TWO ESSAYS ON DEBT FINANCING

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Two Essays on Debt Financing

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

The thesis includes two essays on corporate debt contracting. Both essays investigate the factors that affect corporate financing costs. The first essay investigates the impact of political risk on loan contracting. In the second essay, I focus on the anchoring effect in the debt market and will study how a firm's historical borrowing cost serves as the reference point for the current loan issuance.

Specifically, in the first essay, I take advantage of a firm-specific political risk measure and investigate the corresponding impact on a firm's loan contracting, including both pricing terms and non-pricing terms. I find that firms associated with a higher level of firm-specific political risk are charged with higher loan spreads. This effect is amplified for firms with an opaquer information environment and firms with a higher level of financial constraints. Besides, the firm-level political risk also tightens the non-pricing loan terms, such as increasing the likelihood of collateral requirement and covenant restrictions. I establish the causality using an IV approach, a matched sample analysis, and placebo tests. At last, I find that the relationship-based borrowing and lobbying engagement attenuate this adverse impact of political risk.

In the second essay, I study the anchoring effect in the credit market. I propose a rational explanation where the financial experts (i.e., banks) strategically anchor on borrowers' previous high loan costs and charge higher spread. In detail, I find that at the aggregate level, when the average credit

spreads decrease since the firm's last borrowing, banks charge higher loan costs than they should charge justified by the firm fundamentals. However, the firm does not pay less when the average spreads increase. Similarly, at the firm level, when the model predicted loan spread is lower than the previous actual loan spread, banks charge higher costs. When the predicted spread is higher, the firm does not pay less. This asymmetric relationship suggests that banks strategically refer to the previous high spreads in loan pricing. Further analyses show that the relationship becomes stronger when banks have more information advantage and when firms are more bank dependent. Overall, the result suggests that the observed anchoring behavior in the financial market can also be rational and strategic.

To summarize, the two essays provide new evidence on the potential determinants that could affect the firm's loan contracting. The second essay also suggests that the well-trained financial exerts could take advantage by pretending to suffer the behavioral biases. These findings could deepen our understanding of loan contracting in the financial market.

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Chapter 1: Firm-Level Political Risk and Bank Loan Contracting

1.1 Introduction

Existing studies in this area have documented that political uncertainty will exert a significant influence on an individual firm's real business activities. Both theoretical and empirical studies suggest that political uncertainty will reduce or delay firm-level investment (Julio and Yook, 2012; Gulen and Ion, 2016), depress employment growth (Baker et al., 2016), dampen IPO and SEO activities (Çolak et al., 2017) and increase risk premiums in the stock market (Pástor and Veronesi, 2012; Liu et al., 2017). Largely due to the data limitation, these studies typically focus on the potential influence of the aggregate level of political uncertainty. Recent anecdotal evidence, however, suggests that aggregate shocks do not fully capture a firm's specific exposure to political events. For example, when President Trump posted a tweet saying that Lockheed Martin's F-35 program is too expensive, the stock share price of Lockheed Martin immediately declined by about 2%, shaving $1.2 billion off the firm's market value and the corresponding daily trading volume was more than double compared to the previous day. [1] This example clearly demonstrates that political risk can have a firm-specific component, and that this component can have material economic consequences for the firm. Because different firms differ along many dimensions, such as different business characteristics,

[1] One may argue that this is an industry effect. However, I also checked the stock prices and corresponding trading volumes for three other prominent companies operating in the same aerospace and defense industry (Raytheon (RTX), General Dynamics (GD), and Northrop Grumman (NOC)), I find that their stock prices did not change much, while their trading volumes all decreased with RTX dropped by almost 40% and GD by 24%.

different stages in the business life-cycle, and degree of market competition in the corresponding industry, to assume different firms have homogenous exposure to the aggregate political risk is far from realistic if we consider the potential impact of political risk on different businesses.

Empirical analysis of firm-level exposure to different political risks is relatively limited because of the lack of a comprehensively validated measure to capture an individual firm's political risk. Based on the transcripts of the earnings conference call, Hassan, Hollander, Lent, and Tahoun (2019) (hereafter HHLT 2019) conduct a comprehensive textual analysis and construct an individual firm-level political risk index ($PRisk$). HHLT (2019) define $PRisk$ as the share of conversations with financial analysts that discuss firm-level risks generated from both general political matters and some specific political topics. The identifying assumption underlying this measure is that the more analysts ask politics-related questions during the conference Q&A session or the more managers talk about the political matters in their opening statement, the more likely the firm is exposed to political risk. Unlike aggregate measures of political uncertainty such as those based on election data or the economic policy uncertainty index (EPU) previously complied and shared by Baker et al. (2016), the $PRisk$ measure allows researchers to investigate both the time-series variation and the cross-sectional variation in political risk and arguably it is the cross-sectional variation that is more important. Indeed, HHLT (2019) shows that the variation in the aggregate measure among different periods only accounts for a very small proportion (i.e., about 1%) of the total political risk, whereas firm-level political risk dominates the whole source, which accounts for around 90% of the total variation. This result implies that the conventional models of the political risk cannot describe most of the potential economic impact stemming from the political risk, in which different firms are assumed to show relatively stable exposure to the aggregate political risk. However, while HHLT (2019) further construct and document that firm-level political risk affects firms' investment activities, research on how this innovative $PRisk$ could exert an impact on other corporate outcomes remains scarce.

In this thesis, I will extend this literature by conducting an investigation on how $PRisk$ as captured by Hassan et al.'s (2019) measure affects firms' bank loan financing activities. I focus on firms' bank loan financing contracting in this paper. First of all, loans are the most predominant source of corporate external financing, and this financing source is applicable not only to small firms but also to large corporations (Qian and Strahan, 2007). Second, given the complicated nature of $PRisk$, general investors may not be able to get this information, or at least, they are likely to have some difficulty when they process this information on the political risk, whereas banks can access private information when assessing a borrower's political risk. In case the real firm-level political risk could affect the firm's operation or firm outcomes, banks should be able to price it in the loan contracting. Third, loan contracting is multidimensional, which makes it possible for us to examine the potential influence of $PRisk$ on not only loan costs but also on other loan terms such as covenant restrictions (Huang et al., 2018). I thus view bank loans as an opportune setting to investigate the influences of $PRisk$ on corporate outcomes.

Specifically, I argue that a higher $PRisk$ will increase firms' bank loan costs by increasing their information risk and default risk. First, firms facing a higher level of $PRisk$ are highly possible to also have a larger information risk (Kim et al., 2012). Political risk can increase concerns about political and legal interference with a firm's corporate decision-making process (Gulen and Ion, 2016). Besides, a higher level of $PRisk$ can also increase the individual firm's possibility to default, and further impact a firm's bank loan costs through this increased default probability. HHLT (2019) document that firm-specific political risk reduces the firm's investment activity and distorts the firm's asset allocation decisions, which can threaten business continuity. In addition, firm decisions driven by political and legal considerations, for example, hiring decisions designed to benefit incumbent politicians' re-election campaigns, can adversely affect the firm's investment opportunities, cash flows, and collateral value, thereby increasing its default risk. Taken together, I predict that firms associated with a high level of $PRisk$ will also be associated with high information risk and high default risk, incurring high bank loan costs.

However, this relationship is not without tension. Theoretical work by Hirshleifer and Siew (2003) highlights the different responses to the forms of information presentations. They find that market participants pay more attention to easily processed information than implicit information. When political topics are discussed frequently during the earnings conference calls, analysts and investors will pay more attention to the firm's political risk. Meanwhile, analysts and investors serve as effective external monitors (Hartzell and Starks, 2003). This increased external monitoring exerts the disciplining effect on managers, which can substitute the monitoring effort of banks. Thus, the firm-level political risk may have no impact on loan pricing or even reduces the loan cost due to the improved external scrutiny.

Using a sample of 11,585 loan-level observations in the U.S. from 2002 to 2016, I find that individual firms associated with a higher level of firm-specific political risk are indeed charged by higher loan spreads when seeking bank loan financing. In particular, I document that a one-standard-deviation change in the $PRisk$ will raise the firms' bank loan costs by about six basis points.[2] This amounts to a $1.4 million increase in interest expenses for the typical loan. Thus, the effect of individual $PRisk$ is economically meaningful.

The detrimental effect of $PRisk$ could be caused by some omitted but unobservable variables that may influence both individual firm-level political risk and bank loan costs simultaneously. To mitigate this endogeneity concern, I employ different kinds of sensitivity tests. In all tests, I still find that the positive results continue to exist when I apply the industry and time fixed effects, which suggests that the baseline relationship is not likely to be driven by any persistent industry-level characteristics or unobservable time-invariant factors. In addition, my findings are still robust after I include different loan type and loan purpose indicators in the regression, and after I exclude the 2007–2009 financial crisis period, which implies that neither loan-level attributes nor the excess volatility of the recent financial crisis drives the observed impact of

[2] By comparison, Bharath et al. (2008), Francis et al. (2012), and Hasan et al. (2014) find that a one-standard-deviation increase in the loan borrower's accounting quality, board independence, and effective tax rate decreases bank loan spreads by 6.65, 5.50, and 4.87 basis points, respectively.

$PRisk$ on loan costs. I further alleviate concerns about omitted variables using propensity score matching (PSM) analysis, and the empirical findings are supportive. Although the documented findings are not likely to suffer from the potential reverse causality, I also conduct a lead-lag test and find that only lagged firm-specific political risk impacts loan costs, not the other way around. When I use a firm's political distance and the average of local firms' political risks as instrumental variables (IV) for the focal firm's political risk, I find that the two variables have significant and positive relationships with the focal firm's political risk in the first stage. Moreover, the fitted value of the $PRisk$ continues to be positively related to loan costs in the second-stage regression. The IV analysis survives falsification tests when I instrument non-political risk instead of political risk. Lastly, I conduct a quasi-shock study to further establish the causal link between a firm's $PRisk$ and loan financing cost. I find that firms' loan costs rise (fell) significantly after the firms experience a dramatic increase (decrease) in firm-specific political risk.

To shed further light on the information and default risk channels, I examine how the relation between $PRisk$ and loan costs varies in the cross section. This analysis will not only provide insightful hints on the potential channels through which the documented positive relationship operates, but also will strengthen the identification issue, as this relationship is unlikely to be held if this firm-specific political risk simply reflects some unobserved economic forces. Specifically, I conjecture that the positive impact of $PRisk$ on corporate loan costs should become more pronounced in the presence of factors that exacerbate firms' information and default risks. I examine the conditioning effect of two factors: information opacity and financial constraints. The empirical results confirm that the documented effect of $PRisk$ on loan costs becomes stronger for opaquer and more financially constrained firms, which strengthens support for the information and default risk views, as they are difficult to reconcile with alternative explanations. In addition to bank loan spreads, banks contract on other non-pricing aspects of a loan to facilitate bank monitoring and limit potential loss (Hasan et al., 2014). Empirically, I find that firms associated with a higher level of political risk are also subject to stricter restrictions and more covenants.

Additional analysis is carried out to rule out other alternative explanations for the higher loan costs of firms associated with higher political risk. These tests include examining whether the supply side of loan contracts (i.e., banks' ability or willingness to lend) explains my main findings, whether firm-level political risk is just a proxy for existing controls for a firm-level loan costs, and whether external acquisitions drive the relation between $PRisk$ and firms' bank loan financing. I find none of these alternative interpretations can explain the results. Finally, I document that firms can mitigate the detrimental impact of the firm-specific political risk on the corresponding loan spreads through some real activities, such as engaging in relationship-based lending activities and conducting more lobbying activities. My findings therefore suggest that loan borrowers can survive a volatile political environment by actively managing their own political risks.

My paper makes a contribution in several aspects. First, the increasing importance of political risk in business operations makes a strong incentive for academic studies on how *firm-level* political risk is priced. Extant literature relies primarily on *aggregate*-level political uncertainty to explore potential financing decisions and activities (Çolak et al., 2017).[3] However, HHLT (2019) document that the major source of the variable variation in political risk comes from the firm level instead of from the aggregate level. That is, *aggregate* political risk is far from adequate to reflect the variation in political risk that exists within a firm over different times, nor can it reflect the cross-sectional heterogeneity in political risk across different firms. My study provides the first evidence on the impact of $PRisk$ on firms' financing costs.

Second, my paper also contributes to the studies on the firm-level determinants of loan contracting. Prior studies on the cost of debt financing focus mainly on default risk (Huang et al., 2018) and information asymmetry (Bharath et al., 2008). My study shows that firm-specific political risk is an incrementally significant factor of creditworthiness, above and beyond other loan- and firm-specific determinants known to influence the pricing terms as well as non-pricing terms within the loan contracts. [4]

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[3] For instance, Bali et al. (2017) find that investors will demand extra compensation if they are holding *negative* uncertainty beta stocks. They argue that holding stocks with positive uncertainty beta provides investors with hedging against the unfavorable political shift, these stocks command a lower risk premium.

[4] Using a state-level measurement, Bradley et al. (2016) find similar results that firms' costs of bonds are higher if the firms are located in such a state with a higher level of proximity to political power. My paper distinguishes the study from their study in several different ways. First, my study focuses on the private loan market. Compared with bond investors, banks have access to more private information and have more motivation to scrutinize firms. Second, I use a firm-specific measure of political risk instead of cross state variation in political power. Furthermore, my main findings are unaffected even after controlling for their proximity to political power measures, thus providing additional information to explain loan pricing. The results are available upon request.

Finally, my study helps deepen our understanding of the nature and impact of firm-specific political risk. In previous studies, HHLT (2019) argue that the conventional models are not able to describe much of the potential economic impact on firm outcomes from political risk, in which different individual firms are presumed to exhibit relatively stable exposures to the aggregate political uncertainty. In line with them, I document that the $PRisk$ is relatively less persistent. Specifically, only one- and two-quarter lagged firm-specific political risk exerts an effect on firms' borrowing costs. My results therefore support HHLT's (2019) argument that assuming relatively stable exposure to the aggregate level of political risk may not capture a firm's true political risk.

1.2 Literature Review and Hypotheses Development

As discussed at the onset, aggregate political uncertainty or risk has an important impact on economic activities and corporate decisions, such as reductions in macro-economic growth, decreases in capital investments, reductions in merger and acquisition activities, increases in risk premiums, and delays in IPOs. [5] All of these studies suggest that political uncertainty increases information uncertainty, the cost of capital, and default probability among all firms. However, due to data availability, few studies have been carried out on the influence of $PRisk$ on different corporate strategies of individual firms. I overcome this challenge by using the methodology of HHLT (2019) to

[5] See Julio and Yook (2012), Pástor and Veronesi (2012), Baker et al. (2016), Gulen and Ion (2016), Kelly et al. (2016), Bonaime et al. (2017), and Çolak et al. (2017).

investigate how $PRisk$ could affect different firms' loan contracting through information risk and default risk mechanisms.

Firm-level political risk can distort a firm's external information environment and lead to high level of information asymmetry between different parties, such as managers and investors (Pástor and Veronesi, 2012). Moreover, higher exposure to political risk will increase information ambiguity on how political and legal interferences affect corporate activities (Cohen et al., 2011; Gulen and Ion, 2016). Easley and O'Hara (2004) suggest that borrowers with greater information risk are charged higher loan spreads. Consistent with this view, Bharath et al. (2008) document that firms associated with better accounting quality tend to pay less on bank loans. When firms' responses to political events are not uniform, the difficulty of processing information and monitoring firms will increase greatly. Because of such information asymmetry and costly monitoring, banks impose higher bank loan spreads. Therefore, I predict that firms associated with higher firm-level political risk will also have higher information risk, leading to higher bank loan costs.

Higher firm-level political risk also leads to increasing corporate default risk. Larger exposure to political risk will exert significant negative impacts not only on a firm's investment activity, but also on total factor productivity, and the latter implies a negative long-run effect and a decline in future profits (Hassan et al., 2019). As discussed in the introduction, political and legal interference in a firm's corporate decisions may adversely affect investment opportunities, cash flows, and the value of the collateral. Higher firm-specific political risk and political interference will induce more volatile and asymmetric payoffs for firms, leading them to fail to fulfill their loan contract obligations. Thus, firm-level political risk also leads a firm to suffer a larger default risk. In a theoretical study, Freixas and Rochet (1997) document that when firm's default risk is high, borrowers have a high probability of not paying their debt on time. Consistently, Hasan et al. (2012) document that firms whose earnings are more volatile will be charged higher loan costs. Thus, I predict that to bear the higher level of a firm's default risk, banks charge more for high political risk firms.

Both information risk and default risk channels predict that firms associated with a higher level of political risks will be charged higher bank loan spread. However, this relationtionship is not without tension. High firm-level political risk firms will be associated with high analyst attention and monitoring. There could exist a "mechanical" positive correlation. The firm-level political risk measure is constructed based on the conversation between analysts/investors and firm managers during the earnings call conference. The more they talk about the political words, the higher the firm-level political risk. At the same time, the more they talk about the political words, the more the analysts/investors care about it. The analysts and investors should care more about and also better understand the firm-level political risk. Hirshleifer and Siew (2003) model that market participants respond differently to the forms of information presentations, and find that market participants pay more attention to the easily processed information than implicit information due to limited attention. According to this theoretical work, I predict that when political topics are discussed frequently during the earnings conference calls, analysts and investors will pay more attention to the firm's political risk. Meanwhile, analysts and investors serve as effective external monitors (Hartzell and Starks, 2003). This increased external monitoring exerts the disciplining effect on managers, which can substitute the monitoring effort of banks. Thus, the firm-level political risk may exert no impact on loan pricing or even reduces the loan cost due to the improved external scrutiny.[6]

In short, there are solid reasons for us to expect that I will observe either a positive or a negative relationship. Although there is tension underlying this research question, I predict, on balance, that firms with high firm-level political risk should be charged by higher bank loan spreads. Moreover, if this positive relationship is caused by the increase in the information risk and/or default risk caused by the firm-level political risk, I expect that the relationship will become stronger for firms with factors that increase the volatility of accounting numbers and downside risk. Based on previous studies, I proxy volatility of accounting numbers by financial information opacity and downside risk by the degree of financial constraints. The above discussion leads to my first hypothesis.

H1. *Firms associated with a higher level of firm-specific political risk are charged higher bank loan costs.*

Besides the pricing terms, bank loan contracts also contain multi-dimensional information, including collateral requirements, performance pricing provision, and a number of loan covenants (Qian and Strahan, 2007).

[6] To some degree, the tension argument is not in the same line as the main hypothesis. It is motivated by the mechanical variable construction. It is better to motivate the tension based on some theoretical differences.

Rajan and Winton (1995) argue that banks mitigate information risk by demanding more collateral or by including more extensive covenant restrictions. Empirically, Strahan (1999) finds that banks apply both the pricing terms together with the non-pricing terms of loans as complements to control borrowers' risk. Studies also find that risker borrowers pay higher costs for their loans and are subject to stricter non-pricing terms of loans systematically related to pricing (Hasan et al., 2014). I predict that firm-level political risk also affects a loan's non-pricing terms, as formalized in my second hypothesis.

H2. *Firms associated with a higher level of firm-specific political risk are subject to stricter loan restrictions and more covenants.*

Finally, I explore whether firms hedge against the detrimental impact of political risk on loan spread. Managers connected to politicians or lobbyists can have privileged access to political information (e.g., strategic details of upcoming hearings, current policy positions, potential amendments, etc.), which makes the political environment less opaque to them and thus reduces the costs of debt (e.g., Khwaja and Mian, 2005; Chaney et al., 2011). Moreover, Bharath et al. (2011) document that if there exists a strong relationship with a leading bank, it will directly produce firm-specific valuable and reusable information and significantly decreases the bank's monitoring effort. Firms borrowing from a prior lender obtain lower loan costs and more favorable loan terms. These considerations lead to my final hypothesis.

H3. *The positive relationship between firm-specific political risk and bank loan costs is attenuated by political connections obtained through lobbying activities or relationship-based lending.*

1.3 Sample and Data

I report the sample and data construction in this session. The loan sample comes from the standard DealScan database. To extract the firm accounting data, I use the Compustat/NA. The firm-specific political risk measure is publicly available and is directly extracted from Prof. Hassan's personal website. I illustrate the details in the followings.

1.3.1 Sample

My data are drawn from five main sources. I obtain the $PRisk$ measure by directly downloading data from Prof. Hassan's personal website. Loan data is collected from the commonly used DealScan database, which is compiled by the Loan Pricing Corporation (LPC). The final sample period starts in 2002 and stops in 2016, as the data period for the $PRisk$ measure is only available during this period. The financial information of firms is obtained from Compustat/NA, and the related stock return information is extracted from the Center of Research in Security Prices (CRSP). I also collect information on macroeconomic variables from the Federal Reserve Bank. Consistent with previous research, financial firms whose SIC codes start from 6000 to 6999 and utility industries whose SIC codes start from 4900 to4999 are excluded from my final sample. I further exclude those firms with missing firm-specific political risk data, loan pricing information, or financial information. I winsorize all of the continuous variables at both the 1% and 99%, and my final sample thus consists of 11,585 loan-level observations.

