U.S. political corruption and the cost of bank loans

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Abstract

Analyzing the corruption conviction data reported annually by the U.S. Department of Justice, I find, the regional corruption rate (RCR) from 1990 to 2014 in the areas surrounding firms' headquarters is positively associated with the cost of bank loans. Specifically, a 1% increase in RCR associates with a 4.4 bps increase in loan spread. This result is robust across regressions with additional control variables and one alternative survey measure of corruption, as well as two instrumental variable analyses and propensity score matching. This corruption premium diminishes with a strong lender-borrower relationship, indicating the premium is caused by the uncertainty associated with corruption. Overall, these results suggest that bribes between firms and politicians cause the spillover effects in the loan market; increased transparency in financial reporting serves as a complement with law enforcement to alleviate the potential negative impact of corruption on the U.S. economy.

Keywords: the cost of bank loans, political corruption, information asymmetry

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1. Introduction

The government is entitled to use public resources and power to benefit selective groups (Stigler, 1971); the more important role government plays in the economy, the stronger bargaining power officials will enjoy to seek rent from firms.

Political corruption distorts firms' financial policies. For instance, Smith (2016) finds firms drive cash-holding downward and leverage upward to avoid expropriation by corrupt officials. The reaction of financial markets to the corruption culture in operation environments of firms, nevertheless, remains unknown. In this study, I address this issue by examining the relationship between political corruption and the cost of bank loans in the U.S.

Loan costs could be sensitive to corruption risk because banks calculate these costs based on their private benefit[1]. The transparent political regime of the U.S. has not eradicated corruption. On June 4th, 2018 , Nicholas Martino, the assistant executive at the Pennsylvania Department of Transportation (PennDOT) was convicted for receiving a monetary kickback from a contractor. From 2004 to 2005, Randall Harold "Duke" Cunningham, a Republican congressman and member of the House Defense Appropriations Subcommittee, accepted approximately $2.4 million in bribes from the defense contractors. Specifically, one of the bribers, Mitchell Wade masked the bribes in the financial statements by buying Cunningham's

[1] For instance, China is a developing country in which corruption prevailed in the 1990s and early 2000s. Since 2012, however, a far-reaching anti-corruption campaign has been lauched by President Xi JinPing. Sun, Xu & Zhang (2018) find that Xi's anti-corruption campaign causes banks to lend to non-state-owned enterprises with lower loan spreads and longer maturity as banks' corruption risk exposure increases if they lend to state-owned enterprises.

house in El Mar, Californian for $1,675,000 and placed it in the market. After eight months, he bought the house back at $975,000. By bribing Cunningman, Wade received $150 million from the contracts in total, and after he was convicted, he was sentenced for 30 months jail time. Both cases involve cash transactions between officials and firms. In this study, I focus on this type of corruption.

As Akerlof and Shiller (2010) point out, the bribers always shroud the kickbacks in their financial statements. Cunningham's case proves it. But bribers also receive the preferential government contracts from the bribees. Since banks use borrowers' accounting measures to evaluate risks of bank loans (Akerlof & Shiller, 2010), I develop and examine two competing hypotheses about the association between the cost of bank loans and local corruption.

On the one hand, theoretically speaking, banks are risk averse because they use the deposits of clients to issue loans; this risk attitude is reflected by their demanding the risk premium on loans (Graham, Li, & Qiu, 2008; Houston, Jiang, Lin, & Ma, 2014). Given this risk attitude, corruption is a particularly risky factor for banks to consider when making decisions about loans. Corruption could incur multiple types of risks; without other conduits of information, the information asymmetry associated with corruption will inevitably increase the loan costs since higher information asymmetry lessens the trust between the borrowers and lenders and usually associates with higher monitoring costs (Ivashina, 2009). For example, banks increase the loan price to cover the additional effort for collecting information on a borrower with opaque financial statements. Therefore, banks might increase the loan costs in corrupt areas, for a firm in these areas is more likely to practice opaque financial disclosure policies to mask kickbacks or avoid expropriation (Durnev & Fauver, 2008; Stulz, 2005). In addition, the involvement in corruption scandals increases firms' reputational risk and makes them suffer from litigation setbacks, revenue reductions and stock crashes (Sufi, 2007). Therefore, as creditors, banks could require compensation for their exposure to corruption risks in the same way municipal bond investors do (Butler, Fauver, & Mortal, 2009). To refer to this compensation for corruption risks, I borrow Butler et al. (2009) term "corruption premiums." If banks require corruption premiums, I expect loan costs to increase with local corruption level, and I refer to this as a “prudent banks hypothesis.”

