiment_arranger	-1.290	-1.660	0.161
	(-0.55)	(-0.67)	(0.06)
zSentiment_borrower	0.407	-0.035	-0.471
	(0.31)	(-0.03)	(-0.38)
lnMCAP	-18.447***	-20.154***	-16.440***
	(-7.63)	(-8.00)	(-8.69)
ROA	-2.548***	-2.924***	-2.682***
	(-7.99)	(-7.74)	(-6.64)
LEV	1.783***	1.707***	1.586***
	(13.13)	(12.83)	(11.57)
MTB	4.771**	10.042***	5.428**
	(2.07)	(4.38)	(2.46)
ReturnVol	3.367***	3.435***	2.943***
	(8.18)	(7.58)	(6.60)
Zscore	0.536	-0.018	0.653
	(0.80)	(-0.03)	(0.97)
Observations	12,656	11,815	13,870
R-squared	0.482	0.490	0.474
Bank FE	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes

The table reports the effect of relationship-based lending on the relation between lender's political risk and loan pricing. The dependent variable (*Total cost*) is the total cost of borrowing. The main independent variable is the standardized arranger-level political risk as defined in Hassan et al. [2019]. *PRisk_Arranger* is measured as the average arranger-level political risk over the past four quarters preceding loan origination. Prefix '*z*' indicates that the measure is standardized. *RelationI* is an indicator variable equal to 1 if the total number of lenders that have lent to the borrower over the past 4 transactions is below the median, zero otherwise. *RelationII* is an indicator variable equal to 1 if the total number of lenders that have lent to the borrower over the past 4 years is below the median, zero otherwise. *RelationIII* is an indicator variable equal to 1 if the syndicate size is below the median, zero otherwise. All results are estimated with industry-year and bank fixed effects. Data is at the arranger level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the arranger level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Channels of political risk and the cost of borrowing

VARIABLES	(1) Total cost	(2) Total cost	(3) Total cost	(4) Total cost
zPRisk_portfolio	10.922***	5.415*		
	(3.21)	(1.80)		
zPRisk_network			20.892***	5.734***
			(3.88)	(2.90)
zPRisk_arranger	13.859***	3.537**	14.157***	4.255***
	(3.59)	(2.26)	(3.92)	(2.84)
zPRisk_borrower	3.409**	3.389**	3.279*	3.370**
	(2.03)	(2.18)	(1.98)	(2.17)
zSentiment_borrower	-1.354	-0.511	-1.417	-0.551
	(-0.90)	(-0.33)	(-0.93)	(-0.35)
zSentiment_arranger	6.510	-1.256	6.835	-1.101
	(1.22)	(-0.43)	(1.39)	(-0.39)
lnMCAP	-20.261***	-21.654***	-21.036***	-21.578***
	(-10.22)	(-8.63)	(-9.02)	(-8.41)
ROA	-3.021***	-2.733***	-3.011***	-2.741***
	(-7.76)	(-6.79)	(-7.51)	(-6.79)
LEV	1.815***	1.597***	1.800***	1.601***
	(17.46)	(11.16)	(15.40)	(10.89)
MTB	7.595***	8.402***	8.044***	8.430***
	(3.18)	(3.50)	(3.29)	(3.47)
ReturnVol	3.420***	3.133***	3.352***	3.141***
	(7.73)	(6.73)	(7.94)	(6.88)
Zscore	1.362*	0.967	1.343*	0.957
	(1.74)	(1.27)	(1.72)	(1.26)
Observations	13,397	13,397	13,401	13,401
R-squared	0.408	0.453	0.412	0.453
Bank FE	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes

The table reports the relationship between channels of lender's political risk and loan pricing. The dependent variable (*Total cost*) is the total cost of borrowing. The main independent variable in columns 1 and 2 is the standardized political risk originating from the arranger's portfolio of borrowers where an arranger's portfolio includes all borrowers with outstanding loans originated by the current arranger. Once the portfolio of borrowers is identified, we use four-quarter-average *PRisk* of each borrower measured before the current loan date, along with the count of loans to each borrower over the past three years, and compute the weighted average portfolio risk (*PRisk_portfolio*). The main independent variable in columns 3 and 4 is the standardized political risk originating from the arranger's network where the network for a particular lead arranger constitutes all co-lenders with whom the lead arranger has co-syndicated loans in the past 3 years starting from the quarter preceding the current loan date. Once the network is identified, we use four-quarter-average *PRisk* for each co-lender measured before the current loan date, along with the count of joint-loans with each co-lender, and compute the weighted average network risk (*PRisk_network*). Prefix '*z*' indicates that the measure is standardized. For each channel, we estimate a specification with industry-year fixed effects and a specification with industry-year and bank fixed effects. Data is at the arranger level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the arranger level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Borrower's active political risk management