1.3.2 Variables

1.3.2.1 Loan Spreads

I use the DealScan database to obtain my bank loan information. This database provides comprehensive loan characteristics such as loan start dates, end dates, amounts, spreads, and maturities. Following the literature (Bharath et al., 2008), I include loans that are classified as term loans, loans classified as revolvers, and loans of 364-day facilities, but I exclude non-fund-based loan facilities, which include the loan such as standby letters of credit and loans with very short-term (i.e., bridge loans). To ensure that the spreads between loans are comparable, I restrict my sample to loans whose spreads are based on LIBOR. I link the loan data with the firm's accounting data using the public link-table to map the DealScan firms and Compustat firms, which is provided by Professor Michael Roberts. [7] Following previous work (Bharath et al., 2008), I define loan issuance costs as the all-in-spread drawn (in log format), and denote this variable as $Log(Spread)$.

1.3.2.2 Firm-level Political Risk

Based on the transcripts of the earnings conference call, HHLT (2019) conduct a comprehensive textual analysis and compile the firm-specific political risk measure for U.S. corporations starting from 2002. Using a training library based on undergraduate political textbooks, accounting textbooks, and

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

newspaper reports, they first establish a word library for all the political words and non-political words. Then they further distinguish political topics from non-political topics using the pattern-based sequence classification method, in which they define lexical training libraries of "political" texts and "non-political" texts. The key idea is that, when the firm managers or the analysts talk more related to the political topics, the firm should be associated with a higher level of political risk.

In the detailed construction, to make the identification more reliable, HHLT (2019) use adjacent two-word combination bigrams to represent the text classifications. To achieve this, they deconstruct the conference call transcripts into a set of lists of bigrams. They next count the numbers of bigrams in conjunction with "risk" and its synonyms. They further restrict the distance between the words surrounding a synonym for risk to less than 10 words. Thus, the distance weighted number of the occurrences of political bigrams is defined as the firm-specific political risk, denoted as $PRisk_{i,t}$.

$PRisk_{i,t}$ captures the percentage of the adjusted conversations related to politic associated topics. The adjustment is conducted by the bigrams' total number used in the conference call transcripts. Thus, a larger percentage number of $PRisk_{i,t}$ will suggest the firm has a more severe degree of the firm-level political risk. Following HHLT (2019), I standardize $PRisk_{i,t}$ with its sample to facilitate interpretation.

1.3.2.3 Control Variables

In my mode specification, I select a set of different control variables in Graham et al. (2008). First, I include the existing key firm characteristics. Specifically, I include the firm's total assets ($Size$), using the natural logarithm form, to control for the external information asymmetry and the loan costs related to larger firms (Hasan et al., 2014). I include firm profitability ($Profit$) because it is shown that profitable firms will have lower default risk and better reputations in the credit market and can thus enjoy lower spread (Diamond, 1991). I further include total debt ratio (LEV) because higher existing leverage ratios will lead to higher future default risk (all else being equal), and thus I expect high-leverage firms will face higher bank borrowing costs (Sufi, 2007).

In addition, I include the market-to-book ratios (M/B) for each firm to control for differences in the potential opportunities for future investment. Firms that have better investment opportunities will obtain lower borrowing costs (Diamond, 1991). I also include a factor representing the tangibility of a firm's assets ($Tang$) in the regression model. Banks can claim and convert tangible assets into cash easily if the firm defaults in the future, thus, I expect tangible firms will be associated with lower borrowing spread (Denis and Mihov, 2003). I include a firm's cash flow volatility (CF_Vol) to control for risk related to its total debt commitments. I expect cash flow volatility to have a positive relationship with the corporate borrowing cost (Bharath et al., 2008). In addition, I include Altman's Z-score ($Z\text{-}score$) in the model specification. Previous studies suggests that a higher Z-score implies the firm to be more financially healthy, thus presenting a lower default risk (Hasan et al., 2014). I also control for stock return volatility (T_Vol), which captures the firm's overall risk (Ma et al., 2019). I expect that firms with higher overall risk have to pay higher loan borrowing costs. To make sure all the information is available, I require all of the above-described firm characteristics to be constructed as of the fiscal year prior to each loan issue date.

I further control for other characteristics that may be related to loan pricing, including loan maturity ($Log(Mat)$), and loan amount ($Log(Amt)$) (Graham et al., 2008). I also consider a performance pricing provision ($Perf\_Provision$) as the previous study suggests that including the performance pricing in the loan clauses give the banks more flexibility, and in turn, will affect the loan pricing terms (Chava and Roberts, 2008). A firm's borrowing cost is also affected by the economic situation, so I include default risk ($Default\_Rate$), and the term spread ($Term\_Spread$) (Huang et al., 2018) in the regression model.

1.3.3 Descriptive Statistics

Table 1.1 Panel A reports the year-by-year distribution of the loan issuance number. Among all years, the number of loan-taking firms per year ranges from 151 in 2002 to 639 in 2011. The number of loan issuances from 2002 to 2016 also shifts dramatically, ranging from 218 in 2002 to 1,011 in 2013. [8] The distribution of loans indicates some cyclicality in bank loans issued

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[8] As the data on $PRisk_{i,t}$ start from 2002, bank loans issued in 2002 Q1 are not included in the sample.

among different period, and is consistent with that documented in Becker and Ivashina (2014). Panel B further shows the sample distribution across different industries. As documented by HHLT (2019), the distribution of $PRisk$ demonstrates sector-level (SIC division) clustering. I illustrate this variation between industries by calculating the mean $PRisk$ for each industry, as classified by the first two-digit SIC code. To save space, I only report the top and bottom 5 $PRisk$ industries with at least 30 observations in my final sample. The *Engineering and Management Services* industry has the highest $PRisk$, with a mean of 0.90. In contrast, the *Food Stores* industry has the lowest rank, with 0.25 $PRisk$. The average spread for loan borrowers in the top 5 $PRisk$ industries is about 232 bps, 43 bps higher than that for the bottom 5 $PRisk$ industries. This provides the first intuitive evidence that higher $PRisk$ firms are associated with a higher loan cost.

[Insert Table 1.1 Here]

The summary statistics for the key variables are shown in Table 1.2. The mean (median) $PRisk$ is 0.47 (0.24), and it has a wide range: between 0.07 at the 25% distribution to 0.53 at the 75% distribution. The average interest spread is 211 bps above LIBOR. A typical (average) loan issuance will have an amount of US $520 million with a maturity of 4.47 years. In terms of fundamental characteristics, the profitability of the average loan borrower is 0.14 with a cash flow volatility of 0.1. These descriptive characteristics are comparable with others in the literature (Bharath et al., 2008).

[Insert Table 1.2 Here]

1.4 Empirical findings

In this part, I report the major empirical findings. I first provide the main regression analysis between the firm loan spread and the previous quarter's political risk level. Then I provide a set of additional tests to support my findings.

1.4.1 Regression analysis

Loan pricing is the most critical term in a loan contract. I investigate the impact of firm-specific political risk on the loan cost by using the following regression model:

$$Log(Spread_{t+1}) = \alpha + \beta_1 \times PRisk_{i,t} + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}, \quad (1.1)$$

where i denotes for each individual firm, t denotes the different time, and $X_{i,t}$ denotes a set of different control variables (firm-, loan-, and macro-level controls). The baseline regression estimation for the above regression model is conducted under the OLS regression frame. To adjust the heteroscedasticity of the regression standard errors, the heteroscedasticity robust *t*-statistics are calculated, and the *t*-statistics values are also clustered at the firm and year levels. Previous studies suggest that business loans can be classified into categories and that borrowers may take out loans for various reasons, for example, corporate initiatives, debt repayments, working capital, and takeovers (Huang et al., 2018). The different types and usages of the bank loans will also reflect different levels of risk, so they may be priced differently. Thus, I estimate my model regressions by incorporating loan type and loan purpose fixed effects. I also use 2-digit SIC codes to control for potential differences in firm-specific political risk and loan prices across industries. I consider unobserved time invariant characteristics and include quarter fixed effects.

Table 1.3 reports the empirical results from different model specifications. Column (1) presents the estimates of the loan cost when incorporating only the firm-level controls. The coefficient of $PRisk$ is significantly positive on loan spreads (coeff = 0.036; *t-stat* = 3.93), which suggests that firms associated with higher $PRisk$ are, on average, charged higher interest rates. Economically, a one-standard-deviation increase in the corresponding $PRisk$ will lead the firm to pay extra 6-bps in loan cost. This is equivalent to about US $1.4 million increase in the total interest expense. [9] Thus, the documented impact is economically meaningful.

[Insert Table 1.3 Here]

In Column (2), I also include loan-level control variables, such as loan amount ($Log(Amt)$), loan maturity ($Log(Mat)$), and performance provision ($Perf\_Provision$). I also observe a positive relation between $PRisk$ and $Log(Spread)$. Column (3) is my *baseline model*, where I include loan-, firm-, and macro-level controls and different fixed effects, $PRisk$ is still positively related to $Log(Spread)$ (coeff = 0.022; *t-stat* = 3.08). As none of the fixed effects have a discernable impact on my findings, this analysis helps to

[9] Referring to Table 1.2, a typical loan in my sample has a loan issuance amount of US $520 million and a maturity of 4.47 years. Thus, I calculate the total interest expense for a typical loan as 0.0006×520×4.47=1.4 million.

overcome the concern that my results may be spurious because of omitted correlated variables. The results shown in Table 1.3 together provide evidence that bank charges for credit do indeed differ depending on the firms' level of $PRisk$. Those firms associated with larger $PRisk$ charged higher interest rates. [10]

In addition to the interpretation on the coefficient of key explanatory variables, the coefficients on other characteristics in the above regressions are comparable and consistent with previous literature (Graham et al., 2008; Huang et al., 2018). For example, loan spreads are negatively associated with firm size (coeff = -0.059; *t-stat* = -9.60), profitability (coeff = -0.783; *t-stat* = -8.40), and the inverse measure of financial distress (Z-score) (coeff = -0.031; *t-stat* = -11.21). Loan spreads are positively associated with maturity (coeff = 0.063; *t-stat* = 3.89) and return volatility (coeff = 10.719; *t-stat* = 16.06).

1.4.2 Additional Control Variables

1.4.2.1 Controls for Aggregate Political Uncertainty

To mitigate the concern that the firm-specific political risk might be affected by changes in the political environment, I control for aggregate political uncertainty, partisan conflict index, and geopolitical risk. First, prior studies find that aggregate political uncertainty (PU_a) affects a firm's financing decisions. It might be the case that aggregate political uncertainty affects firm-

[10] My results are robust after excluding the 2008 financial crisis period, controlling for industry-by-time fixed effects, using the raw measure of $PRisk$, and using the alternative measures of loan spreads. The results are available upon request.

level political risk and loan spread simultaneously. Second, Azzimonti's (2018) partisan conflict index (PCI) reflects how frequently the newspaper articles will report opinion disagreement between Republicans and Democrats in a month. Under a high political disagreement scenario, managers could be asked more related questions and might express their opinion on the matter during the earnings conference calls. In other words, there is a concern that the firm-specific political risk may just reflect the intensity of political disagreement. Third, Caldara and Iacoviello (2018) propose a geopolitical risk measure (GRP) to reflect the risk relevant to a set of geopolitical events. When the geopolitical risk is high, for example, during the period of Gulf War, 9/11, and the 2003 Iraq invasion, people are more sensitive to the political environment and analysts could ask more questions in the conference calls. That is, $PRisk$ measure may be another proxy for geopolitical risk. If this is true, I should observe an insignificant coefficient on $PRisk$ after controlling for geopolitical risk.

I thus include the aggregate political uncertainty (PU_a), partisan conflict index (PCI), and geopolitical risk (GRP) one by one into the regression model. Table 1.4 presents my results.[11] Panel A reports that $PRisk$ positively affects borrowing costs after controlling for the three measures. Moreover, since the three political uncertainty measures are monthly time-series data, most of the impacts from PU_a, GRP, and PCI are subsumed into the time fixed effects, leading to the insignificant coefficients on these risk measures. To better reflect the real effect of these three measures, I continue the same test by taking out the

[11] The EPU index is proposed by Baker et al. (2016). To ease comparison, I construct PU_a as the EPU index divided by 100.

time fixed effect. Panel B shows that my results still hold, i.e., the coefficients of $PRisk$ are all significantly positive. At the same time, the coefficients on the three political risk measures become significant, which is consistent with my expectations.

[Insert Table 1.4 Here]

1.4.2.2 Other Additional Controls

To further rule out the concern for other potential omitted variables, I include additional controls in Eq. (1.1). First, the firm-specific political risk measure captures the number of positive bigrams and negative bigrams but ignores the direction, so it is a kind of second-moment measure. Further, the Prisk measure comes from the firm disclosures, and specifically from the earnings call conference transcript. It is not clear whether high values of the political risk measure indicates higher political risk or greater willingness to disclose political risk. It is possible that some firms will be more willing to disclose the political risk, or may even view these political issue as political connection or political resources. Under these cases, the tone of the language should be positive. Thus, to capture these potential measurement errors, to construct and control for the political sentiment measure is necessary. HHLT (2019) address this issue by constructing a measure of political sentiment that incorporates the directions of the political bigrams. Following HHLT (2019), I include political sentiment in my specification in Table 1.4 Panel C, column (1). I continue to find a significantly positive relationship between $PRisk$ and loan spreads (coeff = 0.021; *t-stat* =2.97), which implies that political sentiment does not impact my result on $PRisk$ and loan spreads. I find a negative and insignificant relationship between political sentiment and loan costs (coeff = -0.011; *t-stat* = -1.91).

Second, some other firm specific characteristics may also affect loan spreads. I therefore follow prior studies and add more firm controls. More specifically, I control for loss ($Loss$), as lenders require a premium for firms reporting a loss in their financial statements (Ma et al., 2019). I also include the firm ownership structure, calculated as the shares held by institutional investors ($Insti\_holding$), because banks benefit from the screening and ongoing monitoring of institutional investors and thus should charge lower spreads (Qian and Strahan, 2007). Finally, I control for the stock return ($Return$), which captures the firm's performance in previous quarter, and for capital expenditures ($CAPX$). In column (2) of Table 1.4 Panel C, I still document a significantly positive relation between $PRisk$ and loan spreads (coeff = 0.021; *t-stat* = 3.06), which implies that the documented relation is not affected by potential omitted firm characteristics. The coefficients on the additional controls are comparable with previous studies.

Third, macroeconomic conditions could affect loan pricing. I therefore include several variables to control for macroeconomic cycles. Specifically, I include the inflation rate ($Inflation\_Rate$), the industrial production rate ($Production\_Rate$), a recession dummy ($Recession$), the unemployment rate ($Unemployment\_Rate$), and the short-term rate ($Shorterm\_Rate$) in my baseline model. I measure these macroeconomic factors one month before the loan initiation date, and find the coefficient on $PRisk$ remains significantly positive in column (3). Last, in column (4), I add all additional control variables to Eq. (1.1) at the same time. I find that $PRisk$ continues to be significantly positively associated with borrowing costs.

1.4.3 Firm Fixed Effects

My baseline regression controls only for industry fixed effects. Thus, although unlikely, my results might be driven by some unobservable time-invariant firm characteristics. In my baseline specification, I do not apply the firm fixed effects for several reasons. First, HHLT (2019) document that $PRisk$ measure mainly reflects cross-sectional variations across different firms. Second, firms typically do not issue loans every year. I notice that more than 25% of firms in my sample have less than three bank loan issuances during the whole sample period. Wooldridge (2002) shows that firm fixed effects will lead to inconsistent estimations in short panels when explanatory variables lack enough time-series variations. My sample is thus not suitable for including firm fixed effects due to insufficient time-series variation. To address the concern of unobservable time-invariant firm characteristics and to simultaneously take into account the above-described points, I still employ the firm fixed effects analysis but use only a subset of the sample, which has some time-series variations. Table 1.4 Panel D presents my firm fixed effect analysis results.

In column (1), I require the firm to appear at least in three different quarters to ensure some time-series variation. The number of observations shrinks due to this restriction. Results in column (1) present that $PRisk$ still has a positive association with loan spread, indicating that my core result is still robust. In column (2), I further require that firms must show up in at least five different quarters. The coefficient on $PRisk$ remains positive.

Overall, the results of the different additional control variables suggest that $PRisk$ is positively and significantly related to loan interest rates, which may help in mitigating identification concerns and establishing causality.

1.5 Identification Issues

In my analysis above, I have documented a robust positive relationship between $PRisk$ and loan costs. In the coming section, I will address identification issues to establish the direction of causality. I first conduct lead-lag placebo tests. I find that lagged firm-level political risk can predict future loan spreads, but the reverse does not hold. To further alleviate the reverse-causality concern, I conduct instrumental variable, propensity score matching analyses, and quasi-shock study. My results continue to go through, which further supports the view that the direction of causality runs from firm-level political risk to firms' borrowing costs.

1.5.1 Lead-lag Placebo Tests

I first address the reverse-causality concern using a lead-lag placebo test. If my main results suffer from the reverse causality, then I should observe a significant relation between lag loan costs and lead firm-level political risk. I consider a loan contract in quarter t+1 to test this prediction. Table 1.5, column (4) presents the benchmark one-quarter-lagged $PRisk$ for comparison.

Columns (5) to (7) present results of the placebo test, where I model borrowing costs in quarter t+1 as a function of future (columns (6) and (7)) exposures of $PRisk$. These regressions represent the falsification test of a causal relation between $PRisk$ and loan financing cost, as the risk that has not yet been exposed cannot be evaluated by lenders. I find that none of these columns shows a statistically significant coefficient, and the magnitudes are much smaller than that observed in column (4). This suggests that lenders evaluate and respond to firms' political risk, while political risk that has not yet been exposed does not induce a response from lenders. These results thus support a causal interpretation.

[Insert Table 1.5 Here]

In addition to providing the falsification test, Table 1.5 provides some evidence of the persistence of $PRisk$. Specifically, in columns (1) to (3), I use as the explanatory variable four-, three-, and two-quarter-lagged $PRisk$, respectively. I find that one- and two-quarter-lagged $PRisk$ have a significant influence on the borrowers' bank loan costs, while earlier firm-level political risk (columns (1) and (2)) has no significant impact. These results suggest that the effect has short-term persistence (two quarters in my setting).

1.5.2 Instrumental Variable Analysis

Although my results are not likely to suffer from the reverse causality, there may exist some unknown mechanisms through which higher borrowing costs increase firm-level $PRisk$. I use two instrumental variables to mitigate this concern, namely, the firm’s political distance and the average political risk across other local firms.

Kim et al. (2012) document that political geography will exert a significant and pervasive impact on firm policies. The shifts in firms’ locations will result in a change in overall exposure to policy risk, leading to more difficulties for investors to evaluate the firms’ future growth opportunities and cash flows. Hill et al. (2013) find that firm’s engagement in lobbying activities is negatively affected by the political distance. They argue that politicians and lobbyists typically keep offices. The longer distance to the state capital buildings (politicians’ offices) will increase the need for the services of a lobbyist to communicate with politicians and therefore increase the fixed costs of lobbying engagement. Based on these studies, I use a firm’s political distance as my first instrument. When the firm’s headquarters is far from its state’s capital city, it is more difficult for the firm to communicate with and access information from policymakers. Remote firms are thus exposed to more political risk not only because they are exposed to the direct impact of a policy change but also because they lack information channels to mitigate such impact. Managers of such firms are therefore expected to be asked more questions during earnings conference calls about the firm’s strategy to alleviate the adverse political influence, in line with higher firm-specific political risk. My instrument satisfies the relevance criterion based on this intuition. Moreover, to my best knowledge, there’s no prior literature that ever documents any direct link between political distance and a firm’s loan costs, and thus the instrument also satisfies the exclusion criterion.

Since firms seldom relocate their headquarters, one concern in using geographic distance as an instrumental variable is that it captures the cross-firm variation in a state but not the time-series variation within a firm. To address this concern, I employ a second instrumental variable, $PRisk\_peer$, which is the average political risks of all firms within the same state as the focal firm, less the focal firm itself. Firms headquartered in the same state are affected by the same political environment. Indeed, Mizruchi (1989) documents that geographical proximity between two firms in terms of corporate headquarters and plant locations leads to similar political behaviors. Pirinsky and Wang (2010) further show that when operating in an uncertain environment, managers look to their peers for ideas about appropriate strategic responses. Thus, a firm's political risk should be highly correlated with its peer firms' political exposures, satisfying the relevance criterion. Meanwhile, in line with the exclusion criterion, I see no reason why other firms' political risk would directly affect the focal firm's bank loan costs.

I construct the two instruments as follows. Following Alam et al. (2014), I construct $Political\_distance$ as the distance between the headquarter of a firm and its corresponding state capital city, using zip codes. A higher $Political\_distance$ indicates that the borrower is exposed to higher firm-specific political risk. To construct $PRisk\_peer$, for each firm I calculate the average $PRisk$ of other firms located in the same state as the focal firm. The higher the average political risk across other local firms (i.e., the higher a firm's $PRisk\_peer$), the higher the borrower's own political risk.