On the other hand, banks could benefit if the borrower bribes the official. For instance, bribes help firms cut the “red tape” and create the friendly business environment (Leff, 1964) that accelerates the expansion of the existing firms (Ding, Fang, Lin, & Shi, 2017). Besides, politicians who receive bribes offer privilege and protection to the bribing firm, decreasing the left tail risk and increasing the value of the firm who connected with them (Houston, Jiang, Lin, & Ma, 2014). Also, banks could securitize loans exposed to corruption risks and sell them with other safety assets to transmit these risks to other investors. Yet transactions remain profitable from loan fees as they did with the subprime mortgage during 2008 financial crisis. Thereby, if banks take risks to pursue the benefit the borrower purchases from a politician, I expect loan costs to decrease with corruption level. and I refer to this as a “aggressive banks hypothesis.”

Addoum, Kumar, Le, & Niessen-Ruenzi (2019) find that there are geographic contagious effects in the U.S. banking industry. Banks will increase the cost of bank loans if one bankruptcy event occurs nearby, and this effect is more pronounced if the information asymmetry is higher around the borrower. The risks coming from the information asymmetry associated with negative shocks, rather than coming from information effects or banks’ ability to supply credits, contributes to these contagious effects. Therefore, it is safe to assume that, as a negative information shock, conviction of corruption cases will induce the contagious effects in terms of the cost of bank loans. These effects pass through the price channel (Addoum, Kumar, Le, & Niessen-Ruenzi, 2019), therefore I expect that the contagious effects associated with corruption will be more likely to transfer to the local lending market through the price channel rather than non-price channels.

Therefore, like Butler et al. (2009) and Smith (2016), I use the number of corruption convictions from 94 judicial districts in the U.S. to measure regional corruption level since this measurement accounts for within-district variations. Specifically, I match the number of corruption convictions with each firm using the zip code of that firm's corporate headquarters and divide this number by its corresponding population to obtain regional corruption rates. For example, the regional corruption rate is 0.32 per 10,000 in eastern New York in 1990. This rate means 1 corruption case was convicted per 30,000 persons in the Eastern. A high conviction number represents the high level of corruption in the borrower's operation environment. Jared Smith (2016) uses the same measurement to study the impact of corruption on a firm's financial policies.

The results suggest that loan spreads are associated with higher conviction per capita; neither the maturity nor collateral requirement appears to associate with conviction per capita. Specifically, the loan spread in Southern Alabama, the more corrupt district, *ceteris paribus*, is 2.19 bps (0.1% of the median value of the loan spread) higher than that in Eastern Wisconsin, the less corrupt district.

These results support the "prudent hypothesis": by charging the corruption premium on loans, banks seek the compensation for uncertainty associated with corruption. More broadly, my study indicates banks increase loan costs as compensation for frictions in the lending market.

Both the information asymmetry (Stulz, 2005) and low “animal spirits” (Akerlof & Shiller, 2010) associated with corruption could increase loan costs.[2] Previous studies find a strong borrower-lender relationship decreases the loan spreads in that it decreases the information asymmetry between lenders and borrowers (Blackwell & Winters, 1997; Sufi, 2007). Therefore, if banks require compensation for the information asymmetry related to corruption, I expect a strong lender-borrower relationship decreases the corruption premium. Otherwise, that banks impose this premium due to low “animal spirits” could not be rejected. The evidence is consistent with the former situation: the corruption premium diminishes along with a strong borrower-lender relationship, indicating it is the information asymmetry, rather than low “animal spirits,” associated with corruption that motivates banks to impose a “corruption premium” on the borrower.