VARIABLES	(1) Total Cost	(2) Total Cost	(3) Total Cost	(4) Total Cost	(5) Total Cost	(6) Total Cost
zPRisk	14.513***	6.154	6.426*	7.436**	3.338	1.481
	(2.89)	(1.52)	(1.72)	(2.52)	(1.25)	(0.50)
lnLobby	0.655	1.123				
	(1.08)	(1.29)				
zPRisk x lnLobby	-1.166**	-0.748*				
	(-2.34)	(-1.78)				
lnDonation			0.265	0.292		
			(0.34)	(0.26)		
zPRisk x lnDonation			-0.795*	-1.115***		
			(-1.68)	(-2.83)		
Hedge					0.549	-1.527
					(0.09)	(-0.28)
zPRisk x Hedge					-8.109*	-4.984
					(-1.73)	(-1.14)
zSentiment	-6.704*	-12.438***	-7.589**	-8.236**	-7.357**	-8.311**
	(-1.91)	(-2.67)	(-2.52)	(-2.03)	(-2.45)	(-2.04)
lnMCAP	-19.786***	-66.057***	-10.811***	-42.964***	-10.621***	-42.680***
	(-6.80)	(-7.30)	(-4.15)	(-5.15)	(-4.24)	(-5.14)
ROA	-4.080***	-0.588	-4.789***	-2.173**	-4.783***	-2.163**
	(-5.26)	(-0.60)	(-5.75)	(-2.23)	(-5.76)	(-2.24)
LEV	1.647***	0.269	1.540***	0.434	1.543***	0.445
	(6.42)	(0.60)	(6.15)	(1.18)	(6.19)	(1.20)
MTB	11.603	19.012**	14.064**	17.133**	13.834**	16.659**
	(1.63)	(2.16)	(2.24)	(2.34)	(2.21)	(2.27)
ReturnVol	3.806***	0.497	4.725***	1.386*	4.709***	1.384*
	(4.99)	(0.62)	(5.72)	(1.74)	(5.76)	(1.72)
Zscore	2.542	0.478	-1.539	-4.290	-1.490	-4.195
	(1.02)	(0.11)	(-0.79)	(-1.51)	(-0.77)	(-1.47)
Observations	3,602	3,310	3,246	3,152	3,246	3,152
R-squared	0.374	0.664	0.457	0.665	0.457	0.665
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

The table reports the effect of borrower's lobbying and PAC donation activities on the relationship between political risk and loan pricing. The dependent variable (*Total cost*) is the total cost of borrowing. The main independent variable is standardized firm-level political risk (*PRisk*) as defined in Hassan et al. (2017). *PRisk* is measured as the average firm-level political risk over the past four quarters preceding loan origination. Prefix 'z' indicates that the measure is standardized. *lnLobby* is the log of one plus average lobby expense over the past 4 quarters. *lnDonations* is the log of one plus the sum of average contributions paid to federal election candidates over the past 4 quarters. Hedge is a dummy variable equal to one if the ratio of average donations to Republicans to average donations to Democrats is between the 25th and 75th percentile of the sample. We estimate the relationship with a specification with industry-year fixed effects and a specification with industry-year and firm fixed effects. Data is at the borrower level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the borrower level, are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Lender's passive management of political risk

VARIABLES	(1) Syndicate size	(2) Syndicate size	(3) Lead share	(4) Lead share	(5) Secured	(6) Secured
zPRisk_arranger	0.151*	0.132*	-0.552***	-0.454**	0.026***	0.009*
	(1.76)	(1.78)	(-3.21)	(-2.05)	(3.62)	(1.88)
zPRisk	0.146**	0.141**	0.073	0.098	0.012***	0.012***
	(2.48)	(2.43)	(0.34)	(0.44)	(4.11)	(4.24)
zSentiment_arranger	0.057	0.188*	-0.285	-1.132***	0.005	-0.004
	(0.56)	(1.72)	(-1.00)	(-2.95)	(0.68)	(-0.64)
zSentiment_borrower	0.011	0.024	-0.163	-0.186	-0.002	-0.002
	(0.15)	(0.31)	(-0.47)	(-0.56)	(-0.62)	(-0.61)
lnMCAP	2.395***	2.348***	-4.657***	-4.470***	-0.104***	-0.105***
	(35.61)	(34.49)	(-10.17)	(-9.88)	(-32.21)	(-27.16)
ROA	0.003	0.005	-0.128**	-0.126**	-0.005***	-0.004***
	(0.28)	(0.50)	(-2.61)	(-2.58)	(-4.21)	(-3.90)
LEV	0.009	0.012*	-0.131***	-0.127***	0.005***	0.004***
	(1.32)	(1.89)	(-5.59)	(-5.31)	(12.77)	(10.76)
MTB	-1.545***	-1.528***	3.151***	3.104***	-0.004	-0.003
	(-12.08)	(-12.24)	(7.25)	(7.64)	(-0.86)	(-0.61)
ReturnVol	-0.009	-0.013	0.425***	0.421***	0.010***	0.010***
	(-0.65)	(-1.00)	(4.93)	(4.89)	(9.83)	(9.08)
Zscore	-0.061*	-0.062**	0.157*	0.153*	0.002	0.002
	(-2.00)	(-2.01)	(1.86)	(1.96)	(1.08)	(0.99)
Observations	17,715	17,715	5,095	5,094	17,715	17,715
R-squared	0.357	0.365	0.426	0.441	0.381	0.395
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	No	Yes	No	Yes

The table reports the effect of political risk on non-pricing terms. The dependent variable in column 1 and 2 (*Syndicate size*) is the number of lenders in a syndicate. The dependent variable in column 3 and 4 (*Lead share*) is the amount of loan retained by the lead arrangers. The dependent variable in column 5 and 6 (*Secured*) is an indicator variable equal 1 if the loan is secured, zero otherwise. The main independent variable is the standardized arranger-level political risk as defined in Hassan et al. [2019]. *PRisk_Arranger* is measured as the average arranger-level political risk over the past four quarters preceding loan origination. Prefix '*z*' indicates that the measure is standardized. For each dependent variable, we estimate a specification with industry-year fixed effects and a specification with industry-year and bank fixed effects. Data is at the arranger level and variables are defined in Appendix Table A1. Robust t-statistics, clustered at the bank level, are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.