I report my findings in Table 1.6. For the first stage test, I regress $PRisk$ on $Political\_distance$ and $PRisk\_peer$, as well as including all of the other controls employed in the baseline regressions. Column (1) presents the first-stage result. I find that both instruments – $Political\_distance$ and $PRisk\_peer$ – are significantly positively associated with $PRisk$. Moreover, the F-statistic is 44.41, and thus my instruments are not likely to be weak instruments. In the second stage, I repeat my baseline analysis but replace the variable of interest with instrumented $PRisk$. Column (2) reports that the coefficient on instrumented $PRisk$ continues to exhibit a positive effect on the loan spread (coeff = 0.212, *t-stat* = 2.85). [12] At the same time, the Hansen J-statistic has a p-value of 0.58 for the instrumented political risk regression measure. This result suggests that I cannot reject the null that the instruments are uncorrelated with the error term, which provides some comfort that the instruments satisfy the exclusion restriction. The instrumental variable estimation therefore confirms the causal effect.[13]

[12] The economic magnitude of the $PRisk$ effect is a little larger than those in the baseline regressions (six basis points). Based on the coefficient of column (2) in Table 1.6, the economic magnitude is a 9.44 basis point increase in a firm's bank loan cost (0.211×0.212×211 = 9.44).

[13] For the distance IV, one may argue that state capitals are usually business/finance centers and the banks could also locate in the capital cities. Thus, this IV could be directly related to bank loan costs. In unreported results, I roughly check that there are at least 1/3 of US states that the capital city is not the largest city or the economic center. To some degree, the capital city is more related to politics. For example, at the country level, New York is the most famous US city, but Washington DC is the capital. I also agree that the banks could also located in the capital city, and this political distance will have some overlap with the distance to banks. To mitigate this concern, I tried to exclude the observations that the lead bank locates in the capital city. The results still hold. For the second IV, one may argue that local firms share a lot in common. . For example, firms with similar technologies are likely to cluster in the same state and that unobserved differences in technology drive both loan spreads and political risk exposures. This IV may capture something else that are directly related to loan costs. I also note there exist some criticisms on the industry/local average of lagged variable as the valid IVs. However, some existing literature still use this average as the IV. There could exist some similarity in the macro-economics, but how this could affect the specific firm's policy is not so clear. Specifically I also control for the firm fixed effects and time fixed effects. The major variation should come from the cross-sectional difference. I acknowledge there could exist such

[Insert Table 1.6 Here]

I employ a falsification test for my instruments by regressing loan costs on a measure of non-political risk that captures conversations on topics not related to political risk during earnings conference calls. In columns (3) and column (4), which present the falsification test, I find that the falsification test does not produce statistically significant results. Thus, it is a firm-specific political risk rather than a non-political risk that has a significant positive effect on loan interest rates. This finding helps further mitigate endogeneity concerns related to OLS estimation of the impact on loan pricing.

1.5.3 Propensity Score Matching

In this subsection, I demonstrate an alternative regression approach. Specifically, I apply PSM analysis, which enables me to compare the impact of high-level versus low-level $PRisk$, and at the same time to precisely control for other firm characteristics shown in Table 1.7, Panel A. To achieve this, I first define an indicator $DPRisk$, which is set to be 1 if a firm's $PRisk$ falls in the top 10% in that quarter (i.e., high-risk treatment firms) and zero if $PRisk$ is in the bottom 50% (i.e., low risk control group). [14] In the next step, for each treatment firm, to identify a matching firm from the control group, I run a logit model regression of $DPRisk$ on all the other variables. Because there are no

potential weakness, but at least, both IVs could pass the relevance test and exclusion test, and are empirically valid.

[14] Results are similar when I define the control group as firms whose $PRisk$ falls in the bottom 30%, 40%, and 60%. The matching sample results also continue to hold when I define the treatment group as firms whose $PRisk$ falls in the top 15% and 20%.

soundly documented firm-level political risk predictors in previous literature, to keep a safe margin, I include all variables. The fitted value of $DPRisk$ from the first stage regression will capture the probability (i.e., propensity score) for a firm to be in the treatment group. In the second step, to select a matched sample for each treatment firm-quarter observation, I will select the observation with the closest estimated probability. In addition, the matching sample should be selected from the same 2-digit SIC industry and the same year quarter. This procedure leads to a matched sample of 1,702 loan facilities, which comprise 851 facilities for borrowing firms with high political risk (i.e., the treatment observation) and 851 facilities for borrowing firms with low political risk (i.e. the control observation).

[Insert Table 1.7 Here]

Panel B reports the regression results using the PSM sample. The coefficient on $PRisk$ in the PSM sample is 0.048 (*t-stat* =1.99), which indicates that the loan spread of the treatment firms is about 4.8% higher than that of the matched non-treatment firms. Using a typical loan spread of 211 bps, the loan spread difference between the treatment firms and the matched non-treated firm is about 11 bps. Overall, the potential omitted variables or unobservable confounding effects are not likely to generate a positive relationship between $PRisk$ and borrowing firms' bank loan costs.

1.5.4 Quasi-shock Analysis

To further establish the causal link between a firm's $PRisk$ and loan financing cost, I explore the sudden changes in the firm $PRisk$ measure and conduct a quasi-shock study. One may argue that political risk does not suddenly change for no reason. However, when there exists such a sudden and significant change, the outsiders or the banks could still treat it as a shock to the firm's political environment. The observed situation of the political risk change will affect their decision making. Intuitively, when there is a sudden increase or decrease in the firm's exposure to the political risk, banks may pay more attention when evaluating the firm's condition. The contracting terms are thus more likely to reflect the impact of political risk.

To define a quasi-shock, I follow the literature on tariff reduction and product market competition. More specifically, I first estimate the annual $PRisk$ by using the average of the quarterly $PRisk$ within the year. I then calculate the absolute annual change of $PRisk$. If the annual change of $PRisk$ in a certain year is at least three times larger than the average annual change among all the years for the individual firm, I define that year as a shock year. I exclude the transitory changes by comparing the annual $PRisk$ change in the ± 3-year window of the shock year. If there exists an opposite significant shock in the three-year window, I exclude these shocks. I use a similar algebra to identify either a significant and persistent increase or decrease in the firm's political risk. With these criteria, I identify 280 $PRisk$ reduction events and 233 $PRisk$ increase events during the 2002-2016 sample period.

To measure the impact of the significant change in $PRisk$ on a firm's loan cost, I define a dummy variable, $Post$, which equals one if the loan issuance year is within the 3-year period *after* the shock year and zero if the year is within the 3 years *before* the shock year. I include the loans within the 3-year window only because my quasi shock is estimated using the 3-year window. I further require the firm to have at least one loan observation before the shock year and one loan observation after the shock year. I exclude bank loans in the shock year to better isolate the effect of the significant change in firm-specific political risks. I then run the regression of Eq. (1.1) using this sub-sample and replace $PRisk$ with the $Post$ dummy.

Column (1) in Table 1.8 reports the results for the dramatical increase scenario and column (2) for the dramatical decrease scenario. In Column (1), the variable $Post$ is associated with a significantly positive coefficient (coeff = 0.135; *t-stat* =2.09), suggesting that a firm's bank loan cost increases by about 13.5% when the firm experiences a significant increase in the political risk. The magnitude is six times larger than my baseline result (coeff = 0.022), suggesting that the surge of a firm's political risk leads to a sizeable increase in loan spreads. Similarly, when there is a shock causing a dramatic decrease in $Prisk$, the coefficient of $Post$ is significantly negative on loan costs (coeff = -0.212; *t-stat* =-2.23), and the magnitude is about ten times larger than the baseline regression coefficient. Collectively, this quasi-shock analysis helps to identify the causal relation between $Prisk$ and loan costs.

[Insert Table 1.8 Here]

1.6 Cross-sectional Analysis

In the previous analysis, I have documented that on average, more politically risky firms are charged higher interest rates on loans. I interpret this positive relation as the result of an increase in the information risk and/or default risk caused by $PRisk$. In the following section, I further test the validity of this interpretation by investigating the cross-sectional differences in the impact on bank loan costs. I specifically aim to confirm that the detrimental impact on its bank loan price is accentuated in the presence of factors that increase the volatility of accounting numbers and downside risk. Based on previous studies, I consider the following factors, including (1) financial information opacity, and (2) the degree of financial constraints. I develop and test my assumptions of the moderating effects of these factors on the relation between $PRisk$ and loan costs.

1.6.1 The Role of Financial Information Opacity

Banks assess the financial health of loan borrowers based on their financial statements (Chaney, Faccio, and Parsley, 2011). Thus, I predict that when a firm's financial information is opaque, banks will ask for more compensation from borrowers as they are exposed to greater $PRisk$, because the financial numbers of a firm with an opaque environment may lack credibility. Firms with high political risk have already been associated with complex information environment and high information asymmetry. Firm-level political risk could both increase the information uncertainty for the insiders and increase the information asymmetry between insiders and outsiders. The opaque financial information environment will make the situation more complex, which further increase banks' cost to access and process information. For example, the due diligence could take more time and become more costly. Banks are more likely to impose unfavorable terms on firms with less predictable accounts (Easley and O'Hara, 2004). The firm-level political risk in such an environment may also be greater, as financial reports can be more volatile and less precise in predicting the firms' future performance, and thus they may be charged more by banks. Therefore, I predict that the documented effect of $PRisk$ on loan costs will be stronger for firms with more opaque financial information.

Following previous research (Das, Guo, and Zhang, 2006; Ma et al., 2019), I consider three measures of a firm's financial information opacity. The first measure is firm size, proxied by the firm's total assets ($Size$). Larger firms, on average, are less subject to information opacity (Hasan et al., 2014). The second proxy for a firm's information environment is tangibility ($Tang$). Tangible assets are much easier for the banks to evaluate and claim and reduce the likelihood that shareholders substitute high risk for low-risk assets, which decreases the information asymmetry. Higher tangibility is therefore expected to result in lower borrowing costs (Denis and Mihov, 2003). My third measure is the level of analyst coverage ($AnalystCov$), which is an important characteristic of a firm's information environment. Das, Guo, and Zhang (2006) find that firms covered by more analysts have better information environments, so a greater analyst following is likely to result in less opaque financial information for a borrower. To investigate the potential impact of financial information opacity on the $PRisk$-loan cost relation, I modify my baseline regressions by including the interaction term between $PRisk$ and each of the three information opacity measures discussed above.

Table 1.9 reports the findings for the three measures in columns (1) to (3), respectively. The coefficient on the interaction term $PRisk \times Size$ exhibits a significantly negative coefficient (coeff = -0.011; *t-stat* = -2.60), implying that the impact on loan costs becomes accentuated for smaller firms. The variable $PRisk \times Tang$ is associated with a significantly negative coefficient (coeff = -0.049; *t-stat* = -2.11), suggesting that the $PRisk$-loan cost relation is weaker among firms with more tangible assets. Finally, the interaction term $PRisk \times AnalystCov$ is also associated with significant negative coefficients, indicating that analyst coverage helps to reduce additional borrowing costs due to higher $PRisk$. These results provide additional support for the notion that the impact of $PRisk$ becomes amplified (mitigated) when the firms are associated with more (less) opaque financial information.

[Insert Table 1.9 Here]

1.6.2 The Role of Financial Constraints

Financial constraints are market frictions that can disable a firm from funding all of its desired investments (i.e., positive net present value). This inability to obtain capital may be "due to credit constraints or inability to borrow, inability to issue equity, dependence on bank loans, or illiquidity of assets" (Lamont, Polk, and Saaá-Requejo, 2001). The literature suggests that financial constraints directly affect a firm's ability to undertake potentially profitable investment decisions and also affect the firm's choice of the optimal capital structure (Hennessy and Whited, 2007). When the political risk of firms with existing high financial constraints is also at a high level, there will be a high probability that these firms will have to delay or even give up some profitable projects. Thus, banks are more likely to charge such loan seekers high interest. Thus, I expect a firm's financial constraints to amplify the relation between $PRisk$ and loan interest rates.

I examine this by considering several proposed measures of financial constraints (Rajan and Zingales, 1998; Khwaja and Mian, 2005). My first measure is external financing dependency (Exf). In general, the cost of external financing increases if a firm is highly dependent on it, which hinders the growth of the firm (Duchin, Ozbas, and Sensoy, 2010). The second measure is cash flow volatility (CF_Vol). Higher cash flow volatility indicates a higher degree of uncertainty regarding a firm's future performance and a higher likelihood that it will default on loans (Bharath et al., 2008; Graham et al., 2008; Ma et al., 2019). Hadlock and Pierce (2010) construct the Hadlock and Pierce index (HP_Index) using the size and age of firms to estimate their financial constraints. This index serves as my last measure, with a higher score indicating a higher financial constraint. I provide details of the construction of these measures in the Appendix. To test the influence of corporate financial constraints on the $PRisk$-loan spread relation, I modify my baseline regressions to include the interaction term between $PRisk$ and each of the three measures of financial constraints discussed above.

Table 1.10 presents the results, with the first three columns showing those for the three measures. First, the coefficient of $PRisk \times Exf$ is positively significant, which supports that the detrimental impact of $PRisk$ on corporate loan costs becomes more pronounced for firms who are more dependent on external financing. The coefficient of $PRisk \times CF\_Vol$ is also significantly positive, suggesting that the influence of $PRisk$ on a firm's loan cost is more significant for firms with a high level of future uncertainty. Last, I observe a positively significant coefficient on the interaction term $PRisk \times HP\_Index,$ suggesting that creditors charge a higher cost when borrowers exhibit high levels of political risk, particularly if they suffer from greater financial constraints. The results thus generally support my assumption that the impact of $PRisk$ on loan interest rates is more pronounced (mitigated) in firms with greater (lesser) financial constraints. The cross-sectional results support those findings presented in the previous sections in this chapter.

[Insert Table 1.10 Here]

Overall, these results collectively suggest that Prisk will affect the loan cost from both the default risk channel and the information risk channel. The default channel could be more intuitive and more importance, but the information risk could still play a role by affecting the banks' assessment of the borrowing firm's default risk. The empirical results also support both channels.

1.7 Additional Analyses: Loan Covenants and Restrictions

Bank loan contracts contain multi-dimensional information on the risks affecting borrowers in addition to the pricing term or loan spread information.

Rajan and Winton (1995) suggest that banks seek to mitigate any information risk by monitoring some borrowers more vigilantly, which typically involves demanding more collateral and covenants. Previous studies have documented that banks typically set customized contracts that may involve both pricing and non-pricing terms to facilitate banks' monitoring after the loan issuance and help the banks to control for the potential losses (Qian and Strahan, 2007; Huang et al., 2018). I measure the relation between covenant restrictions and firm-specific political uncertainty with the following regression:

$$Restrictions_{i,t+1} = \alpha + \beta_1 \times PRisk_{i,t} + \beta_X \times X_{i,t} + \varepsilon_{i,t+1}, \quad (1.2)$$

where $Restrictions$ represents different types of restrictive covenants used.[15] I also include all the firm-, loan-, and macro-level control variables in Eq. (1.1).

1.7.1 Number of Loan Covenants

To test the effect of $PRisk$ on the intensity of different types of restrictive covenants, I calculate the total number of financial and general covenants for each loan deal. I find 30 different covenants in the DealScan database, including 18 types of financial and 12 types of general covenants. I construct three covenant variables. $TotCovIndex$ represents the total number of loan covenants (including both financial and general covenants) required for bank loan issuance. $GenCovIndex$ represents the number of general covenants, which are related to restrictions on prepayments, dividends, voting rights, or

[15] I do not test the loan amount and loan maturity. The loan amount or the loan maturity may be more closely related to the firm investment need. In some cases, when the investment is not so flexible, the firms will not be willing to scarify these conditions.

other business activities. $FinCovIndex$ represents the number of financial covenants. Following previous studies (Graham et al., 2008; Huang et al., 2018), I conduct an OLS regression on the number of loan covenants. As in my previous analyses, I expect $PRisk$ to have a positive relation with loan contracting restrictions, and that a higher $PRisk$ will lead to more total, general, and financial covenants.

Table 1.11 presents the findings regarding covenant restrictions in loan contracts. Column (1) shows that $PRisk$ is positively related to the number of total covenants at the 1% significance level (coeff = 0.121; *t-stat* =3.51), which indicates that firms with high $PRisk$ are subjected to tighter contracts in terms of the total number of covenants. The other two columns show that general and financial covenants also impose tighter contracts on firms with higher exposure to political risk. Overall, Table 1.11 supports the notion that borrowers with higher $PRisk$ are subjected to more total, general, and financial covenants.

[Insert Table 1.11 Here]

1.7.2 Strength of Loan Restrictions

Tighter loans are reflected in both an increased number of covenants and stronger contracts. Graham et al. (2008) state that loan contracts after restatement announcements have a higher likelihood of including secure and higher transaction fees due to the increasing complexity and riskiness of the loans. Next, I examine how $PRisk$ affects the strength of tightness requirements, including the collateral requirement, debt issuance sweep restriction, and transaction fees.

I conduct the regressions based on Eq. (1.2) with alternative dependent variables. First, I consider two specific requirements. I define $DDebt$ as an indicator that has the value of 1 if the loan contract includes any type of debt issuance sweep restrictions, and zero otherwise. $DSecured$ is an indicator that has the value of 1 if the bank loan contract requires some collateral, and zero otherwise. $Annual\_fee$ is defined as the annual charge against the entire loan commitment amount, no matter it is used or unused; this is also known as a facility fee. Following previous studies (e.g., Graham et al., 2008; Huang et al., 2018), I conduct probit regressions for the indicator variables and an OLS regression for the annual fee. [16] The last three columns of Table 1.11 present the results. $PRisk$ is positively and significantly associated with each of the three restriction measures. Thus, lenders will impose additional contracting requirements on the collateral requirements and debt issuance sweep restrictions. They will also charge higher annual fees. The results documented in this section provide a consistent interpretation of my prediction in **H2**.

1.8 Alternative Explanations

In Table 1.12 I consider several alternative explanations. First, it may be the case that the positive relationship between $PRisk$ and firms' loan costs is

[16] Due to limited data availability, my regressions of annual fees are based on only 1,935 observations of annual fees. The observations involving such fees account for 17% of my full sample, consistent with the 19% of Graham et al. (2008).

due to the lender's characteristics. That is, politically risky firms borrow loans from banks that charge higher costs on average. To test this alternative explanation, I include lender fixed effects and control for lender political risk. If this story holds, the coefficient on $PRisk$ should be insignificant if I control for leading banks' characteristics. I find that my main results for borrowers exposed to political risk continue to exist after I control for (i) lender fixed effects (Table 1.12, Panel A, column (1)), (ii) leading banks' political risks (column (2)), and (iii) leading banks' political risks and lender fixed effects (column (3)). Thus, even within the same bank, politically risky firms are charged a higher loan spread.

[Insert Table 1.12 Here]

Next, I examine whether a firm-specific political risk is an idiosyncratic risk that affects loan spreads, or whether it is simply a proxy for existing firm-level controls for loan pricing. To test this question, I form decile groups based on $PRisk$ and report the median values for firm fundamental attributes. Table 1.12, Panel B shows no monotonic pattern in any of the firm characteristics considered, which indicates that decile groups do not differ in terms of fundamental characteristics for borrowers exposed to different levels of political risk. Thus, the firm-specific political risk does not directly reflect any existing firm characteristics.

One may also argue that the documented relation may be influenced by other external financing activities, in particular, debt-financed acquisitions. However, using a firm's acquisition intensity as a measure of the firm's debt-financed acquisitions, my results in Table 1.12, Panel C suggest that the impact of $PRisk$ on loan spreads holds across high- and low-acquisition-intensity firms. Thus, external acquisitions do not seem to drive the relation I document between $PRisk$ and firms' loan financing costs.

1.9 Active Strategies to Manage Firm-level Political Risk

Above I document that $PRisk$ has adverse effects on borrowers' loans, such as higher loan spreads and tighter covenant restrictions. A natural question that arises is whether borrowers hedge against such political risk. To answer the question, in this section, I investigate the extent to which firms attempt to mitigate the detrimental impact of political risk by engaging in lobbying activities or by pursuing relationship-based loans. Prior literature shows that managers seek to manage political risk and improve access to debt financing by engaging in lobbying (Faccio, Masulis, and McConnell, 2006; Khwaja and Mian, 2005). Following this literature, I expect borrowers to be more likely to invest in lobbying activities when facing high idiosyncratic political risk. Since lobbying activities can lead to economic support through implicit government guarantees, I also expect lobbying firms to enjoy preferential loan pricing compared with non-lobbying firms.

I obtain lobbying data from the Center for Responsible Politics (CRP), which tracks the lobbying money in politics, and its effect on political elections and policies. [17] I present results on the extent to which firms alleviate the

[17] The website of CRP is OpenSecrets.org, which allows users to publicly access clear and unbiased information about federal campaign contributions, lobbying engagement by firms, the contribution amount, and the corresponding lobbying issues. This database has no common identifier with Compustat, so I manually match company names in CRP with those in

negative effects of $PRisk$ through lobbying in Table 1.13, Panel A. In column (1) I employ logit regression analysis to test the likelihood of politically risky firms engaging in lobbying. The results show a significantly positive coefficient on $PRisk$, which suggests that firms with higher level of political risk are more likely to engage in lobbying. In column (2) I instead add an interaction term to my baseline regression to assess the influence of lobbying. I find a negative coefficient on $PRisk \times Lobbying$, which is consistent with greater politically risky firms engaging in lobbying to mitigate lenders' concerns and hence decrease their borrowing costs.