Loan costs decrease if credit-risk exposures are diversified (Pavel, Phillis, & others, 1987), consistent with the finding that geographically diversified firms pay less risk premium (Dischinger, Knoll, & Riedel, 2014). Therefore, I expect geographical diversification decreases

[2] “Animal spirits“refers to the sentiments out from investors’ non-economic motivations rather than the rational calculations based on investors’ cognitive processes (Ruccio and Amariglio, 2003; Akerlof and Shiller, 2010): Keynes (1936) defines "animal spirits" as irrational confidence amid uncertainty. Akerlof and Shiller (2010) further discuss animal spirits in the context of corruption. High spirits represent high level confidence (Keynes, 1936), and low spirits represent low level confidence (Akerlof and Shiller, 2010). In this paper, I will use animal spirits to mean bankers’ irrational confidence levels in terms of a cash transaction between the borrower and a local official ‘s deliberate illicit practice.

the corruption premium because firms are exposed to higher corruption risks if their headquarters are located in one place instead of several places (Bai, Jayachandran, Malesky, & Olken, 2013).

These results, especially the finding that the borrowers need to pay a "corruption premium," are robust to a range of tests from two instrumental variable (IV) analyses--addressing omitted variable bias, propensity score matching addressing endogeneity in general--to, adjusted baseline models--including additional variables, one qualitative and three alternative quantitative measures of corruption, respectively.

First, Campante and Do (2014) find that the natural log of the distance between the population and a capital in a state is positively associated with corruption, for the isolated capital is subject to less scrutiny. But this distance is in an ambiguous relationship with banks' loan decisions, thus I use it as an instrumental variable for corruption. Then I construct a second instrumental variable for corruption based on the frequency of corruption and the total search volume from the Google Trends data. The higher the value of this variable, the more interested people are in corruption, associated with a higher local corruption level (Enestor Dos Santos, 2018). But loan decisions appear not depend on a populace's interest in corruption. The results hold in both instrumental-variable two step regressions: corruption positively associates with loan costs. I also use the propensity score matching technique to mitigate the endogeneity in general. I apply treatment to firms in corrupt areas and match each observation of a treatment group with that of a control group based on covariates in baseline models: results have not changed.

To further test the robustness of the baseline results, I include additional variables related to loan costs (Ertugrul, Lei, Qiu, & Wan, 2017) as well as those related to corruption (Smith, 2016) into regressions.These two adjusted regression specifications yield similar results as baseline ones do. In addition, results barely change as three alternative quantitative measures of corruption are used as predictors. Finally, results hold after one perception based, qualitative measure of corruption is included into regressions, addressing the criticism that some corruption offences are not convicted due to the variation of law enforcement within judicial districts.

I tell a story about loan costs in terms of corruption from the demand side: whether borrowers need to pay corruption premiums to banks. Using the conviction numbers, which are reported by the U.S. Department of Justice, from 1990 to 2014, I show that loan spreads in corrupt areas are higher than non-corrupt areas, and a 1 percent increase in regional corruption rates is associated with an increase of 4.387 basis points of raw spread. Information asymmetry (Akerlof, 1970), rather than sheerly “animal spirits”(Akerlof & Shiller, 2010; Keynes, 1937), causes this corruption premium.

The aforementioned results are consistent with the “prudent banks” hypothesis: by charging the corruption premium on loans, banks seek the compensation for uncertainty associated with corruption. More broadly, my study indicates banks increase loan costs as compensation for frictions in the lending market.

This paper contributes to the literature on the determinants of the cost of bank loans (Dichev & Skinner, 2002; Drucker & Puri, 2008; Houston et al., 2014). Specifically, Banks’ optimal risk-return trade-offs determine the financial contract they offer (Nini, Smith, & Sufi,2009). Adding evidence to the aforementioned studies, my study shows that, although bribery brings privilege to the briber, corruption jeopardizes the trust between banks and borrowers, resulting in an increase in the loan spread. This finding is a double-edged sword for economic growth; on the one hand, that corruption corruption erodes the trust between banks and firms in addition to setting obstacles for the finances of firm investment, making an economic contraction more likely. On the other hand, this disciplines local officials since economic contraction hurts their electoral campaigns. Furthermore, the prudent attitude of banks could also decrease the systematic left-tail risk.