[Insert Table 1.13 Here]

Firms can also alleviate the adverse effects of political risk by pursuing relationship-based loans. Banks typically obtain a borrower's operating information and monitor managers to facilitate the execution of loan covenants. For politically risky firms, banks must also interact with the management team in the face of changes in the political environment. A firm-bank relationship characterized by a high level of transparency and trust can reduce the lender's informational and monitoring costs and in turn the borrower's bank loan costs.

A loan contract is defined as a relationship-based loan ($Relation$) if a loan issuer had any previous lending relationship with the lead bank, and as a transactional loan otherwise (Bharath et al., 2011). In Table 1.13, Panel B, I report results for the subsample of relationship-based loans (RLOAN) in column (1), for the transactional loans (TLOAN) in column (2), and for the full

Compustat.

sample in column (3). The results show that firm-level political risk has no effect on relationship-based loans, but significantly increases loan spreads for transactional loans. When I turn attention to the full sample in column (3), I find that the interaction $PRisk \times Relation$ affects loan pricing negatively, suggesting that relationship-based loans significantly alleviate the effect of political risk on loan spreads.

Overall, the results in Table 1.13 suggest that firms may not be subject to the full negative effects of political risk. In particular, In particular, I show, consistent with my predictions in **H3**, that firms can mitigate the detrimental impact of political risk on the costs of their bank loan borrowing by actively pursuing strategies such as lobbying or relationship-based financing. I thus provide evidence on two possible ways borrowers can survive in a volatile political environment.

1.10 Conclusion

How the impact of political uncertainty, no matter aggregate level or firm-specific level, could affect the firm-level outcomes has attracted an increasing deal of academic attention, especially after the global financial crisis. Previous literature mainly documents the impact of aggregate-level political uncertainty. However, different firms can be associated with different levels or even different types of political risks. Except for the concurrent paper by HHLT (2019), most research only investigates the influence of political uncertainty at the aggregate level. To further extend our understanding of the firm-level heterogeneity, in this paper, I empirically examine the relation between *firm-level* political risk (i.e., $PRisk$) and corporate bank loan contracting. Specifically, I explore the effects of $PRisk$ on bank loan costs and other non-price loan terms. Based on prior theory and empirical research, I conjecture that firms exposed to higher political risk will be subject to more unfavorable pricing and non-pricing bank loan terms.

In the empirical test, based on a comprehensive large sample of U.S. firms' bank loan contracts during the 2002 to 2016 period, I document that individual firms associated with higher levels of $PRisk$ are charged higher loan spreads when taking bank loans. When I investigate the channels behind this effect, I find that the impact of $PRisk$ is more significant for firms with higher information opacity, firms with lower analyst following, and for firms facing greater financial constraints. In addition to affecting the costs of bank loans, firms with a higher level of firm-level political risk are subject to tighter non-pricing loan terms, in particular, more covenants, more collateral requirements, and higher transaction fees. Finally, I document that individual firms can mitigate the adverse effect of the associated firm-specific political risk by conducting some "real" activities, such as engaging in relationship-based lending activities and conducting more lobbying activities.

Chapter 2: Rational Anchoring: The Impact of Borrowing History on Debt Contracting

2.1 Introduction

Since Hirshleifer (2001) states that anchoring is a “dynamic psychology-based asset-pricing theory in its infancy” (p. 1535), an increasing number of studies have explored this psychological bias in economics and finance. Previous studies documents that the anchoring heuristic plays an important role in the pricing of initial public offerings (Loughran and Ritter, 2002), the pricing of seasoned equity offerings (Dittmar, Duchin, and Zhang, 2020), the pricing of merger and acquisition offerings (Baker, Pan, and Wurgler, 2012), stock returns (Li and Yu, 2012; Chang, et al., 2019), loan contracting (Dougal, et al, 2015), and sell-side analyst forecasts (Cen, Hilary, and Wei, 2013). Most of the papers attribute the observed anchoring outcome as an effect of the human behavioral bias, and I label this explanation as “behavioral anchoring”. However, this explanation may become less convincing when the decision-makers are well-trained financial experts, for example, the loan officers who are specialized in bank loan contracts. In this paper, I explore another potential explanation for the observed anchoring outcome, and I label it as “rational anchoring”.

In the earlier study, Tversky and Kahneman (1974) state that the anchoring effect refers to a belief formation process under which the price begins at a specific initial value. This specific starting point must be salient, but perhaps is entirely irrelevant to the current situation. In most cases, the decision-makers suffer this behavior bias *unconsciously* and do not intend to take advantage of the specific starting point. However, it is possible that the one with more information advantage or with higher bargaining power *intentionally* refers to the specific reference point during contract negotiation and gains benefit from this rational and strategic anchoring. Throughout this paper, I use “behavioral anchoring” and “rational anchoring” to describe these two types of anchoring.

I explore the potential rational anchoring effect in the credit market during the post-crisis period for several reasons.[18] First, bank loans are documented to be the major external financing resources, and account for a large proportion of debt borrowings (Dennis, Nandy, and Sharpe, 2000). Most of the firms will get involved in some bank loans. Second, the loan contracting has some unique features. Unlike the SEOs, the banks are the ultimate stakeholder in the loan contract, while in SEOs, investment banks will sell the shares to other investors, acting as the financial intermediary. Different from M&As, loan contracting generally does not involve the control right. Compared with the stock prices, loan prices are far sparse, making the previous loan contracting more salient. This helps to identify the anchoring effect more clearly. In addition, the 2007-2009 global financial crisis has brought a structural change in the credit market, which may change the relative bargaining power between firms and banks. It not only leads to liquidity issues and a “credit crunch” in lending activities, but also accelerates the implementation of tighter regulations on risk management

[18] Anchoring effect in the loan market means the loan negotiation parties use the historical spread as the reference point to set the current loan price. Dougal, Engelberg, Parsons, and Van Wesep (DEPW henceforth) (2015) document that the firm’s borrowing history affects the current loan contracting using a sample ending in 2008, and attribute the findings to human psychology bias, i.e., “behavioral anchoring”. I will distinguish my paper from their paper in later sections.

(Berger and Udell, 1994; Watanabe, 2007). In July 2008, US banks implemented a revised capital framework set by the Basel Committee (Basel II), which included tier 3 capital to regulatory capital and tightened regulatory capital ratio.[19] Based on the statistics provided by Federal Reserve Bank, the average US bank's capital adequacy exhibits a dramatic increase since 2008, as shown in Figure 2.1.[20] Thus, it is necessary to examine the potential rational anchoring effect in the credit market and the impact of the global financial crisis on the behavior of the loan contracting parties.

[Insert Figure 2.1 Here]

I fill the gap by providing findings in three sets. First, using a sample of 10,060 loan-level observations for publicly traded firms during 2009–2016, I confirm that the anchoring effect exists in the credit market, i.e., the borrowing history affects the borrower's current loan cost. In particular, I find that when average credit spreads have fallen since the firm's nearest previous borrowing, the current loan pricing is positively related to the historical credit spreads, and the loan borrower pays a premium. Economically, the loan premium is about 8% (around 22 bps) higher when average credit spreads have fallen significantly.[21] However, when aggregate credit spreads have risen greatly since the firm's nearest previous borrowing, aggregate spread evolution will not

[19] Basel I requires banks to maintain capital adequacy of at least 8% of their risk-weighted assets with at least 4% in the form of Tier 1 capital and 2% in the form of common equity. Basel II further requires operational risk-weighted assets to be included in total risk-weighted assets.
[20] Prior to the global financial crisis, the Basel Committee published the second set of regulations for international banks (i.e., Basel II). Basel II improves the regulations for the capital requirement of Basel I by taking into consideration of operational risks into credit risks. It also tightens the supervisory review process for banks.
[21] Based on the summary statistics in Table 1, the average issuance cost for a typical loan is 275 bps in my sample. Thus, the borrowing history effect for a typical loan is 8%×275=22bps.

affect the borrower's current cost, i.e., the loan borrower does not enjoy a discount. I control for the loan type × year × credit rating fixed effect in the regressions so that my main findings documented in this paper are not driven by the impact of different loan types, credit ratings, or unobservable time-invariant factors. I also conduct different kinds of robustness tests to make sure that these findings 1) are robust to different constructions on aggregate spread evolution; 2) are robust after considering current firm-level factors; 3) the insignificant relationship under the spreads rising scenario is not driven by sampling biases.

In the second part, I disentangle and rule out several other possible explanations for the effect of historical credit spreads on current loan costs. The first possibility is the coincidence between borrowing history and the borrower's current credit risks. As borrowing history matters only when aggregate spreads fell, it is possible that firms borrowed at a higher credit spread period may have larger credit risks than firms borrowed at a lower credit spreads period. The high borrowing history may suggest that these firms are financially constrained and are not able to wait for the credit market recovers. Thus, this possibility argues that banks charge more on the current loans because of the borrowers' higher credit risks, rather than their borrowing histories per se. To test this risk-based explanation, I use a regression framework by investigating nine measures of a borrower's creditworthiness. The result shows that most credit risk measures are not significantly associated with the trend of aggregate spread evolution, implying that borrowing history does not significantly correlate with the current firm fundamentals. Thus, the positive relationship between borrowing history and current loan cost under the spread falling scenario is not attributable to the borrower's credit risks.

The second possibility is relationship loans. Firms tend to build a good relationship with the bank they ever borrowed from. The relationship loans can also benefit the bank by facilitating monitoring and increasing the transparency of a borrower's accounting information. It is possible that the bank may agree to charge less when the credit market is tight because of the good relationship with borrowers, and the borrower agrees to return the bank's favor and pays higher costs in the following loans. Then it may lead to a positive relationship between current loan pricing and previous loan cost if the last aggregate spreads were high. However, I find the relationship loan argument is not valid. First, this argument indicates a two-side explanation. Some firms pay more to return favors at current loans, and some other firms seek help and obtain discounts from their relationship banks. If the borrowing history effect is attributed to the relationship loans, I should also find a significant effect on loan interests when aggregate spreads have risen, while I do not. Moreover, I directly test the possibility of the relationship loans argument using a subsample analysis. I find that spread evolution affects current loan costs no matter whether the firm has or does not have a prior relationship with the bank. As the firm will not get favor from new banks based on the relationship loan argument, the subsample analysis result, therefore, helps to refute the relationship loan explanation.

After ruling out the above possibilities, I further provide a firm-level test to support the anchoring explanation. I decompose a firm's current realized loan cost into three parts, including a model-predicted loan cost, the spread evolution since the last borrowing, and the previous residual. I then use a two-step econometric model to study the effect of firm-specific borrowing costs. In the first step, I run a standard cross-sectional model to predict the loan cost, and the model shows a high explanatory power for the predicted loan costs. In the next step (i.e., step 2), I regress the current realized loan cost on the three components. I find that on average, the spread evolution affects the realized loan cost. But this relationship is completely driven by the cases when the historical borrowing cost is higher than the predicted cost. This result confirms the key finding using the aggregate credit spreads, suggesting that banks refer to the firm's borrowing history to determine the loan price, and it only happens when the firm's last borrowing cost was high.

In the last set, I distinguish whether the documented anchoring effect is "behavioral anchoring" or "rational anchoring". I first examine the possibility of psychological bias, i.e., both lenders and borrowers suffer the psychological process unintendedly. I predict that if both parties suffer the behavioral anchoring, the reference salience should affect the anchoring outcome. The nearer the previous loan, the stronger impact of the loan history. I break up the whole sample into five subsamples based on the loan issuance gap between the current loan and the previous loan, defined as the time gap (in years) between the current loans and the most recent borrowing. If contracting parties are subject to anchoring without intention, the coefficient on spread evolution should monotonically decrease as the loan issuance gap increases, as human memories diminish along with time. However, my result shows that the coefficient on spread evolution does not exhibit a decreasing trend and thus rejects the psychological bias conjecture.

Next, I discuss the intentional usage of this anchoring effect, i.e., rational anchoring. As I have shown that the anchoring effect is asymmetric and only banks get premiums, it is more likely that banks use the anchoring effect strategically to make more benefits. First, the banks should be able to conduct such a strategy as banks generally have some information advantage. The theoretical foundation is the hold-up theory, which suggests that banks possess more bargaining power in the loan negotiation during tight credit conditions. Banks have superior private information on borrowers, which enables the banks to "hold up" the borrower. In case that, the current borrower wants to switch to a new lender, it will probably be pegged as a lemon in the credit market no matter whether its true financial condition is good or not (Diamond and Rajan, 2000). In addition, the 2007–2008 global financial crisis not only deteriorates the loan market, but also affects other capital markets adversely. This in turn increases the firms' switching costs because of the reduced access to other capital markets (Ivashina and Scharfstein, 2010). In line with this, I show that borrowers in the post-crisis period tend to be larger firms (measured by the total assets), have lower leverage, and have better financial quality than before. The tightening credit market enables banks more bargaining power in the loan negotiations, thus enabling banks to achieve the anchoring strategy to benefit themselves.

To provide more evidence on the rational anchoring strategy, I test the role of borrowers' bargaining power by introducing the interaction between spread evolution and bargaining power measures into the regression model. I use two sets of measures to capture a borrower's bargaining power. The first set captures the firm's financial situation, including the firm's cash flow and leverage. The second set is the borrower's ability of access to public capital markets. Santos and Winton (2008) document that firms with broader sources of funds are less likely to depend on bank loans and thus have more bargaining power. My result shows that the anchoring effect becomes weaker when firms have better financial quality and more access to the bond market, suggesting that banks get less benefit from the anchoring strategy when the borrowers have stronger bargaining power.

A potential natural question is that: if banks are fully rational (e.g., act to maximize their own benefits), why they do not set loan costs as high as they can, but rather anchor on prior loan costs? The basic findings in this chapter suggests that banks have already charge higher loan cost than they should charge based on the borrowing firm's risk profile when the firm's previous loan cost is high. The banks are already trying to maximize their own benefits. When the firm has a low historical borrowing cost, the bank will set the loan cost based on the firm fundamental and ignore the previous low borrowing cost. The results suggest banks anchor to firms' high borrowing cost intentionally. Anchoring to the firm's history provides the bank a decent loan negotiation tool. In addition, it is hard to justify what is "as high as they can".

Taken together, my results support a strategic usage of the anchoring effect in the loan pricing, and the success of the strategy depends on the bargaining power of the two parties. My findings in this paper complement the growing research literature on the importance of the anchoring effect or reference points. Previous studies document that the anchoring heuristic affects the pricing of initial public offerings (Loughran and Ritter, 2002), the pricing of seasoned equity offerings (Dittmar, Duchin, and Zhang, 2020), the pricing of merger and acquisition offerings (Baker, Pan, and Wurgler, 2012), stock returns (Li and Yu, 2012; Chang, Lin, Luo, and Ren, 2019), and even bank loan costs (Dougal, Engelberg, Parsons, and Van Wesep, 2015). Most of these findings are attributed to unintentional anchoring. My findings extend this growing literature by exploring the possibility of strategic anchoring and suggest that well-trained financial experts may strategically take advantage of behavioral biases to maximize their utility.

My findings also emphasize the importance of bargaining power in loan pricing. Diamond and Rajan (2000) model that the monopoly information held by banks affects the balance of bargaining power between banks and loan borrowers. Santos and Winton (2019) show that the balance of bargaining power between two parties matters to the loan cost and that banks charge more spread for firms who are bank dependent and with low cash flows. In line with this, I find that partial anchoring (where the anchor on the borrowing history holds only when the past cost is high) is a reflection of the banks' increasing bargaining power. These findings present complementary evidence for the potential negotiation process of loan issuance.

2.2 Data and Sampling Procedure

I start from the universe Dealscan database of the Loan Pricing Corporation to identify loan borrowers. The loan contracting information is obtained from WRDS Dealscan, including the loan issuance date, loan type, contracting parties, loan amount, loan maturity, loan spread, and other related information.[22] To make the result interpretation clearer, I only include two types of loans, and also require the loan maturity to be at least 1 year in the sample, namely, the term loans and the revolver loans. I further verify that these two types of loans account for about 70% of the loans in Dealscan database, thus the sample selection bias is minor. To identify a reliable corporate borrowing history, I require the borrowers take out the same type of loan at least two times. I further require the time gap (in terms of years) between the two consecutive loans to be at least 1 year to make sure that the new loans are not simply a reclassification or renegotiation of existing loans. Lastly, I exclude those loans with missing loan pricing information. The final sample covers 29,077 loan-level observations from 1987 to 2016. I use the post-2008 sample as the main testing sample, which covers 10,060 loan-level observations. [23]

To control for different firm characteristics, I extract the firm accounting-related information from Compustat and extract the stock

[22] There are two major sources from which to extract the Dealscan database, WRDS Dealscan, and Reuters Dealscan. All loan-level data are the same in the two sources. Reuters Dealscan contains additional information, such as Loan Pricing Corporation news, analysis, ratings, and secondary pricing information.

[23] The sample period is restricted by the link table for Compustat and Dealscan. I thank Prof. Michael R. Roberts for sharing his link table for the two databases. To ease comparison, I also present the descriptive result and regression results for the 1987–2008 period in the online appendix.

information from CRSP. The firms' bond issuance information is extracted from the Securities Data Corporation, which helps to identify whether the firms have access to the bond market. The summary statistics for loan characteristics and borrower characteristics are reported in Table 2.1. A typical loan borrower has average total assets of $9,503 million and average sales of $1,353 million. The borrower's total assets and sales are more than twice those in the pre-2008 period. This implies that the loan market after the financial crisis becomes more selective and the successful loan borrowers are more likely to be larger in terms of both assets and sales. In terms of loan characteristics, a typical loan has a maturity of 54 months, a loan amount of $510 million, and a spread of 275 bps above the LIBOR. Additionally, the large increase in average loan spreads in the post-2008 period (from 206 bps to 275 bps) also provides evidence that the loan market becomes tighter after the crisis.

[Insert Table 2.1 Here]

2.3 Borrowing History and Loan Costs

I formally investigate whether a firm's current loan cost is affected by its borrowing history, which is measured by the aggregate spread evolution since its last loan borrowing. Before I conduct any regression analysis, I first show the time-series trend of the aggregate spread. I calculate the yearly average spreads for all term loans and long-term revolvers separately and plot the overall trend in Figure 2.2.

[Insert Figure 2.2 Here]

The yearly average credit spread exhibits a dramatic decrease in the mid-1990s and a continuous increase during the Internet bubble. Afterward, it first decreases and then surges to the highest point during the financial crisis. Specifically, during this period, the term loan spread increases by 44% and the long revolvers even exhibit a sharper increase of 69%. After 2009, the average spreads gradually drop and become stable in recent years.

The fluctuations in term loans and long-term revolvers shown in Figure 2.2 indicate the sources of variation in aggregate credit spreads. Moreover, although DEPW (2015) examine this spread evolution effect using the pre-crisis period, the large variations in average spreads post-crisis motivate me to re-examine the borrowing history effect on the credit market for recent years. The financial crisis causes much larger variations in the credit spreads and its effect on the credit market could last for a long period.

2.3.1 Anchoring Effect: The Reference Role of Borrowing History

To test the anchoring effect (i.e., the impact of previous borrowing history on current loan pricing), I define several variables to measure the borrowing history. Specifically, I first use two dummy variables: $SpdRose_{i,j,t*\rightarrow t}$ is an indicator variable, which equals 1 if the aggregate spreads rose by 25% or more since the firm's previous loan issuance and 0 otherwise. $SpdFell_{i,j,t*\rightarrow t}$ is the other indicator variable, which equals 1 if the aggregate spreads fell by 25% or more since the last borrowing and 0 otherwise. $t*$ denotes the most recent year in which the firm borrowed, and t is the current year when the firm borrows. In addition to the dummy indicators, I also define a continuous variable to show the spread evolution: $\Delta Agg.Log(Spd)_{i,j,t*\rightarrow t}$ is defined as the log-difference in aggregate spreads between the borrower's previous loan financing and current loan financing. Furthermore, I investigate the effect of spread evolution in both spread risen (i.e., aggregate spreads have increased since the firm's previous borrowing) and spread fallen scenarios (i.e., aggregate spreads have decreased since the firm's previous borrowing). Relatedly, I construct $|\Delta Agg.Log(Spd)^{F}_{i,j,t*\rightarrow t}|$ to capture the magnitude of aggregate spread evolution when the spreads have fallen. $\Delta Agg.Log(Spd)^{R}_{i,j,t*\rightarrow t}$ is constructed to capture the magnitude of aggregate spread evolution under the spread risen case. To empirically test the anchoring effect, I apply the regression framework as follows.

$$\begin{aligned} Log\left(Spd_{i,j,t}\right) = \quad & \alpha + \beta_1 \times Agg.Spd\ Evolution_{\ i,j,t*\rightarrow t} \\ & + \beta_2 \times year \times loan\ type_{\ i,j,t} + \varepsilon_{i,t}, \end{aligned} \tag{2.1}$$

where $Log(Spd)_{i,j,t}$ is a firm's loan issuance cost (in log format). Following previous studies (Ivashina, 2009), a loan borrower's spread is measured as the total spread paid (net of upfront fees) over the LIBOR for every dollar drawn down from the loan. For the aggregate spread evolution variable ($Agg.Spd\ Evolution_{\ i,j,t*\rightarrow t}$), under different regression specifications, it will be one of the different variables as defined above. Firms borrowing term loans or revolvers in different years may be associated with different risk levels and thus may have different cost charges. To address this, I control for the *Year* $\times$ *Loan Type* fixed effect to ensure my findings are not affected by different loan types or unobservable time-invariant factors. Coefficient β_1 captures the anchoring effect. A significant non-zero coefficient will indicate that previous borrowing history serves as a reference (or partial reference) on current loan contracting.