More broadly, my findings add to a better understanding of how corruption affects the cost of borrowings and the economy accordingly. In finance, corruption has most often been discussed concerning developing countries (Ding et al., 2017) or in an international setting (Jain, Kuvvet, & Pagano, 2014). This focus creates an illusion that corruption solely matters in emerging markets. My study adds to the few pieces of literature examining the impact of corruption on mature financial markets [3]. The stronger law enforcement in developed countries combats the corruption in a more efficient way than weaker legal structures in most developing countries; however banks' risk sensitivity to corruption also increases along with the high efficiency of detecting and convicting corruption cases. The finding that corruption increases the loan costs in the U.S. unveils the ubiquitous presence of the impact of corruption on financing.

Second, whether corruption "sands" or "greases" the wheel of economic growth (Méon & Sekkat, 2005) has widely been discussed in the economic literature (Ades & Di Tella, 1999; Ding et al., 2017; Guriev, 2004; Leff, 1964), but most of these studies focus on the interaction of corruption and macro variables (Sun et al., 2018) as Smith (2016) suggests; my finding adds

[3] Butler, Fauver and Mortal have followed this trend and from this perspective examined the relationship between political corruption and political corruption and the cost of municipal bonds in their 2009 study " Corruption, Political connections, and Municipal Finance." In another recent study, Smith examines the relationship between political corruption and the financial policies of U.S. firms in his 2016 study "U.S. Political Corruption and Firm Financial Policies."

micro evidence to this discussion by providing a specific channel through which corruption influences the economy.

Through the prism of loan costs, this study also reminds regulators that the oversimplified view of corruption risk (Loewenstein, 2000; Taleb, 2005) without rational calculation could hobble economic expansion. As major players in lending markets, banks provide the liquidity that promotes local economic growth. Banks are wary about the corruption risk and in turn charge higher loan spreads simply based on the corruption level in which the borrowers' headquarters are located. This behavior creates negative externality for borrowers with integrity in these areas--these well-behaved firms are forced to pay external costs for corruption schemes they are not involved in. Therefore, regulations that help build trust between banks and firms, such as increasing the standard of corporate disclosure policies, rather than those that make banks become over-conservative are in demand to support local economic expansion in corrupt areas.

Furthermore, from Butler et al. (2009) to Smith (2016), quantitative approaches are in use to study the interplay between financial variables and corruption. As for this quantitative research, omitted variable bias, however, is the elephant in the room. To address this bias, I propose a valid instrumental variable (the frequency of corruption at state level scaled by the total search volume based on the Google Trends data) with which to further consolidate the positive relationship between corruption and the cost of bank loans.

Finally, this paper best fits with the literature on the positive relationship between information asymmetry and loan costs (Ertugrul et al., 2017). It also connects literatures on the impact of political corruption on municipal bond pricing (Butler et al., 2009), bank monitoring (Vashishtha, 2014), relation banking (Schenone, 2010) and behavior economics (Akerlof &

Shiller, 2010). It also informs regulators that, transparency not only plays the pivotal role in crushing corruption but also minimizes the spillover effects of corruption in the lending market. Therefore, transparency alleviates the negative impact of corruption on the real economy.

2. Hypothesis Development

Political corruption gives banks two opposite incentives to evaluate the creditworthiness of borrowers. On the one hand, banks are risk-averse towards corruption risk and require a "corruption premium" (Butler et al., 2009) as compensation. On the other hand, banks desire the privilege bribery brings about and loan growth, so they are willing to decrease loan costs. Both risk and return are associated with corruption, and the trade-off decision-making of banks is unclear.

2.1 The "Prudent Banks" Hypothesis

Addoum, Kumer, Le, & Niessen-Ruenzi (2019) point out that banks increase loan spreads in the area near a negative shock and it is the risks risen from the information asymmetry associated with negative shocks, rather than information effects or banks' ability to supply credits, that contributes to these contagious effects.

Therefore, if banks (as creditors) are risk averse (Acharya, Amihud, & Litov, 2011; Brockman & Unlu, 2009; Denis & Osobov, 2008; Nini, Smith, & Sufi, 2009), I expect loan costs (specifically loan spreads) to positively relate to corruption in the U.S.