Table 2.2 reports the main findings. I find that the anchoring effect exists in the credit market as the aggregate spread evolution affects the new loan costs significantly, but the impact only exists when the aggregate spreads have fallen. In detail, column (1) shows a significant coefficient on *ΔAgg.Log(Spd)*, suggesting that a firm's borrowing history affects the loan pricing significantly. Moreover, I show that the impact of spread evolution depends on the loan path. The estimated coefficients on *SpdFell* and $|\Delta Agg.Log(Spd)^F|$ are significantly positive in columns (2) and (4), which show the cases when the aggregate spreads have fallen. However, in columns (3) and (5), the coefficients on *SpdRose* and $\Delta Agg.Log(Spd)^R$ are insignificant, suggesting a firm's loan pricing is not affected by spread evolution when aggregate spreads have risen.

[Insert Table 2.2 Here]

In Table 2.2, when constructing the time-series trend of the aggregate spread, I pool the loan observations across different credit ratings together. Thus, for each loan type (i.e., term loan or revolver loan), only one time-series trend is constructed. To establish a stricter and more comparable comparison, I further estimate the aggregate spread ***within*** a credit rating for each loan type. In particular, I construct seven rating groups based on a firm's ratings ranging from AA/AAA to no rating. [24] In this case, I will have seven average loan

[24] I obtain the information on the firm's S&P long-term debt ratings from the Compustat database.

spreads for each loan type each year, giving a total of 14 time-series indexes for the average credit spreads. I then repeat the analysis of aggregate spreads evolution within credit rating groups, using the following regression model

$$\begin{aligned} Log\left(Spd_{i,j,t}\right) = \quad & \alpha + \beta_1 \times Agg.Spd\ Evolution_{\ i,j,r,t* \to t} \\ & + \beta_2 \times Year \times Loan\ type \times Rating_{i,j,r,t} \ + \\ & \varepsilon_{i,j,r,t}, \end{aligned} \tag{2.2}$$

Where the variables of interest are the aggregate spread evolution measures, constructed within each credit group. I also include *Year* × *Loan type* × *Rating* fixed effect in the regression to make sure the main finding is not affected by different loan types, credit ratings, or unobservable time-invariant factors.

Table 2.3 Panel A reports the results of the borrowing history effect within rating groups. In Panel B, I further require the firm's current credit rating to be the same as when it last borrowed. Overall, the pattern is consistent with that using pooled sample as in Table 2.2. I find that on average, the firms' current loan costs are affected by the spread evolution negatively and significantly, shown in Panel A column (1). Similarly, this effect is asymmetric: it occurs only when aggregate spreads have fallen, shown in columns (2) and (4); when aggregate spreads have risen, the coefficients on spread evolution are insignificant, shown in columns (3) and (5). Table 3 Panel B shows that the pattern also holds for firms with no rating change between previous borrowing and current borrowing. Thus, the results are not contaminated by the firm's ratings.

Overall, Table 2.2 and Table 2.3 show that aggregate spreads change affects a firm's loan pricing, while this effect depends on the loan path (i.e., whether the aggregate spreads have risen or fallen). These findings have important implications. First, the anchoring effect indeed exists in the credit market. The borrowing history acts as the reference or partial reference for the current loan contracting. Otherwise, the previous contracting outcome should not affect the current contract as the previous information has already become outdated. Second, the positive coefficients under the spread falling cases indicate that firms will pay premiums in current loans when firms' previous borrowings occur at periods of higher aggregate credit spreads. The economical magnitude is non-trivial. For example, In Table 2.2 Column (2), the estimated coefficient of 0.08 suggests that firms will pay additional 22 bps (275 × 0.08) for the current loans. Third, the asymmetric finding suggests that when the aggregate spreads increase, firms do not pay less. The previous borrowing history at a lower cost will not affect the current loan contracting. Overall, the results suggest the borrowing history only matters when the banks could enjoy some benefit if the banks refer to this historical information in new loan contracts.

[Insert Table 2.3 Here]

2.3.2 Effect of Borrowing History: Subsample Analysis

As shown in Figure 2.2, the aggregate loan spread is highest around 2009 and decreases gradually in the following years. Mechanically, all firms borrowing in 2009 will have borrowing histories of lower loan spreads. Even firms borrowing from 2010 to 2012 will have a higher probability of having a lower borrowing history. This mechanical data distribution may generate potential sample selection bias. Thus, I divide the post-2008 sample into two equal subsamples: the 2009–2012 subsample and the 2013–2016 subsample, and repeat the main analysis using subsamples.

Table 2.4 reports the subsample analysis results. Panel A shows the results for the 2009–2012 subsample. The first two columns present the results based on the aggregate spread change estimated across credit rating groups, and the later columns present the results using the aggregate spread change estimated within credit groups. This table shows that the coefficient on $|\Delta Agg.Log(Spd)^{F}|$ in column (1) is significant at the 5% level. After further considering the credit rating fixed effect, the estimated coefficient is still statistically significant as shown in column (3). On the other hand, in columns (2) and (4), the coefficients on $\Delta Agg.Log(Spd)^{R}$ are both insignificant. The results are materially the same as using the whole sample. Besides, this test helps to alleviate the concerns of sample selection bias. The numbers of observations in columns (2) and (4) are about three times those in columns (1) and (3), suggesting that more firms are associated with the increasing aggregate spreads. This is consistent with the dramatic increase of the aggregate spread in 2008 and 2009. However, the spread evolution measures in columns (1) and (3) still exhibit positive and significant relationships with current loan costs but become insignificant in columns (2) and (4). Thus, the asymmetric findings on the impact of borrowing history are not likely to be affected by sample limitation or selection bias.

Panel B reports the result for the 2013–2016 subsample. As expected, the number of observations under spreads fallen case is much larger than that under spreads risen case. Although the sample distribution is opposite to that in Panel A, the results are still consistent. The coefficients on $|\Delta Agg.Log(Spd)^F|$ in columns (1) and (3) are statistically significant during this subsample period. The coefficient on $\Delta Agg.Log(Spd)^R$ is insignificant in column (4).

[Insert Table 2.4 Here]

Taken together, Table 2.2 to Table 2.4 suggest that firm's borrowing history indeed affects its current loan pricing, but the impact depends on the specific loan path. If aggregate spreads have fallen, the borrowing history effect leads the firm to pay more spreads for its current borrowing. The effect disappears when the aggregate spreads have risen. These findings are helpful to address the concerns of sample selection bias or limited sample observation.

2.4 Anchoring Explanation and Other Possibilities

I have documented that firm's borrowing history will affect its current loan pricing during the post-crisis period and attribute the findings to an anchoring explanation. There may also exist different explanations. For example, it is also possible that the borrowing history co-moves with some potential firm risks. In this section, I further analyze different possibilities to explain the relationship between current loan cost and the spread evolution.

2.4.1 Borrower's Credit Risk

The first potential explanation is rational contracting based on borrower risk profile. It might be that firms borrowed during high aggregate spreads period are risker. Although I have controlled for the credit rating in all regressions, the ratings may not necessarily reflect all the risks. To compensate for the potentially high risks, banks charge higher spreads.

However, this explanation has at least two limitations. First, if the firms are indeed risker one, there are no obvious reasons to explain why these firms could achieve to borrow bank loans when the credit market is tighter (i.e., aggregate spreads are higher). Previous literature shows that when the credit market is tight, creditors favor larger and safer borrowers. Second, the rational risk-based explanation is not able to explain the asymmetric impact of the firm's borrowing history. If firms pay some premium when the aggregate credit spreads fall since the last borrowing, I also expect the firms should pay less if the aggregate spreads increase since the previous borrowing.

In addition to the above discussion, I empirically test the risk-based explanation in the following. I apply the framework below to test the relationship between the aggregate spread evolution and firms' credit risks.

$$Credit\ risk_{\ i,t,j,r} = \quad \alpha + \ \beta_1 \times Agg.Spd\ Evolution_{\ i,j,r,t*\rightarrow t}$$

$$+ \beta_2 \times Year \times Loan\ type \times Rating_{i,j,r,t} + \varepsilon_{i,j,r,t}, \quad (2.3)$$

Since the effect of borrowing history holds only when the current aggregate spreads were lower, I focus on $|\Delta Agg.Log(Spd)^F|$ in this regression.[25] The dependent variable used in equation (2.3) includes different empirical measures of a firm's credit risk. The first set of credit risk measures focuses on the firm's debt quality and incorporates the measures such as current ratio (*CURR*), debt-to-asset ratio (*LEV*), and change in credit ratings (*ΔRATE*). A higher current ratio and lower leverage reflect higher creditworthiness. A positive *ΔRATE* indicates the firm has been upgraded since the last borrowing. The second set reflects a firm's credit risk through accounting performance and uses two primary measures: sales growth (*SALE_G*) and earnings (*EARN*). Firms with better financial performance and higher sales growth have good creditworthiness. The third set includes measures of a borrower's stock performance, such as market-to-book ratio (*M/B*), trailing stock returns (*RET*), and trailing return volatility (*VOL*). Firms with more growth potential, higher returns on the stock market, and lower volatility are regarded as being less risky. The detailed definitions on the three sets of credit risk measures are provided in Appendix.

For these variables' construction, most of the credit risk measures are constructed using the most recent quarterly information. Besides, I also use two future measures *F.RET* and *ΔRATE* to capture banks' potential perception of the borrower creditworthiness. For example, if a firm has some private information

[25] The unreported result shows that eight of nine credit risks have a non-significant relationship with $\Delta Agg.Log(Spd)^R$, which also rejects the credit risk argument.

on its on-going R&D activities, firm managers may conditionally release some information to the lenders during the loan contracting process. Such kind of information is probably reflected by the future stock performance or rating changes. In this case, the future stock return and changes in credit rating may also reflect the borrower's current credit risk.

Table 2.5 presents the results of firm creditworthiness. The coefficients on $|\Delta Agg.Log(Spd)^F|$ are insignificant for most measures of credit risk, suggesting that aggregate credit spreads evolution has no significant relationship with a borrower's credit risk. Although Column (3) shows that the sales growth rate has a negative relation with $|\Delta Agg.Log(Spd)^F|$, in unreported result, it also has a negative relation with $\Delta Agg.Log(Spd)^R$, which also fails to support the risk-based conjecture. Therefore, the borrower's credit risks cannot explain the documented finding between a firm's previous borrowing history and its current borrowing cost.

[Insert Table 2.5 Here]

2.4.2 Anchoring Explanation: Fixation on Previous Loan Cost

In the previous section, I exclude the credit risk explanation and find that firms that last borrowed in higher spread years are not fundamentally riskier. Another possibility would be the last borrowing cost of the firm itself, which is apparent historical information for both firm managers and loan lenders.

To test the impact of the firm-specific borrowing history on the current loan costs, I adopt a two-step econometric model. In the first step, I validate and calibrate the factor loadings of different loan cost determinants. Each year, I run a cross-sectional regression model of the loan cost on a battery of firm-level and loan-level factors taken from Ivashina (2009). The firm-level characteristics include the firm sales (*SALES*), the firm assets (*SIZE*), firm profitability (*ROA*), firm current ratio (*CUR*), the debt-to-assets ratio (*LEV*), and stock volatility (*VOL*). The loan-specific factors indicate the loan features, such as the logarithm of the loan issuance amount (*Log(AMT)*), loan maturity (*MAT*), the market share of lead bank has in each loan facility (*BANK_SHR*), and the number of lead lenders in a loan syndicate (*NLEND*). Moreover, several loan covenant requirements are also included as indicator variables, namely, the collateral requirement indicator (*COLL*), financial covenant indicator (*COV*), performance pricing indicator (*PERF*), and prime rate indicator (*PRIM*). The detailed variable definitions are shown in Appendix A2.1.

The predictive regressions of loan spreads are conducted year by year with controlling of different fixed effects including a firm's S&P long-term debt ratings, the detailed loan type, the corresponding loan purpose, and dummy indicators for the lead arranger. Table 2.6 reports the average coefficients for different determinants. The result shows that the adjusted R^2 is 0.662, suggesting that the regression model has high explanatory power for the loan cost. The coefficients on the observable characteristics are comparable with the previous literature.

[Insert Table 2.6 Here]

In the second step, I examine the anchoring effect based on a borrower's firm-specific borrowing history. In this test, I also consider the effect of predicted loan cost and the previous residue. I decompose the realized loan cost at time t into three main parts and estimate the relationships using the following expression:

$$s_{i,t} = \beta\hat{s}_{i,t} + \delta(s_{i,r} - \hat{s}_{i,t}) + \Upsilon(s_{i,r} - \hat{s}_{i,r}) + \epsilon_{i,t} \qquad (2.4)$$

where s is the log realized spread, which is *Log(Spd)* in previous tables. $\hat{s}$ is the predicted spread based on the first-stage cross-sectional regression. t and r represent the years of a firm's current borrowing and most recent borrowing. The first part $\hat{s}_{i,t}$ refers to the model predicted spread at time t (*PRED_SPD*), which is predicted from the observable characteristics in the first-step model. The coefficient β captures the effectiveness of the predictive regression and should be close to 1 if the regression model accurately predicts the realized spread. The second part $s_{i,r} - \hat{s}_{i,t}$ is the firm-specific spread evolution (*SPD_EVO*), which is the log difference between the firm's previous loan spread and its current model predicted loan spread. The coefficient of the spread evolution δ captures the anchoring effect (i.e., the firm's previous borrowing cost servers as the reference point). If the anchoring effect holds in the loan financing, then δ should be significantly different from 0. The last part $s_{i,r} - \hat{s}_{i,r}$ is the previous residual (*PREV_RES*), which is the log difference between the previously realized and previously predicted loan spread. The coefficient of the previous residual γ captures the effect of previous unpredicted information. This is unobservable at the current time, and the range of γ could be from zero to one.

Table 2.7 presents the regression result of firm-specific spread evolution on its loan cost, as well as the result of previous residual and predicted loan cost. First, Table 2.7 shows that the predictive model used in the first step is effective. The coefficient on the model-predicted spread (*PRED_SPD*) is 0.95 for the full sample, which is very close to 1, consistent with the expectation. When I run the regression separately in columns (2) and (3), the coefficients of *PRED_SPD* are still close to 1. This finding is also consistent with the high adjusted R^2 shown in Table 2.6.

Using the aggregate spread evolution, I document an asymmetric relationship between the previous loan history and the current loan spread. In case the fixation on firm-specific borrowing cost drives the result, I should observe the same pattern using the firm-specific loan evolution in the second step. Specifically, when the model predicted spread is lower than the previously realized loan spread, the firm's borrowing history matters and leads the firm to pay a premium, while when the model predicted spread is higher than the previous loan spread, firms do not pay less.

The empirical results in Table 2.7 confirm the above prediction. The coefficients of the *SPD_EVO* in Table 2.7 exhibit an asymmetric pattern. Using the whole sample, I show a significantly positive relationship between *SPD_EVO* and *Log(Spd).* However, *SPD_EVO* only shows a significantly positive coefficient shown in column (2) when the historical realized spread is higher. In addition, the coefficient of *SPD_EVO* becomes insignificant when the predicted loan cost is higher. Overall, this empirical pattern supports the main findings and shows that the conditional borrowing history effect is driven by the fixation on firms' previous borrowing costs. [26]

[Insert Table 2.7 Here]

2.4.3 Relationship Borrowing

After disentangling the firm-specific borrowing histories, I continue to address other possible possibilities. Regarding my findings on the spread fallen scenario, one may argue that this finding is driven by relationship borrowing, i.e., firms borrow at a lower cost when the credit market is tight, and to return the favor, they pay higher costs when the credit market loosens. This seems possible at first glance but fails to explain the conditional findings in the loan market. Relationship borrowing indicates a bilateral relationship. If my finding is driven by relationship borrowing, I would find significant coefficients of *SPD_EVO* for both past spreads higher and lower than predicted spreads. However, Table 2.7 shows that the significant relationship disappears when the last borrowing cost is low (Column (3)).

I further directly explore the possibility of relationship lending. To test this, I employ subsample analysis based on whether the bank loans are taken from the same lead banks. I then re-conduct the second step estimation of firm-specific spread evolution. The first two columns in Table 2.8 present the subsample analysis on average and the last two columns present the results for the spread fallen scenario. If relationship lending explains the main findings, I

[26] Table 7 also reports that the coefficients of the previous residual for different samples are all greater than 0 and less than 1, which is consistent with my expectation.

should observe an insignificant coefficient on *SPD_EVO* when the lead banks are different.

Table 2.8 shows that *SPD_EVO* exhibit positive and significant effects in both subsamples, regardless of the firms borrowed from the same lenders or different lenders. These findings refute the possibility of relationship lending. Another point worth mentioning is that when comparing the coefficients in the first two columns, the anchoring effect is greater for the same lender sample, suggesting that borrowing from the same lead banks pays more than borrowing from new banks. Similarly, when the previous spreads were higher, firms pay more costs if they borrow from the banks, they have prior relationships. This is also inconsistent with the argument that cooperation between firms and relationship banks drives my finding.

[Insert Table 2.8 Here]

2.5 Rational Anchoring or Behavioral Anchoring

Previously I documented an asymmetric anchoring effect in the loan market. In this section, I provide further discussions on several related questions, such as which market participants will suffer more from the anchoring, are the anchoring unconsciously or intendedly, and how the anchoring could be successful.

2.5.1 Reflection of Psychological Bias?

The anchoring bias comes from the psychology literature, and it reflects a common human behavioral bias. Thus, it is natural to attribute the observed impact to unconscious behavior. If this is the case, both sides of the contract will suffer, leading to the symmetric (or at least partially symmetric) pattern. No matter whether the previous loan cost is higher or lower than the predicted spread, the current cost should fixate on the previous loan cost. However, I find the anchoring effect in the loan market is a conditional effect, which holds only when the last borrowing cost was higher. Moreover, this conditional effect always benefits banks, and enables banks to charge firms more loan costs than justified by the firm fundamentals. Thus, it is highly likely that banks take advantage of the anchoring bias intendedly. This result is also in line with the intuition that bank officers are relatively more professional and well-trained in lending activities, compared to the borrowers.

To further support the theoretical analysis, I explore some testable predictions. If the anchoring outcomes purely come from the unconscious psychical bias, I expect the information salience should affect the outcomes. Specifically, I expect a stronger anchoring effect when the previous loan happens in a recent year and the effect should decay as the time gap increases between the previous loan and the current one. To conduct the test, I break up the whole sample into five subsamples based on the time gap between the current loan financing and the most recent borrowing year. The loan borrowing gap years could range from within a year to over 4 years.[27] The unintended anchoring argument predicts that the anchoring effect monotonically decreases with the gap years.

I report the result in Table 2.9 and find that the anchoring effect does not exhibit decreasing trend. When comparing the first two columns, the coefficient of *SPD_EVO* in the second column (i.e., loan borrowing time difference is between 1 year and 2 years) is larger than that in the first column (i.e., loan borrowing time difference is within 1 year) in terms of magnitude and significance (0.44 > 0.39). This suggests that the anchoring heuristic on the credit market does not decrease as the time gap increases, inconsistent with the unintended anchoring argument. Moreover, from columns (3) to (4), the coefficient of *SPD_EVO* increases again with an increasing loan issuance gap. Overall, the results in Table 2.9 reject the unconscious psychological bias explanation.

[Insert Table 2.9 Here]

2.5.2 Anchor Strategy and Bargaining Power

Since the anchoring effect in the loan market is not likely driven by unconscious psychological bias, I further explore some supportive evidence on a strategic anchoring explanation. In a frictionless market, the historical loan spread should not affect the current loan contracting as the previous loan spread only reflects outdated information. However, in reality, it is quite natural for

[27] To test for the intended versus unintended anchoring effect, I relax the restriction that repeat loans have a gap of more than 1 year. This exception applies only to the results in Table 2.9.

both parties to start the negotiation by referring to the most recent loan contract, as this reference is especially salient to both parties. The borrower tries to prove their performance and firm quality to bargain for more favorable terms. The bank assesses the materials to evaluate the risk of the firm. At the same time, banks could also have an information advantage as they could learn from other comparable loan contracts in the industry (Murfin and Pratt, 2019). The banks could have a relatively stronger bargaining power during the contracting process.