First, the U.S. has stronger legal institutions than many others do. This makes banks in the U.S. more sensitive to corruption risk to demand a corruption premium. Being considered as one of the least corrupt nations in the world (Smith, 2016), the strong legal institutions in the U.S. increase the conviction rate of corruption cases, making the loan spreads more sensitive to corruption risks; no lenders are willing to lend to a firm that is likely to suffer from hefty litigation costs or forceful turnover of CEO because of convicted corruption cases (Dinç, 2005; Houston et al., 2014). Contrastively, in some developing countries, banks lend to the bribing firm at low costs per the politician's requirements (Houston et al., 2014).

Second, the uniqueness of the U.S. lending market encourages banks to impose risk premiums as compensation for default risk. Different from banks in other developed countries such as Germany and Japan, banks in the U.S. are less likely to participate in corporate governance of firms (Black & Gilson, 1998). Therefore, it is rational for banks in the U.S. to charge risk premiums to compensate default risk as substitutes. Also, different from their peers in Germany or Japan, banks in the U.S. play in a more competitive lending market consisting of privately-owned banks that lend for investment's sake rather than per politicians' willingness (Houston et al., 2014). Therefore, banks in the U.S. are more sensitive to the default risk that they are more likely to choose safe assets ceteris paribus (Johb H. Boyd and Gianni De Nicolo, 2005).

Four types of risk could lead banks to impose incremental premiums on loans. First, as firms conduct opaque financial practices either to avert extortion or to disguise kickbacks required by politicians (Durnev & Fauver, 2008; Stulz, 2005), information asymmetry arises between lenders and borrowers, ramping up loan prices due to a consequential increase in the uncertainty and monitoring costs (Vashishtha, 2014). Specifically, loan spreads, rather than non-price term, serve as premiums to compensate for the information asymmetry associated with a negative shock (Addoum et al., 2019).

Second, a convicted corruption case destroys a firm's reputation, a valuable asset to mitigate the information asymmetry (Sufi, 2007): the convicted firm not only loses the opportunity to decrease the borrowing costs but also suffers from additional reputational risk.

With this soaring reputational risk, in short term, it is difficult for the firm to raise emergency funds to cover huge litigation costs and fines to settle the lawsuit. In long term, as Benjiamin Franklin points out “It takes many good deeds to build a good reputation, and only one bad one to lose it”; a plagued reputation as well as the negative signals it sends to the market linger in people’s minds for a long time, making the firm struggle to restore the trust with regulators and customers.This further spooks investors and impedes the firm’s efforts to raise external funds.

Third, as the briber is usually imprisoned, a forceful CEO turnover and other executive reshuffles caused by the convicted case undermines the lender-borrower relationship and increases firm volatility. This internal tumultuousness results in higher loan costs (Bharath, Dahiya, Saunders, & Srinivasan, 2009; Schenone, 2010). Lastly, that the firm shields cash and increases leverage (Smith, 2016) in response to corruption decreases firm liquidity, resulting in higher loan costs (Strahan, 1999).

Therefore, the “prudent banks” hypothesis is proposed below:

“Prudent banks” hypothesis. If banks are risk-averse towards corruption, then the *Regional Corruption Rate* is positively associated with the cost of bank loans.

If the “prudent banks” hypothesis is valid, the borrower, however, could pay less or even no “corruption premium” through some channels. As this discussion refers, an increase in loan costs could be due to information asymmetry associated with corruption (Dell’Ariccia & Marquez, 2004; Durnev & Fauver, 2008; Stulz, 2005). Therefore, if banks access better information flow through strong lender-borrower relationship, the trust will be restored and loan costs will decrease (Bharath et al., 2009) : the more informative the borrower, the more efficient for bank monitoring (Engelberg, Gao, & Parsons, 2012) and the less uncertainty (Bodenhorn, 2001) associated with corruption.

Apart from economic incentives that motivate banks to increase the cost of bank loans, "animal spirits" (Akerlof & Shiller, 2010; Beckhart & Keynes, 1936; Keynes, 1937) could also engender corruption premiums. The increasing of loan costs might be fully driven by the resistance to corruption. In order to better understand this process, I will briefly turn to the Great Depression as an example. During the Great Depression, the interest rate was nudged to an abnormally low level, however, businessman still hesitated to lend from banks for investment since they fear the future of capitalism (Akerlof & Shiller, 2010). The same fear might be experienced on a smaller scale by contemporary bankers in terms of corruption; if bankers lose trust in the borrowers' integrity, specifically the borrowers' adherence to principals, the corruption risks will spook banks so that banks will not issue cheaper credits. This risk aversion remains true even if some specific borrowers manage to decrease the information asymmetry themselves.

To shed light on whether an increase in loan costs is based on rational calculation or merely out of "animal spirits" (Akerlof & Shiller, 2010; Keynes, 1937), I develop the testable hypothesis below:

The information asymmetry associated with corruption engenders a corruption premium; a strong bank-firm relationship reduces or even diminishes this premium.

If this hypothesis is valid, consistent with the literature on bank-firm relationship, banks respond to corruption as rational market players (Akerlof & Shiller, 2010) since they incorporate the information into their loan pricing models and adjust the costs accordingly.

2.2 The "Aggressive Banks" Hypothesis

On the other hand, if banks want to exploit the benefit through corporate bribery, will they become aggressive risk takers, imposing a lower risk premium on loans?

Historically, the examples of bankers issuing loans without proper risk evaluation are abundant, and moral hazard could lead banks to have high risk tolerance towards corruption. For instance, during the 2008-2014 Spain financial crisis, banks in Spain loaned to the real estate companies that bribed officials to gain preferential government grants (Christos Lycos, 2015). This behavior was one of the causes of the following recession in Spain. Their peers in the U.S. are also proved to be aggressive risk-takers by the 2007-2008 financial crisis, as evidenced by the revealing of tremendous corruption cases during this crisis and the fact that conviction per capita peaked in 2008 (see Table A.2.)

During this crisis, banks in the U.S. loaned to unqualified borrowers without stringent due diligence for huge origination fees. Later on, they securitized and packaged these questionable assets with safe ones and sold the bundled loans to the capital market immediately. Banks did this to avert the default risk, proving that either high animal spirits or innovative financial instruments can help them reap the high return without bearing corresponding risk exposure. Banks became risk takers during the financial crisis; after all, they were "too big to fail" and were bailed out by the government.

From a bank's perspective, conspicuous benefits occur as its borrower bribes the local official, encouraging the bank to impose low premiums in exchange for huge return and loan fees.

First, bribing officials is a way to cut through the red tape (Guriev, 2004) to gain a large market share, driving the borrower's profitability up and default risks down accordingly. Second, bribing an official for a "pay-for-play" scheme grants the firm preferential government contracts, increasing the borrower's revenue and enhancing its creditworthiness. Finally, the connection established through bribing the politician could create value for this particular firm by protecting it from left-tail risk (Houston et al., 2014).

Thus, the "aggressive banks" hypothesis is proposed below:

Aggressive banks hypothesis: if banks are risk-takers in terms of corruption, then the *Regional Corruption Rate* is negatively associated with the cost of bank loans.

3. Data and variables

I collect conviction data from 1979 to 2017 from the Report to Congress on the Activities and Operations of the Public Integrity Section issued by the DOJ. Loan data are from 1990 to 2014, sourced from the Dealscan database. Firm characteristics data are from Compustat. The period (1990-2014) of loan data restricts the sample size, leaving 22,816 loan-year observations during 1990-2014 in the final sample.

3.1. Corruption Variable

To proxy for the local-level corruption, I collect the annual number of convictions for political corruption in each U.S. judicial district. This number is from the Annual Report to Congress on the Activities and Operations of the Public Integrity Section issued by the Criminal Division of the United States Department of Justice (DOJ). I divide this number by its corresponding population estimates (Fisman & Gatti, 2002) and hand match it to the zip code of each corporate headquarters to generate the *Regional Corruption Rate* variable. I use this variable to examine the relationship between the cost of bank loans and corruption in an objective manner[4]. I do not choose the aggregate number of convictions at the state level as Butler et al. (2009) do because Table 1 shows variations exist across districts.

[4] Smith (2016) uses the same variable to examine the relationship between firm financial policies and corruption in the U.S.