When a firm's historical loan costs were higher than its current model predicted cost, banks have incentives to use the last borrowing cost as a reference and overcharge borrowers. More importantly, the higher the bargaining power banks possess, the more likely they could achieve to charge more. Theoretically, banks gain much bargaining power from the information monopoly in the loan issuance, leading to the "hold-up" phenomenon. Sharpe (1990) documents that banks lent to borrowers to gather more information (often of a proprietary nature) through evaluation and screening in prior lending. Compared to other banks, the incumbent bank gains a competitive edge and is perceived as the better-informed party. Due to an adverse selection issue, when a firm approaches a new bank for financing, the firm would be considered of low quality (because the incumbent bank could be considered unwilling to provide funds). Thus, the hold-up problem leads the firm to borrow from incumbent banks, even paying a higher cost than the justified cost. Consistently, Ioannidou and Ongena (2010) find that banks reduce the loan spread to attract new borrowers and increase the spread greatly in the following loans.

[Insert Table 2.10 Here]

I test how bank information monopoly affects the anchoring strategy and report the result in Table 2.10. I undertake a subsample analysis based on the number of lenders in the loan syndication, and then re-examine the anchoring effect in each subsample. Column (1) reports the result when the loan is arranged by a solo bank and the following columns report the results when the number of lenders increases. I show that the coefficient of *SPD_EVO* is largest in column (1) if a loan has a solo arranger. The coefficient decreases monotonically with the increasing number of lead lenders. These findings suggest that when banks have more proprietary information, they get more premium from the anchoring strategy. Besides, Table 2.8 shows that the coefficients of *SPD_EVO* for relationship loans are larger than those in new loans, which also supports the role of information monopoly. Therefore, my finding shows that the anchoring effect in the loan market is not attributed to pure psychological bias. More importantly, it shows that more proprietary information enables banks more bargaining power to overcharge the borrowers.

In addition to the analysis from the banks' aspect, the bargaining power can also be reflected in firms' dependency on bank finance. Firms that are more dependent on bank finance have less bargaining power in the negotiations. Following Santos and Winton (2019), I measure a firm's dependency on bank finance from three dimensions: its interest coverage, leverage, and bond market access in the previous three years. I define three indicators of firms that are less dependent on the loan market. Specifically, *IntH* is an indicator that is equal to 1 if a firm's interest coverage ratio is higher than the median ratio, and 0 otherwise. *LevL* is defined as 1 if the firm has below-median leverage and 0 otherwise. If firms have access to public debt markets, they can better signal the firm quality and less depending on the loan market, I define *Bond* as an indicator that takes the value of 1 if the firm has issued public bonds in the previous 3 years and 0 otherwise. I then test how a firm's bargaining power affects the anchor effect. I re-run the second step of firm-specific regression and include the interaction between the firm's bargaining power measures and loan evolution. I predict that the main effect is attenuated for firms with greater bargaining power, and the coefficients of the interaction terms in the regression should be significantly negative.

The results of the testing of the role of bank dependency are reported in Table 2.11. The coefficients of *SPD_EVO* all are positive and significant, supporting the anchoring effect in the loan market. Moreover, the interaction terms between *SPD_EVO* and firms' loan dependency measures are all negatively significant. Specifically, in Column (1), *IntH* × *SPD_EVO* is negatively associated with current loan costs, suggesting that the anchoring effect is less pronounced when firms have an interest coverage ratio higher than the median. Consistently, the coefficient of *LevL* × *SPD_EVO* in column (2) is also negative and significant, suggesting that the anchoring effect is less pronounced when firms have lower leverage than the median. In addition, *Bond* × *SPD_EVO* also has a negative coefficient, suggesting that financing from the bond market can mitigate the adverse effect of the anchoring strategy.

Collectively, the results suggest the anchoring effect is a strategic behavior of banks. Banks gain more benefit by referring to the previous high loan spread when they have more proprietary information about loan borrowers, or the borrowing firms are more dependent on bank finance.

[Insert Table 2.11]

2.6 Further Discussion

Dougal et al. (2015) also investigate the anchoring effect in the credit market. Their results suggest that aggregate spread evolution affects the current loan cost, no matter whether the aggregate spreads have fallen or risen. They further explain their findings as an unconscious behavioral bias as both banks and firms suffer the unintended anchoring bias. However, they only use the loan contracting sample before the global financial crisis, which ignores the potential impact of such a large "disaster" on the banking industry (Ivashina and Scharfstein, 2010). Besides, it is a bit hard to believe that the professional and well-trained bankers still suffer the anchoring bias and bring loss to the bank. Dougal et al. (2015) also state that "professional lenders are less subject to anchoring bias, as perhaps might be expected, but neither side of a deal is completely immune" (Page 1077).

To double-check potential data/coding issues and reconcile with Dougal et al. (2015), I duplicate the findings on the effect of aggregate spreads evolution using the pre-crisis period. I find a very similar result to Dougal et al. (2015) in terms of coefficient significance and magnitude. However, when I focus on the post-crisis period, the path of aggregate spread evolution matters, and spread evolution affects borrower loan costs only when aggregate spreads have fallen since the last borrowing. Besides, Dougal et al. (2015) do not completely rule out the rational anchoring explanation. Thus, the different findings should be driven by the different testing samples, and the financial crisis may bring a shock to the balanced (or quasi-balanced) bargaining power between banks and firms.

First, the global financial crisis in 2007–2009 adversely affects the firm's access to capital markets. Holmstrom and Tirole (1997) find that poor economic conditions create a credit crunch, and this affects the borrowing market negatively. Erel et al. (2012) find that capital raising is pro-cyclical for borrowers with noninvestment-grade ratings and countercyclical for borrowers classified with investment-grade ratings. I conjecture that the financial crisis increases the difficulty for firms to access external capital and switch the lenders, as a result, the banks will gain more bargaining power in the short run.[28]

Second, the financial crisis may induce some structural change in the entire banking industry. The crisis reflects significant weaknesses in the regulatory and supervisory system, leading to a major revamping of regulation efforts. The capital restriction is a core element of this effort, which will affect the credit supply and lending activity. In July 2008, US banks adopted Basel II regulation, and are required to maintain a minimum 8% regulatory capital ratio with considering the operational risks.[29] Furthermore, US banks implemented

[28] Table 2.8 presents similar findings. Recall that when borrowing from the same lender, the anchoring to a high historical cost becomes stronger, suggesting that the same lender has more bargaining power than new lenders. This finding is in line with the hold-up cost theory, and banks increase their bargaining power via the hold-up issue.

[29] Besides setting up regulatory capital ratio and tier 3 capital, Basel II also offers a more complex framework to measure capital requirements after considering credit risk.

Basel III in 2014. Relatedly, Figure 1 shows that U.S. banks have more regulatory capital nowadays relative to their risk-weighted assets than what they held before the crisis.

Previous studies show that the stricter capital requirement may lead to capital crunches, whereby banks choose to shrink their lending activities to achieve a higher capital ratio (Watanabe, 2007; Aiyar, Calomiris, and Wieladek, 2015). This is highly likely to happen as it is costly for banks to raise equity during the first several years after the crisis (Ivashina and Scharfstein, 2010; Aiyar, Calomiris, and Wieladek, 2016). Empirical evidence confirms that banks decide to reduce the lending amount when the required capital requirements increase. Previous studies in the 1990s document that capital shortfall resulting from the increased capital requirements will lead to a reducing supply of credit for banks (Berger and Udell, 1994). Aiyar, Calomiris, and Wieladek (2015) argue that banks will cut the lending if they have a larger incentive to raise the equity-to-asset ratios.

Overall, although Dougal et al. (2015) attribute their finding to unconscious behavioral bias, their results could not rule out a rational and strategical anchoring explanation. It is completely possible that the firms could also use the intentional anchoring strategy and succeed to gain some benefit when the credit market is in normal or slack conditions. The unexpected financial crisis may exert great pressure on the banking industry or even result in some structural changes. The limited capital supply motivates banks to charge higher spread, and at the same time, also increases banks' bargaining power against firms as the capital demand and capital supply change.

2.7 Conclusion

Behavioral finance has attracted much academic attention in the recent literature. It is an intuitive and convincing argument that people generally suffer from behavioral biases. However, why well-trained financial professionals and sophisticated intuitions suffer from behavioral biases as common individuals do is unclear. By investigating loan contracting between banks and firms, I provide evidence that financial professionals intentionally take advantage of behavioral biases as a negotiation strategy. I find that after the global financial crisis, banks benefit from anchoring to firms' previous high loan costs. Banks charge higher spreads than justified by firm fundamentals if a firm's previous loan spread is high. However, the new loan costs do not anchor to the borrowing history when the previous loan cost is low, such that borrowing firms do not enjoy a discount. The asymmetrical relation rejects the hypothesis of the unintentional anchoring heuristic. Further analyses also reject risk-based explanations and support the explanations of strategic and intentional anchoring. My study highlights the possibility that observed behavioral biases in the financial market could also be a result of rational decision-making. Whether other behavioral findings in the current literature are behavioral biases or rational results would be an interesting topic for future study.

Figures and Tables

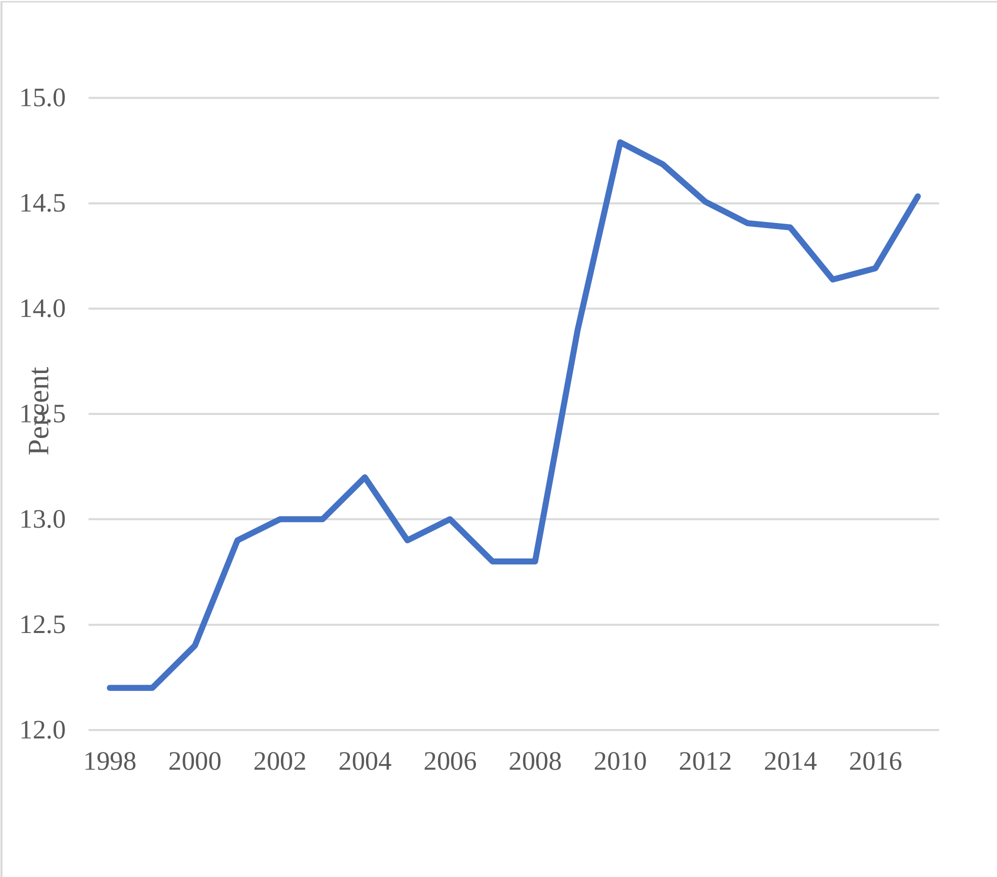

Figure 2.1. Time Trend of Regulatory Capital Ratio

This figure shows the time-series trend of regulatory capital to bank's risk-weighted assets ratio. After US regulators implement Basel II in 2008, this ratio exhibits a dramatic increase.

Source: FRED https://fred.stlouisfed.org

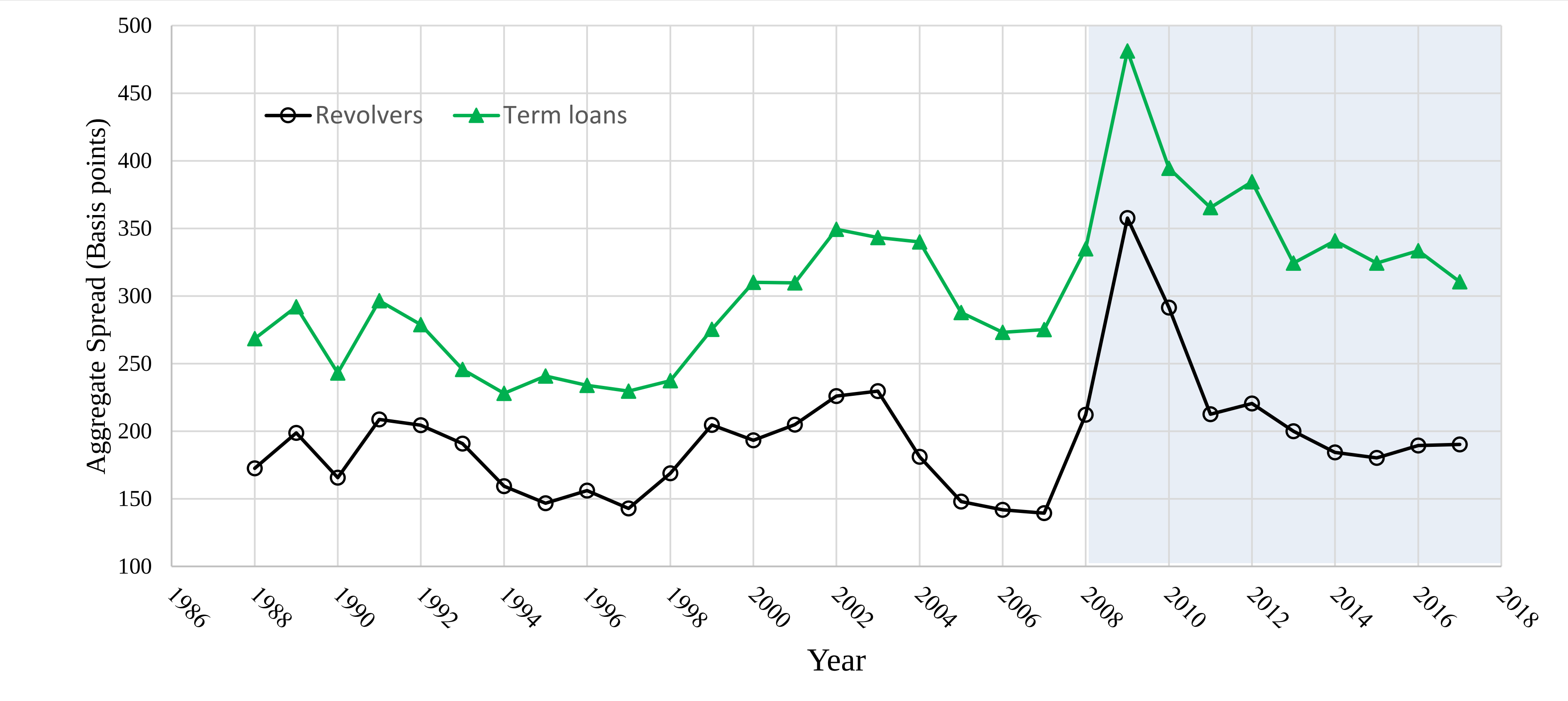

Figure 2.2. Time Trend of Aggregate Credit Spreads

This figure shows the yearly average credit spreads for term loans and long-term revolvers. The shaded part highlights the post-2008 period as the main sample period.

Table 1.1. Sample Distributions

This table reports the sample distribution of bank loan issuances for the period of 2002:Q2-2017:Q1. This time period has been selected to match the availability of $PRisk$. Panel A reports the year-by-year distribution. Panel B further reports the mean firm-level political risk and loan cost in different industries. The industry classification is 2-digits SIC code. The number of observations is the number of bank loans in that industry. I require the number of observations to be no less than 30. $PRisk\_mean$ is the mean of firm-level political risk.

Panel A. Sample distribution year by year

Year	Firm Frequency	Loan Frequency
2002	151	218
2003	443	647
2004	611	934
2005	586	944
2006	561	891
2007	555	890
2008	378	530
2009	278	381
2010	420	616
2011	639	995
2012	546	843
2013	590	1,011
2014	588	976
2015	542	878
2016	469	787
2017:Q1	31	44
Total	7,388	11,585

Panel B. Sample distribution by industry

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

Table 1.2. Summary Statistics

This table reports the summary statistics of the different variables

Variable (Obs. = 11,585)	Mean	Std Dev	25%	Median	75%
$Spread\ (bps)$	211	144	125	175	275
$PRisk$	0.47	0.79	0.07	0.24	0.53
$Size$	7.64	1.54	6.55	7.56	8.60
M/B	3.38	7.19	1.38	2.14	3.41
LEV	1.22	4.23	0.32	0.61	1.13
$Profit$	0.14	0.08	0.09	0.13	0.17
$Tang$	0.53	0.39	0.21	0.43	0.79
$Z\text{-}score$	3.58	2.99	1.88	2.91	4.38
CF_Vol	0.10	0.37	0.06	0.09	0.13
T_Vol	0.02	0.01	0.02	0.02	0.03
$Log(Mat)$	3.90	0.47	3.87	4.09	4.09
$Log(Amt)$	19.25	1.34	18.42	19.34	20.21
$Maturity\ (month)$	53.68	17.55	48.00	60.00	60.00
$Loan\ Amount\ (million)$	520	928	100	250	600
$Perf\_Provision$	0.45	0.50	0.00	0.00	1.00
$Default\_Rate$	1.02	0.36	0.84	0.92	1.14
$Term\_Spread$	1.75	1.02	1.14	1.87	2.57

Table 1.3. Main Regression

This table presents the results of firm-specific political risk effect on loan pricing. $Log(Spread)$ is loan spread (over LIBOR) of each individual loan contract (in log format). $PRisk$ is firm-specific political risk, constructed by HHLT (2019). Column (1) includes a set of firm-level controls, column (2) adds the loan-level control variables, and column (3) reports the baseline results. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)$	(1) Firm-Control	(2) Loan-Control	(3) Baseline
$PRisk$	0.036***	0.026***	0.022***
	(3.931)	(3.137)	(3.084)
$Size$	-0.152***	-0.071***	-0.059***
	(-23.232)	(-9.671)	(-9.603)
M/B	-0.000	0.001	0.001
	(-0.002)	(1.327)	(1.010)
LEV	0.009**	0.008***	0.005**
	(2.529)	(2.639)	(2.114)
$Profit$	-0.806***	-0.730***	-0.783***
	(-6.779)	(-6.559)	(-8.402)
$Tang$	-0.093***	-0.100***	-0.027
	(-5.022)	(-4.453)	(-1.397)
$Z\text{-}score$	-0.047***	-0.037***	-0.031***
	(-12.550)	(-10.913)	(-11.213)
CF_Vol	0.042***	0.021*	0.019*
	(2.583)	(1.912)	(1.650)
T_Vol	13.882***	13.003***	10.719***
	(17.548)	(16.579)	(16.056)
$Log(Mat)$		0.367***	0.063***
		(22.985)	(3.887)
$Log(Amt)$		-0.143***	-0.130***
		(-17.835)	(-18.878)
$Perf\_Provision$		-0.153***	-0.055***
		(-12.114)	(-4.862)
$Default\_Rate$			0.039
			(0.567)
$Term\_Spread$			0.098***
			(2.659)
Intercept	6.233***	6.987***	8.232***
	(98.552)	(50.989)	(48.612)
Loan purpose / Type FE	No	No	Yes
Industry FE	No	Yes	Yes
Year quarter FE	Yes	Yes	Yes
Observations	11,585	11,585	11,585
Adjusted R^2	0.390	0.503	0.639

Table 1.4. Additional Analyses

This table reports the results of predicting bank loan cost with firm-level political risk by using more control variables. Panel A presents the results by controlling for other related political uncertainty measures. Column (1) presents result by including aggregate political uncertainty. Column (2) presents the result by including partisan conflict index. Column (3) presents the result by including geopolitical index. Panel B presents results by controlling for additional firm specific variables. Column (1) presents the result by including political sentiment. Column (2) presents the result by including more firm-level control variables. Column (3) presents the result by including more macro-level control variables. Column (4) presents the result by including all additional control variables. Panel C reports the results of predicting bank loan cost with firm-level political risk by considering firm fixed effects. Column (1) presents the firm fixed effects analysis results of a sub-sample which requires the firm to appear at least in three different quarters. Column (2) presents the firm fixed effects analysis results of a sub-sample which requires the firm to appear at least in five different quarters. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Controlling for political uncertainty measures

Dep Var = $Log(Spread)$	(1) + PUa	(2) + PCI	(3) + GPR
$PRisk$	0.022***	0.022***	0.022***
	(3.073)	(3.082)	(3.073)
PUa	0.040		
	(1.306)		
PCI		0.019	
		(0.548)	
GPR			-0.007
			(-0.323)
Baseline controls	Yes	Yes	Yes
Loan purpose / Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes
Observations	11,585	11,585	11,585
Adjusted R^2	0.639	0.639	0.639

Panel B. Controlling for political uncertainty measures without time fixed effect

Variable	Dependent variable: $Log(Spread)$		
	(1) + PUa	(2) + PCI	(3) + GPR
$PRisk$	0.016**	0.016**	0.016**
	(2.191)	(2.239)	(2.207)
PUa	0.041**		
	(1.999)		
PCI		0.135***	
		(5.670)	
GPR			0.022**
			(1.979)
Baseline controls	Yes	Yes	Yes
Loan purpose / Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year quarter FE	No	No	No
Observations	11,585	11,585	11,585
Adjusted R^2	0.629	0.629	0.630

Panel C. Controlling for other additional variables

Dep Var = $Log(Spread)$	(1) + Political sentiment	(2) + Additional firm controls	(3) + Additional macro controls	(4) + All additional
$PRisk$	0.021***	0.021***	0.022***	0.021***
	(2.967)	(3.056)	(3.086)	(2.954)
$PSentiment$	-0.011*			-0.010*
	(-1.905)			(-1.795)
$Loss$		0.103***		0.104***
		(6.794)		(6.870)
$CAPX$		-0.016**		-0.017**
		(-2.086)		(-2.119)
$Return$		-0.346***		-0.340***
		(-4.390)		(-4.313)
$Insti\_holding$		0.064***		0.064***
		(3.146)		(3.113)
$Production\_Rate$			-0.029**	-0.029**
			(-2.255)	(-2.206)
$Inflation\_Rate$			0.015	0.013
			(0.829)	(0.736)
$Recession$			-0.004	0.008
			(-0.042)	(0.094)
$Unemployment\_Rat$			-0.529	-0.200
			(-0.115)	(-0.043)
$Shorterm\_Rate$			-0.542	-0.478
			(-1.155)	(-1.014)
Baseline controls	Yes	Yes	Yes	Yes
Loan purpose / Type	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes	Yes
Observations	11,585	11,463	11,585	11,463
Adjusted R^2	0.639	0.643	0.639	0.643

Panel D. Controlling for firm fixed effects

Dep Var = $Log(Spread)$	(1) Firm FE sub-sample1	(2) Firm FE sub-sample2
$PRisk$	0.026***	0.027***
	(2.986)	(2.745)
Baseline controls	Yes	Yes
Loan purpose / Type FE	Yes	Yes
Industry FE	No	No
Firm FE	Yes	Yes
Year quarter FE	Yes	Yes
Observations	5,943	4,116
Adjusted R^2	0.768	0.773

Table 1.5. Lead-lag Placebo Tests

This table reports the impact of leads and lags of the risk measure on the firm's loan spread. Column (4) repeats the baseline results ($PRisk$ in quarter t) and serves as benchmark. In columns (1) and (3), I replace the 1-period lag $PRisk_{i,t}$ with 2-period-lag, 3-period-lag, and 4-period-lag firm-level political risks as the key variables. In columns (5) and (7), I replace the 1-period lag $PRisk_{i,t}$ with contemporary 1-period-lead and 2-period-lead firm-level political risks as the key variables. Columns (5) to (7) serve as placebo tests. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)_{i,t+1}$	(1) $PRisk$ in Qtr t-3	(2) $PRisk$ in Qtr t-2	(3) $PRisk$ in Qtr t-1	(4) $PRisk$ in Qtr t	(5) $PRisk$ in Qtr t+1	(6) $PRisk$ in Qtr t+2	(7) $PRisk$ in Qtr t+3
$PRisk_{i.t-3}$	0.005						
	(0.733)						
$PRisk_{i,t-2}$		0.004					
		(0.724)					
$PRisk_{i,t-1}$			0.015**				
			(2.226)				
$PRisk_{i,t}$				0.022***			
				(3.084)			
$PRisk_{i,t+1}$					0.002		
					(0.291)		
$PRisk_{i,t+2}$						0.003	
						(0.388)	
$PRisk_{i,t+3}$							0.007
							(0.959)
Intercept	8.335***	8.230***	8.244***	8.232***	8.297***	8.340***	8.397***
	(46.490)	(46.500)	(47.170)	(48.612)	(47.072)	(47.031)	(46.569)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose/Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,382	10,733	10,997	11,585	10,751	10,465	10,153
Adjusted R2	0.642	0.639	0.639	0.639	0.636	0.635	0.635

Table 1.6. Instrumental Variable Regression

This table reports the IV test results. My instrumental variables are $PRisk\_peer$ and $Political\_distance$. $Prisk\_peer$ is the average $PRisk$ of all firms within the same state except the firm itself. $Political\_distance$ is the distance between the borrower's headquarter city and its state capital city. $NPRisk$ is the measure of non-political risk. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) IV (First stage)	(2) IV (Second stage)	(3) Placebo (First stage)	(4) Placebo (Second stage)
$PRisk\_peer$	0.462***		0.014	
	(4.776)		(0.176)	
$Political\_distance$	0.021**		0.017	
	(2.148)		(1.633)	
$PRisk(Intrumented)$		0.212***		
		(2.848)		
$NPRisk(Intrumented)$				0.513
				(1.268)
$Size$	0.014	-0.061***	-0.003	-0.056***
	(1.429)	(-9.552)	(-0.249)	(-5.622)
M/B	-0.000	0.001	-0.000	0.001
	(-0.288)	(1.127)	(-0.077)	(0.826)
LEV	-0.000	0.005**	-0.000	0.005**
	(-0.014)	(2.033)	(-0.201)	(2.064)
$Profit$	-0.321**	-0.719***	0.112	-0.836***
	(-1.976)	(-7.388)	(0.604)	(-5.852)
$Tang$	0.003	-0.018	0.050	-0.044
	(0.085)	(-0.917)	(1.322)	(-1.286)
$Z\text{-}score$	0.013**	-0.033***	-0.009**	-0.026***
	(2.410)	(-10.894)	(-2.391)	(-5.308)
CF_Vol	-0.024*	0.019*	0.042***	-0.005
	(-1.745)	(1.900)	(2.843)	(-0.263)
T_Vol	-2.154**	11.185***	-1.667	11.548***
	(-2.242)	(16.392)	(-1.357)	(10.869)
$Log(Mat)$	0.017	0.065***	0.034	0.051*
	(0.652)	(3.348)	(1.195)	(1.850)
$Log(Amt)$	0.006	-0.129***	-0.012	-0.121***
	(0.794)	(-18.038)	(-0.694)	(-8.956)
$Perf\_Provision$	-0.025	-0.055***	-0.011	-0.055***
	(-1.226)	(-4.800)	(-0.385)	(-2.693)
$Default\_Rate$	-0.051	0.050	0.090	-0.007
	(-0.473)	(0.707)	(0.699)	(-0.064)
$Term\_Spread$	-0.169**	0.137***	-0.006	0.103*
	(-2.404)	(3.453)	(-0.071)	(1.875)
Intercept	0.339	8.026***	0.587*	7.126***
	(1.380)	(44.684)	(1.826)	(22.063)
Loan purpose / Type FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes	Yes
Observations	10,992	10,992	10,992	10,992
Adjusted R^2	0.051	0.635	0.018	0.265

Table 1.7. Matching Analysis

This table presents the PSM test results. *DPRisk* is an indicator, which is equal to one if the firm-level political risk ranks the top 10% that quarter (treatment group) and zero if firm-level political risk ranks on or below 50% (control group). Panel A reports the difference of characteristics in both groups. Panel B reports the PSM sample result. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Firm-, loan- and macro-level characteristics

Variables	Treatment group	Control group	t-statistics
$Size$	7.75	7.68	1.002
M/B	3.26	3.31	-0.212
LEV	1.02	0.98	0.512
$Profit$	0.14	0.14	0.888
$Tang$	0.50	0.48	0.983
$Z\text{-}score$	3.61	3.61	-0.011
CF_Vol	0.12	0.11	1.082
T_Vol	0.23	0.23	0.775
$Log(Mat)$	3.89	3.88	0.600
$Log(Amt)$	19.33	19.36	-0.390
$Perf\_Provision$	0.45	0.47	-1.02
$Default\_Rate$	1.01	1.01	-0.179
$Term\_Spread$	1.71	1.73	-0.381

Panel B. PSM sample result

	Dependent variable: $Log(Spread)$
$DPRisk$	0.048**
	(1.993)
Baseline controls	Yes
Loan purpose FE	Yes
Loan type FE	Yes
Industry FE	Yes
Year quarter FE	Yes
Observations	1,702
Adjusted R^2	0.650

Table 1.8. Quasi-shock Analysis

This table reports the shock analysis results. $Post$ is an indicator variable measuring the year of significant change of firm specific political risks. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)$	(1) $Prisk$ increase	(2) $Prisk$ decrease
$Post$	0.135**	-0.212**
	(2.088)	(-2.226)
$Size$	-0.018	-0.085***
	(-0.402)	(-2.593)
M/B	-0.001	0.003
	(-0.582)	(0.171)
LEV	0.088***	-0.018
	(2.828)	(-0.277)
$Profit$	0.210	-0.022
	(0.231)	(-0.028)
$Tang$	0.014	0.081
	(0.063)	(0.452)
$Z\text{-}score$	0.012	-0.073***
	(0.959)	(-3.420)
CF_Vol	0.964*	1.274***
	(1.838)	(2.635)
T_Vol	17.830***	1.933
	(4.047)	(0.461)
$Log(Mat)$	0.121*	0.002
	(1.731)	(0.014)
$Log(Amt)$	-0.157***	-0.220***
	(-5.083)	(-5.999)
$Perf\_Provision$	-0.078	-0.002
	(-1.246)	(-0.023)
$Default\_Rate$	0.144	0.853***
	(1.378)	(2.782)
$Term\_Spread$	0.221***	0.193
	(7.676)	(0.872)
Intercept	7.571***	8.874***
	(15.215)	(8.828)
Loan purpose / Type FE	Yes	Yes
Industry FE	Yes	Yes
Year quarter FE	Yes	Yes
Observations	305	295
Adjusted R^2	0.766	0.503

Table 1.9. Cross-sectional Test: The Role of Financial Information Opacity

This table reports estimates of cross-sectional analyses exploring the role of financial information opacity. $Size$ refers to firm size. $Tang$ refers to a firm's tangibility. $AnalystCov$ refers to analyst coverage. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)$	(1)	(2)	(3)
$PRisk$	0.106***	0.044***	0.044***
	(3.323)	(4.590)	(3.891)
$PRisk \times Size$	-0.011***		
	(-2.603)		
$PRisk \times Tang$		-0.049**	
		(-2.109)	
$PRisk \times AnalystCov$			-0.012**
			(-2.111)
$AnalystCov$			-0.050***
			(-5.683)
$Size$	-0.053***	-0.059***	-0.040***
	(-8.344)	(-9.582)	(-5.901)
M/B	0.001	0.001	0.001
	(1.023)	(0.966)	(1.374)
LEV	0.005**	0.005**	0.004*
	(2.101)	(2.117)	(1.784)
$Profit$	-0.776***	-0.785***	-0.730***
	(-8.372)	(-8.412)	(-7.986)
$Tang$	-0.027	-0.005	-0.032*
	(-1.396)	(-0.235)	(-1.685)
$Z\text{-}score$	-0.032***	-0.031***	-0.028***
	(-11.491)	(-11.209)	(-10.345)
CF_Vol	0.019*	0.019	0.018*
	(1.646)	(1.628)	(1.757)
T_Vol	10.731***	10.704***	10.657***
	(16.067)	(16.050)	(15.993)
$Log(Mat)$	0.063***	0.062***	0.065***
	(3.344)	(3.342)	(3.515)
$Log(Amt)$	-0.129***	-0.129***	-0.129***
	(-18.818)	(-18.869)	(-18.967)
$Perf\_Provision$	-0.055***	-0.054***	-0.053***
	(-4.856)	(-4.834)	(-4.767)
$Default\_Rate$	0.039	0.034	0.045
	(0.563)	(0.496)	(0.668)
$Term\_Spread$	0.098***	0.097***	0.099***
	(2.657)	(2.635)	(2.671)
Intercept	8.192***	8.228***	8.145***
	(48.147)	(48.591)	(48.032)
Loan purpose / Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes
Observations	11,585	11,585	11,585
Adjusted R^2	0.640	0.640	0.641

Table 1.10. Cross-sectional Test: The Role of Financial Constraints

This table reports estimates of cross-sectional analyses exploring the role of financial constraints. Exf refers to a firm's external financing dependency. CF_Vol refers to cash flow volatility. HP_Index is constructed by Hadlock and Pierce (2010). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)$	(1)	(2)	(3)
$PRisk$	0.018**	0.003	0.135**
	(2.471)	(0.344)	(2.519)
$PRisk \times Exf$	0.027***		
	(3.837)		
$PRisk \times CF\_Vol$		0.126***	
		(3.168)	
$PRisk \times HP\_Index$			0.029**
			(1.983)
Exf	-0.000		
	(-0.006)		
HP_Index			0.115***
			(8.416)
$Size$	-0.058***	-0.058***	-0.033***
	(-9.459)	(-9.455)	(-5.105)
M/B	0.001	0.001	0.000
	(0.912)	(0.972)	(0.598)
LEV	0.005**	0.005**	0.006**
	(2.115)	(2.105)	(2.307)
$Profit$	-0.735***	-0.771***	-0.773***
	(-7.856)	(-8.281)	(-8.421)
$Tang$	-0.026	-0.026	0.000
	(-1.351)	(-1.366)	(0.014)
$Z\text{-}score$	-0.031***	-0.031***	-0.032***
	(-11.299)	(-11.244)	(-11.544)
CF_Vol	0.020*	-0.006	0.014
	(1.689)	(-0.605)	(1.381)
T_Vol	10.627***	10.747***	10.079***
	(16.033)	(16.110)	(15.329)
$Log(Mat)$	0.067***	0.063***	0.065***
	(3.588)	(3.396)	(3.485)
$Log(Amt)$	-0.130***	-0.129***	-0.131***
	(-18.825)	(-18.825)	(-19.563)
$Perf\_Provision$	-0.054***	-0.054***	-0.054***
	(-4.795)	(-4.811)	(-4.905)
$Default\_Rate$	0.046	0.040	0.036
	(0.669)	(0.578)	(0.523)
$Term\_Spread$	0.101***	0.097***	0.105***
	(2.735)	(2.617)	(2.836)
Intercept	8.199***	8.224***	8.486***
	(48.430)	(48.550)	(49.624)
Loan purpose FE	Yes	Yes	Yes
Loan type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes
Observations	11,559	11,585	11,585
Adjusted R^2	0.640	0.640	0.644

Table 1.11. Non-pricing Loan Terms

This table presents the regression results for $PRisk$ effect on non-pricing loan terms. $TotCovIndex$ is the total covenant index. $GenCovIndex$ is the general covenant index. $FinCovIndex$ is the financial covenant index. $DDebt$ is an indicator variable measuring a contract's debt issuance sweep restriction. $DSecured$ is an indicator variable measuring a contract's collateral requirement. $Annual\_fee$ is the annual charge against the entire loan commitment amount. The regressions in columns (4) and (5) are performed by Logit. The regressions in the other columns are performed by OLS. The baseline control variables from Table 1.3 are included in the regressions. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var	$TotCovIndex$	$GenCovIndex$	$FinCovIndex$	$DDebt$	$DSecured$	$Annual\_fee$
	(1)	(2)	(3)	(4)	(5)	(6)
$PRisk$	0.121***	0.073***	0.048***	0.109***	0.119***	0.691*
	(3.510)	(3.271)	(2.761)	(2.709)	(2.867)	(1.941)
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose / Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,585	11,585	11,585	11,505	11,585	1,933
Adjusted R^2	0.386	0.349	0.338	0.222	0.329	0.494

Table 1.12. Firm-level Political Risk and Loan Pricing: Alterative Explanations

This table presents the results on alternative explanations Panel A reports estimates exploring lender's willingness or ability to lend. Panel B reports the univariate estimates on the existing firm-level controls of loan pricing. I report the means of firm characteristics in 10 groups, sorted by firm-level political risk. Size is the median total assets of firms (in millions). Panel C reports estimates exploring whether a $PRisk$ - loan cost relationship is driven by external acquisition activities. $High\_aqc$ is the sub-sample of firms within the top tercile of acquisition expenditures and Low_aqc is the sub-sample of remaining firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Affected by lender's willingness to lend?

Dep Var = $Log(Spread)$	(1) + Lender FE	(2) + Lender $PRisk$	(3) + Lender FE and Lender $PRisk$
$PRisk$	0.019***	0.021***	0.020**
	(2.697)	(2.605)	(2.540)
$PRisk\_lender$	-	0.018**	0.010
	-	(2.573)	(1.349)
Baseline controls	Yes	Yes	Yes
Lender FE	Yes	No	Yes
Loan purpose / Type FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year quarter FE	Yes	Yes	Yes
Observations	11,046	9,660	9,660
Adjusted R^2	0.658	0.645	0.657

Panel B. $PRisk$ is the proxy for existing firm-level attributes?

Group	1	2	3	4	5	6	7	8	9	10
$Size$	1186	2264	2007	2072	2105	2151	2006	2050	1755	2094
M/B	2.04	2.17	2.17	2.15	2.28	2.10	2.09	2.13	2.12	2.11
$Tang$	0.46	0.43	0.41	0.44	0.43	0.45	0.45	0.49	0.38	0.38
$Profit$	0.12	0.13	0.13	0.13	0.13	0.12	0.13	0.13	0.12	0.13
Z-score	2.95	2.90	2.89	2.98	2.93	2.92	2.82	2.85	2.82	3.01
Age	17	21	19	19	19	19	19	19	18	20

Panel C. Affected by external acquisitions?

Dep Var = Log(Spread)	(1) $High\_aqc$	(2) Low_aqc
$PRisk$	0.023**	0.020**
	(2.017)	(2.275)
Baseline controls	Yes	Yes
Loan purpose / Type FE	Yes	Yes
Industry FE	Yes	Yes
Year quarter FE	Yes	Yes
Observations	2,479	9,106
Adjusted R^2	0.638	0.643
p-value of Difference	0.880	

Table 1.13. The Role of Lobbying Activities and Relationship Loans

This table reports the estimates of how politically risky borrowers alleviate the negative effect of political risk through lobbying activities and relationship loans. $Lobbying$ is an indicator variable measuring a firm's lobbying engagement. $Relation$ is an indicator variable measuring a firm's bank connection. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep Var = $Log(Spread)$	(1)	(2)
$PRisk$	0.109***	0.043***
	(3.264)	(4.797)
$PRisk \times Lobbying$	-0.077**	
	(-2.073)	
$PRisk \times Relation$		-0.033***
		(-2.588)
$Lobbying$	0.085	
	(1.377)	
$Relation$		-0.011
		(-0.822)
Baseline controls	Yes	Yes
Loan purpose / Type FE	Yes	Yes
Industry FE	Yes	Yes
Year quarter FE	Yes	Yes
Observations	3,251	11,585
Adjusted R^2	0.710	0.640

Table 2.1. Descriptive Statistics

This table presents summary statistics of the key variables for two samples of repeat loans. For each variable, I report the mean, standard deviation, and 25th, 50th, and 75th percentiles.

Panel A. Summary statistics for the pre-2008 period

	Mean	SD	25th	50th	75th
Loan Spread	206	133	102	193	278
Loan Amount	239	534	35	96	241
Loan Maturity	52	22	37	52	63
Firm Size	3,489	10,408	256	719	2,209
Firm Sales	587	1423	57	153	462
ROA	0.02	0.02	0.01	0.01	0.02

Panel B. Summary statistics for the post-2008 period

	Mean	SD	25th	50th	75th
Loan Spread	275	161	169	225	338
Loan Amount	510	762	111	270	613
Loan Maturity	54	15	51	56	59
Firm Size	9,503	19,649	1,062	2,830	7,711
Firm Sales	1353	2647	168	450	1261
ROA	0.01	0.01	0.01	0.01	0.02

Table 2.2. Borrowing Path and Loan Cost

This table reports the results of a firm's borrowing history effect on its current loan pricing. The aggregate spread is constructed using all loan observations within the same loan type, regardless of the borrower rating. *SpdFell* (*SpdRose*) is a dummy variable that equals 1 when the aggregate spreads fell (rose) by 25% or more since the firm last borrowed. *ΔAgg.Log(Spd)* is the log difference in aggregate spreads from a firm's previous to its current loan issuance. $|\Delta Agg.Log(Spd)^F|$ is the magnitude of log-difference in aggregate spreads when spreads have fallen. $\Delta Agg.Log(Spd)^R$ is the magnitude of log-difference in aggregate spreads when spreads have risen. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels. The sample period covers 2009 to 2016.