As Smith (2016) mentions, it is difficult to access the actual number of cases that directly influence firms since the DOJ has only reported the total number of convictions rather than the number of convictions based on different categories of corruption. For example, the DOJ has not reported the number of convictions involved into illicit cash transaction between political officials and firms—the type of corruption cases I focus on in this study. Dass, Nanda, & Xiao (2017), however, find that, geographically, corruption offences positively correlate with each other. Therefore, it is plausible for *Regional Corruption Rate* to serve as a proxy for local -level corruption, and the higher the *Regional Corruption Rate*, the more corrupt the area.

I also include the state-fixed effects into regressions to control for variations related to state-level corruption such as characteristics of state legislators (their honesty, finance literacy , their corruptibility). I have not lagged the conviction variable because convictions usually lag behind occurrences of extortion or bribery.The data on *Regional Corruption Rate* are available from 1979 to 2017, however, they are restricted by the sample period of bank loans. The final sample covers the period 1990 to 2014.

To alleviate the concern that some offenders might not be convicted, I re-estimate the baseline models after replacing *Regional Corruption Rate* with one survey variable: State Integrity Investigation (*SII*) in the State Integrity Project. This project was conducted by the Center for Public Integrity in 2012. This cross-sectional dataset consists of the grade each state scored on corruption. The higher the score, the less corrupt the state.

<Insert Table 1 about here>

3.2. The cost of bank loans

For the price terms of bank loans, I use two measures that appear in previous studies (Ertugrul et al., 2017; Prilmeier, 2017). The first measurement for the price term of bank loans is raw loan spreads (*allindrawn*), Dealscan all-in spread drawn measured in basis points (bps), and the second one is *ln(allindrawn)*, the natural log of *allindrawn*.The final sample consists of 22,922 loan-year observations over the period 1990-2014.

For the non-price terms of bank loans, I include both maturity and the collateral requirements. *ln(maturity)* is the natural log of maturity measured in months. *Security* is a dummy variable equaling one if the banks require the borrower to pledge collaterals and zero otherwise (Ertugrul et al., 2017).

Non-price terms have impacts on loan spreads (Ertugrul et al., 2017). ln(maturity) is positively related to the loan spreads since longer maturity indicates higher creditworthiness and lower information asymmetry of a borrower (Wittenberg-Moerman, 2008). But academia and industry hold divergent views regarding the relationship between Security and loan spreads. Bharath et al. (2011) find secured loans are associated with higher loan spreads. Bankers in the business world, however, tend to seek a balance between the loan spreads and collateral requirements to maximize volume of loans: typically, they will decrease the loan spreads if the borrower provides collateral.

3.3. Loan characteristics variables

Loan characteristics also have impacts on loan spreads (Ertugrul et al., 2017). *Loan size*, the natural log of the facility amount in Dealscan, is associated with loan spreads; large loan size attains economies of scale, bringing loan spreads down (Berger & Udell, 1990; Graham et al., 2008). I also include loan type and purpose dummies into regressions (Ertugrul et al., 2017); different types and purposes of loans entail different risks and affect loan spreads in different ways accordingly.

For robustness check, I include *president dummy* into regressions to control for law enforcement. The *president dummy* equals one if the loan was issued during the presidency of George Bush (1990 to 1992), equals two if the loan was issued during the presidency of Bill Clinton (1992 to 2000), equals three if the loan was issued during the presidency of George W. Bush (2000 to 2008) and equals four if the loan was issued during the presidency of Barack Obama (2008 to 2014).

3.4. Bank-firm relationship variables

The idea is to capture the effect of information asymmetry on corruption premiums. Therefore, I use *loan-to-asset ratio* to measure the strength of the lender-borrower relationship that mitigates the information asymmetry of the borrower. The larger the *loan-to-asset ratio*, the more important the loan to the borrower, and the more influences banks have on the borrower's executives for a more effective information-gathering process and better monitoring (Dass & Massa, 2011; Rajan, 1992), decreasing the information asymmetry accordingly.