Dep Var = Log(Spd)	(1)	(2)	(3)	(4)	(5)
ΔAgg.Log(Spd)	-0.06***				
	(0.01)				
SpdFell		0.08***			
		(0.00)			
SpdRose			0.01		
			(0.52)		
$\|\Delta Agg.Log(Spd)^F\|$				0.30***	
				(0.00)	
$\Delta Agg.Log(Spd)^R$					0.04
					(0.46)
Constant	5.42***	5.41***	5.42***	5.26***	5.52***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year × loan-type FE	Yes	Yes	Yes	Yes	Yes
Nobs	10,060	10,060	10,060	5,130	4,930
Adj_R^2	0.264	0.265	0.264	0.213	0.269

Table 2.3. Borrowing Path and Loan Cost within Rating Groups

This table reports the results of a firm's borrowing history effect on its current loan pricing. The aggregate spread is constructed using all loan observations within the same loan type and within the same rating groups. In Panel B, I further require the borrowers to have the same rating as it last borrowed. *SpdFell* (*SpdRose*) is a dummy variable that equals 1 when the aggregate spreads fell (rose) by 25% or more since the firm last borrowed. *ΔAgg.Log(Spd)* is the log-difference in aggregate spreads from a firm's previous to its current loan issuance. $|\Delta Agg.Log(Spd)^F|$ is the magnitude of log-difference in aggregate spreads when spreads have fallen. $\Delta Agg.Log(Spd)^R$ is the magnitude of log-difference in aggregate spreads when spreads have risen. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Panel A. Effect of borrowing history within rating groups

Dep Var = Log(Spd)	(1)	(2)	(3)	(4)	(5)
ΔAgg.Log(Spd)	-0.07***				
	(0.00)				
SpdFell		0.08***			
		(0.00)			
SpdRose			-0.00		
			(0.78)		
$\lvert\Delta Agg.Log(Spd)^F\rvert$				0.26***	
				(0.00)	
$\Delta Agg.Log(Spd)^R$					-0.01
					(0.59)
Constant	5.43***	5.41***	5.42***	5.26***	5.55***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year × Loan-type × Rating FE	Yes	Yes	Yes	Yes	Yes
Same rating	No	No	No	No	No
Nobs	10,047	10,047	10,047	5,180	4,858
Adj_R^2	0.479	0.479	0.477	0.433	0.481

Panel B. Effect of borrowing history within rating groups considering the credit rating switch

Dep Var = Log(Spd)	(1)	(2)	(3)	(4)	(5)
ΔAgg.Log(Spd)	-0.06***				
	(0.00)				
SpdFell		0.05***			
		(0.00)			
SpdRose			0.00		
			(0.83)		
$\|\Delta$Agg.Log(Spd)$^F\|$				-0.12**	
				(0.05)	
ΔAgg.Log(Spd)^R					0.01
					(0.80)
Constant	5.38***	5.37***	5.37***	5.26***	5.48***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year × Loan-type × Rating FE	Yes	Yes	Yes	Yes	Yes
Same rating	Yes	Yes	Yes	Yes	Yes
Nobs	7,962	7,962	7,962	4,321	3,630
Adj_R^2	0.461	0.461	0.461	0.418	0.472

Table 2.4. Borrowing Path and Loan Cost: Subsample Analysis

This table presents the results of the borrowing history effect on a firm's current borrowing costs using different subsamples. $|\Delta Agg.Log(Spd)^F|$ ($\Delta Agg.Log(Spd)^R$) is the magnitude of log-difference in aggregate spreads between a firm's previous borrowing and current loan issuance, when the spreads have fallen (risen). The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Panel A. Borrowing path and current cost for 2009–2012 subsample

Dep Var = Log(Spd)	Aggregate across rating groups		Aggregate within rating groups	
	(1)	(2)	(3)	(4)
$\lvert\Delta$Agg.Log(Spd)$^F\rvert$	0.35**		0.14**	
	(0.01)		(0.02)	
ΔAgg.Log(Spd)^R		-0.01		-0.02
		(0.83)		(0.34)
Constant	5.36***	5.58***	5.39***	5.60***
	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects	Year × Loan-type		Year × Loan-type × Rating	
Nobs	1,131	3,657	1,348	3,427
Adj_R^2	0.191	0.271	0.419	0.476

Panel B. Borrowing path and current cost for 2013–2016 subsample

Dep Var = Log(Spd)	Aggregate across rating groups		Aggregate within rating groups	
	(1)	(2)	(3)	(4)
$\lvert\Delta$Agg.Log(Spd)$^F\rvert$	0.29***		0.30***	
	(0.00)		(0.00)	
ΔAgg.Log(Spd)^R		0.68**		0.03
		(0.01)		(0.69)
Constant	5.23***	5.35***	5.21***	5.43***
	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects	Year × Loan-type		Year × Loan-type × Rating	
Nobs	3,999	1,273	3,832	1,431
Adj_R^2	0.197	0.234	0.423	0.466

Table 2.5. Borrowing Path and Firm Credit Risk

This table reports the regression results of firm credit risks on the aggregate credit spread change. $|\Delta Agg.Log(Spd)^F|$ is defined as the magnitude of the negative change in aggregate spreads. The firm credit risk is captured by nine measures, including market-to-book ratio (*M/B*), earnings (*EARN*), sales growth (*SALE_G*), stock returns (*RET*), future returns (*F.RET*), stock volatility (*VOL*), current ratio (*CURR*), leverage (*LEV*), and the change in credit rating (*ΔRATE*). Column (9) reports the result of an ordered logistic regression. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Dep Var =	(1) M/B	(2) EARN	(3) SALE_G	(4) RET	(5) F.RET	(6) VOL	(7) CURR	(8) LEV	(9) ΔRATE
$\lvert\Delta Agg.Log(Spd)^F\rvert$	0.24	0.00	-0.14***	0.06	0.00	0.00	0.21	0.05	-1.27
	(0.73)	(0.42)	(0.00)	(0.15)	(0.96)	(0.10)	(0.28)	(0.11)	(0.11)
Constant	2.81***	0.01***	0.10***	0.01**	0.01	0.02***	1.85***	0.61***	
	(0.00)	(0.00)	(0.00)	(0.02)	(0.32)	(0.00)	(0.00)	(0.00)	
Year × loan-type × Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same Credit rating	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	3,193	3,516	3,581	3,283	3,275	3,285	3,019	3,569	2,191
Adj_R^2	0.02	0.05	0.04	0.07	0.06	0.29	0.06	0.19	0.29

Table 2.6. Prediction of Borrowing Spreads

This table reports the results for first-stage predictive regressions. I regress loan spreads on different observable characteristics taken from Ivashina (2009). The table reports the mean and standard deviation (SD) for observable factors, standard errors, and adjusted R^2. The characteristics definition is listed in Appendix A2.1.

	Coefficients		Std. Errors	
	Mean	SD	Mean	SD
SALES	-0.021	0.015	0.031	0.004
SIZE	-0.019	0.017	0.025	0.004
LEV	0.126	0.056	0.084	0.012
ROA	-0.582	0.129	0.159	0.020
CURR	-0.020	0.010	0.025	0.004
RET_VOL	3.735	0.999	1.680	0.139
BANK_SHR	-0.002	0.001	0.001	0.000
Log(AMT)	-0.068	0.011	0.014	0.003
MAT	0.003	0.001	0.002	0.000
NLEND	0.000	0.002	0.005	0.001
COLL	0.173	0.026	0.065	0.006
COV	-0.049	0.027	0.032	0.009
PERF	-0.050	0.028	0.021	0.007
PRIM	0.079	0.213	0.252	0.065
Nobs	1930	468		
Adj.R^2	0.662	0.080		

Table 2.7. Fixation on Previous Loan Cost

This table reports the results of firm-specific historical loan cost on its current borrowing cost. *PRED_SPD* is the model predicted spread, which is obtained using the first-step prediction model. *SPD_EVO* is the spread evolution. *PREV_RES* is the previous residual. The p-values are reported in parentheses and $*$, $**$, and $***$ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Dep Var = Log(Spd)	(1) Full sample	(2) Predicted spread lower than historical spread $s_{i,r} > \hat{s}_{i,t}$	(3) Predicted spread higher than historical spread $s_{i,r} < \hat{s}_{i,t}$
PRED_SPD	0.95***	0.97***	0.99***
	(0.00)	(0.00)	(0.00)
SPD_EVO	0.09***	0.30***	0.02
	(0.00)	(0.00)	(0.11)
PREV_RES	0.20***	0.18***	0.17***
	(0.00)	(0.00)	(0.00)
Constant	0.30***	0.13	0.00
	(0.00)	(0.29)	(0.98)
Fixed effect	Year × loan-type × credit rating		
Nobs	5,666	2,539	3,126
Adj_R^2	0.745	0.733	0.765

Table 2.8. Results on Relationship Lending

This table reports the results for the spread evolution effect on loan costs for relationship loans and non-relationship loans. A loan is classified as a relationship loan if its current lead bank is the same as any one of the previous loans. The p-values are reported in parentheses and $*$, $**$, and $***$ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Dep Var = Log(Spd)	Full Sample		Spreads have Fallen ($s_{i,r} > \hat{s}_{i,t}$)	
	(1) Same Lender	(2) Diff Lender	(3) Same Lender	(4) Diff Lender
PRED_SPD	0.90***	0.97***	0.94***	1.00***
	(0.00)	(0.00)	(0.00)	(0.00)
SPD_EVO	0.15***	0.07***	0.36***	0.24***
	(0.00)	(0.00)	(0.00)	(0.00)
PREV_RES	0.28***	0.11***	0.23***	0.10**
	(0.00)	(0.00)	(0.00)	(0.01)
Constant	0.50***	0.15	0.24*	-0.05
	(0.00)	(0.17)	(0.09)	(0.82)
Fixed effects	Year × loan-type × credit rating		Year × loan-type × credit rating	
Nobs	2,869	2,778	1,546	971
Adj_R^2	0.750	0.737	0.762	0.703

Table 2.9. Explore Anchoring Strategy: The Role of Borrowing History Salience

This table tests the role of information salience on the anchoring effect. *GAP* is the difference in loan issuance time (in years) between the most recent loan borrowing and current loan borrowing. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Dep Var = Log(Spd)	(1) GAP ≤ 1	(2) 1 < GAP ≤ 2	(3) 2 < GAP ≤ 3	(4) 3 < GAP ≤ 4	(5) GAP >4
PRED_SPD	0.93***	0.97***	0.92***	0.90***	1.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SPD_EVO	0.39**	0.44***	0.35***	0.37***	0.07
	(0.03)	(0.00)	(0.00)	(0.00)	(0.34)
PREV_RES	0.29	0.08**	0.19***	0.24***	0.11
	(0.11)	(0.02)	(0.00)	(0.01)	(0.22)
Constant	0.34	0.12	0.34	0.44	-0.22
	(0.40)	(0.45)	(0.19)	(0.42)	(0.69)
Year × Loan-type × Rating FE	Yes	Yes	Yes	Yes	Yes
Nobs	185	1,133	656	246	256
Adj_R^2	0.844	0.775	0.740	0.691	0.619

Table 2.10. Explore Anchoring Strategy: The Role of Number of Lenders

This table disentangles the anchoring effect in the loan market in terms of the banking monopoly information, measured by the number of lead lenders. The p-values are reported in parentheses and $*$, $**$, and $***$ respectively denote statistical significance at the 10%, 5%, and 1% levels.

	Number of lead lenders		
	(1)	(2)	(3)
Dep Var = Log(Spd)	Nlender = 1	$2 \leq$ Nlender ≤ 4	Nlender >4
PRED_SPD	1.16***	1.02***	0.79***
	(0.00)	(0.00)	(0.00)
SPD_EVO	0.12**	0.10***	0.08***
	(0.02)	(0.00)	(0.00)
PREV_RES	0.17*	0.20***	0.19***
	(0.07)	(0.00)	(0.00)
Constant	-0.93**	-0.09	1.11***
	(0.02)	(0.60)	(0.00)
Year × Loan-type × Rating FE	Yes	Yes	Yes
Nobs	283	1,107	3,786
Adj_R^2	0.739	0.704	0.725

Table 2.11. Explore Anchoring Strategy: The Firm's Bank-dependency

This table reports the results of the role of firm's bank dependency on the anchoring effect. *SPD_EVO* is the spread evolution. *IntH, LevL, and Bond* are dummy variables that equal 1 if the firm has an above-median interest coverage ratio, if the firm has below-median leverage, or if the firm has access to the public bond market in the previous 3 years, and 0 otherwise. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Dep Var = Log(Spd)	(1)	(2)	(3)
PRED_SPD	0.96***	0.96***	0.97***
	(0.00)	(0.00)	(0.00)
SPD_EVO	0.35***	0.23***	0.30***
	(0.00)	(0.00)	(0.00)
IntH × SPD_EVO	-0.12**		
	(0.01)		
LevL × SPD_EVO		-0.13***	
		(0.00)	
Bond × SPD_EVO			-0.29***
			(0.00)
PREV_RES	0.19***	0.18***	0.18***
	(0.00)	(0.00)	(0.00)
IntH	-0.01		
	(0.87)		
LevL		-0.01	
		(0.44)	
Bond			0.04
			(0.32)
Constant	0.16	0.18	0.13
	(0.23)	(0.15)	(0.29)
Year × Loan-type × Rating FE	Yes	Yes	Yes
Nobs	2,454	2,525	2,525
Adj_R^2	0.738	0.735	0.733

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Appendices

Appendix A1.1: Variable Definition for Chapter 1

Variable	Definition
Key Variables	
$PRisk$	Firm-level political risk, standardized into N(0,1).
$NPRisk$	Firm-level non-political risk, standardized into N(0,1).
Contract Characteristics	
$Log(Spread)$	Natural logarithm of loan spread (over LIBOR) for each individual loan contract.
$Log(Amt)$	Natural logarithm of the loan issuance amount.
$Log(Mat)$	Natural logarithm of loan issuance maturity (in months).
$TotCovIndex$	The number of total covenants.
$GenCovIndex$	The number of general covenants.
$FinCovIndex$	The number of financial covenants.
$Perf\_Provision$	Binary dummy that equals 1 if the contract includes performance pricing provisions, and zero otherwise.
$Loan\ Type$	Dummy variable for different loan types.
$Loan\ Purpose$	Dummy variable for different loan purposes.
Firm Characteristics	
$Size$	The natural logarithm of a firm's total assets.
$Tang$	Tangibility, measured by total property, plant, and equipment, scaled by total assets.
LEV	Leverage, measured by the total debt, scaled by the market value of equity.
M/B	Market-to-book ratio.
$Profit$	Profitability, measured by operating income before depreciation, scaled by total assets.
$Z\text{-}score$	Modified Altman's Z-score, calculated as (1.2×(ACT – LCT) + 1.4×RE + 3.3×EBIT + 0.999×SALE)/AT + 0.6×CSHO × PRCC_C/ (DLTT + DLC).
CF_Vol	Cash flow volatility, measured by the standard deviation of a firm's quarterly cash flows from operations over the previous four fiscal years, scaled by total debt.
T_Vol	Return volatility, measured by the standard deviation of a firm's daily stock return over the fiscal year.
HP_Index	HP index, calculated as (−0.737×Assets + 0.043×Assets^2 − 0.040×Age).
Exf	External financing dependency, calculated as (Capital expenditures (CAPX) – funds from operations (FOPT/capital expenditures (CAPX).
$Loss$	Binary dummy that equals one if the firm reports a loss, and zero otherwise.
$CAPX$	Capital expenditures, measured by the natural logarithm of capital expenditures.

$Return$	Stock Return, measured by the average of a firm's daily stock return over the previous quarter.
$Insti\_holding$	Institutional holding, measured by the percentage of a firm's shares held by institutional investors.
$AnalystCov$	Analyst coverage, measured by the number of analysts covering the firm.
Economic Characteristics	
PU_a	Aggregate political uncertainty, measured by EPU divided by 100.
$Term\_Spread$	The difference between the 10-year and the 1-year government bond yield.
$Default\_Rate$	The yield spread between Moody's seasoned Baa and Aaa corporate bonds.
$Inflation\_Rate$	Inflation rate, defined as the monthly growth rate of the Consumer Price Index for all urban consumers.
$Production\_Rate$	Production rate, defined as the growth rate as shown by the monthly Industrial Production Index.
$Unemployment\_Rate$	Unemployment rate, defined as the monthly civilian unemployment rate.
$Recession\_Rate$	Binary dummy that equals one if an observation time falls in an NBER business cycle, and zero otherwise.
$Shorterm\_Rate$	Short-term rate, defined as the one-month nominal Treasury bill rate.

Appendix A2.1: Variable Definition for Chapter 2

Variable	Definition
Key Variables	
SpdFell	Binary dummy that equals 1 if the aggregate spreads fell by 25% or more since the firm's previous loan issuance.
SpdRose	Binary dummy that equals1 if the aggregate spreads rose by 25% or more since the firm's previous loan issuance.
$\lvert\Delta$Agg.Log(Spd)$^F\rvert$	The magnitude of log difference in aggregate spreads between the firm's previous borrowing and current borrowing, when the aggregate spreads have fallen.
ΔAgg.Log(Spd)^R	The log difference in aggregate spreads between the firm's previous borrowing and current borrowing, when the aggregate spreads have risen.
PRED_SPD	Predicted spread, estimated from a batch of firm-level and loan-level characteristics.
SPD_EVO	Spread evolution, defined as the log difference between the previous loan spreads and predicted loan spreads.
PREV_RES	Previous residual, defined as the log difference between the previously estimated loan spread and the previously realized loan spread.
Firm Characteristics	
SIZE	Natural logarithm of firm's total assets.
SALES	Sales at close, defined as a firm's sales at the loan origination.
ROA	Profitability, measured as the operating income before depreciation scaled by total assets.
M/B	Market-to-book ratio.
EARN	Earnings, measured as the quarterly earnings scaled by total assets.
SALE_G	Sales growth, measured as the change in sales.
RET	Stock return for a quarter.
F.RET	Future stock return for a quarter.
VOL	Return volatility, defined as the standard deviation of a firm's daily stock return over the quarter.
CURR	Current ratio, which is the ratio of the current assets to current liabilities.
LEV	Leverage, measured as the total debt scaled by total assets.
ΔRATE	Change in credit ratings for a quarter, where the rating change is positive (negative) when the firm has been upgraded (downgraded).
Contract Characteristics	
Log(SPD)	Natural logarithm of loan spread (over LIBOR) for each individual loan contract.
Log(AMT)	Natural logarithm of the loan issuance amount.
MAT	The number of months to loan maturity.
BANK_SHR	Market share of the lead arranger, defined as the share of the loan that is retained by the lead arranger at loan origination.
NLEND	Number of lenders in the loan package.
COLL	Binary dummy that equals 1 if the loan includes financial covenants and 0 otherwise.
PERF	Binary dummy that equals 1 if the loan includes performance pricing provisions, and 0 otherwise.
PRIM	Binary dummy that equals 1 if the base rate is the prime rate, and 0 otherwise.

Appendix Table A2.2. Borrowing Path and Loan Cost during the Pre-crisis Period

This table reports the results of the borrowing path effect on firms' current borrowing costs during the pre-crisis period (i.e., 1987 to 2008). In Panel A, the aggregate spread is constructed using all loan observations within the same loan type, regardless of the borrower rating. In Panel B, the aggregate spread is constructed using all loan observations within the same loan type and within the same rating groups. The p-values are reported in parentheses and ∗, ∗∗, and ∗∗∗ respectively denote statistical significance at the 10%, 5%, and 1% levels.

Panel A. Effect of borrowing history across credit rating groups

Dep Var = Log(Spd)	(1)	(2)	(3)	(4)
SpdRose	-0.11***		-0.11***	
	(0.00)		(0.00)	
SpdFell		0.18***	0.19***	
		(0.00)	(0.00)	
ΔAgg.Log(Spd)				-0.27***
				(0.00)
Constant	5.09***	5.06***	5.08***	5.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Year × loan-type FE	Yes	Yes	Yes	Yes
Nobs	19,017	19,017	19,017	19,017
Adj_R^2	0.177	0.178	0.179	0.179

Appendix Table A2.2. Borrowing Path and Loan Cost during the Pre-crisis Period (cont.)

Panel B. Effect of borrowing history within credit rating groups

Dep Var = Log(Spd)	(1)	(2)	(3)	(4)	(5)	(6)
SpdRose	-0.05***		-0.03**		-0.06***	
	(0.00)		(0.02)		(0.00)	
SpdFell		0.13***	0.13***		0.09***	
		(0.00)	(0.00)		(0.00)	
ΔAgg.Log(Spd)				-0.17***		-0.26***
				(0.00)		(0.00)
Constant	5.08***	5.05***	5.06***	5.07***	5.04***	5.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year × loan-type × credit-rating	Yes	Yes	Yes	Yes	Yes	Yes
Same Rating	No	No	No	No	Yes	Yes
Nobs	18,870	18,870	18,870	18,870	14,899	14,899
Adj_R^2	0.534	0.536	0.536	0.538	0.514	0.515