3.5. Firm-level control variables

Firms' financial characteristics affect the cost of bank loans in several dimensions. First, *ln(asset)*, the natural log of a firm's total asset, decreases loan costs since big firms are not only more stable but also receives more media coverage than small ones, alleviating the information asymmetry. Second, *Tangibility*, the tangible assets of borrowers, decreases loan costs because lenders are allowed to recover the tangible assets of the borrower to compensate default risk; the higher the *Tangibility*, the less banks' exposure to default risk. Third, *Profitability*, the financial performance of borrowers, also negatively associates with loan costs since better financial performance decreases the default risk. Fourth, high market-to-book (*M/B*) ratio drives down loan costs. After controlling for *Tangibility* and *Profitability,* M/B proxies for the incremental value over total book value that creditors are entitled to claim if the firm is insolvent; high M/B reduces banks' default risk exposure as similarly as high *Tangibility* does. Finally, Graham et al.(2008) indicate that *Loan size* drives down loan costs as well.

Leverage, nevertheless, increases loan costs since high-leveraged firms are more likely to default than low leveraged ones (Dhaliwal, Lee, & Fargher, 1991). Also, typically, corporations with speculative-grade bonds (*Spegrade*) have lower credit worthiness than corporations with investment-grade ones, driving up the loan costs for the former ones (Wittenberg-Moerman, 2008). I also include cash ratio since banks prefer the borrower to have high cash-holding (Harford, Klasa, & Maxwell, 2014) and firms reduce the cash holding to avoid expropriation risk (Smith, 2016).

The data for these firm-level control variables are all from Compustat. All the above variables are one year lagged. Financial services firms and utility firms are excluded.

<Insert Table A about here>

3.6. Summary statistics

Table A.1. indicates that the tests that allow within-state variations could increase the power of the tests (Smith, 2016). For instance, Table A.1. shows the conviction number of Illinois Northern is 165.52% of that of Illinois Central, justifying the argument that using the number of convictions at judicial district level rather than state level could increase the power of the tests. To address the prominent variations across districts, I follow Jared Smith (2016) to winsorize regional corruption rates at 1% and 99% level.

Table A.2. suggests that the conviction number peaked in 2008 during the 2007-2008 financial crisis. Table 1 shows the average loan spread is 222 basis points and the average loan maturity is 48 months. Besides, nearly half of the loans are secured, suggesting the lending market in the U.S. is competitive (Inderst & Mueller, 2007).

The first measurement for the price term of bank loans is raw loan spreads (*allindrawn*), Dealscan all-in spread drawn measured in basis points (bps), and the second one is *ln(allindrawn)*, the natural log of *allindrawn*.

<Insert Table 1 about here>

3.7. Univariate tests

Table 2 shows the results of univariate tests: the loan spreads in corrupt areas (the districts whose district medians of *Regional Corruption Rate* lie in the top quartile of all district medians) are higher than non-corrupt areas (the districts whose district medians of *Regional Corruption Rate* lie in the bottom quartile of all district medians); on average, *ln(allindrawn)* in corrupt areas is 0.04 bps higher than that in non-corrupt areas, 0.1% of the sample mean. Tangibility in corrupt areas is 7 percent lower than non-corrupt areas, indicating creditors will find it more difficult to recover tangible assets in corrupt areas than non-corrupt areas. These results are consistent with the "prudent banks" hypothesis that banks demand premiums on the borrowers in corrupt areas. But since both firm and loan characteristics have profound impacts on the cost of bank loans, I use multivariate regression analysis to further explore the relationship between corruption and loan costs in the next section.

<Insert Table 2 about here>

4. Results: Corruption and the cost of bank loans

All the empirical settings in this paper are subject to the assumptions below: First, since sample is restricted to data in the U.S., country-level variations in institutions and regulations are controlled. Second, since it is loan spreads rather than maturity or requirements for collaterals that vary with stronger or weaker creditor protection (BAE & Goyal, 2009; Carey & Nini, 2007). Thus, should there difference of the cost of bank loans among countries with various degrees of creditor protection, loan spreads, rather than maturity or requirements for collaterals, will reflect this difference. Third, Smith (2016) indicates that firms choose financial policies rather than headquarters reallocation to avoid extortion by local officials. Lastly, since the occurrences of different types of corruption are positively correlated with each other at a local level(Smith, 2016), *Regional Corruption Rate* is a proxy for the local culture of corruption, alleviating the concern that the DOJ has not classified the number of convictions for corruption based on corruption types. Finally, thanks to the supervision of the federal judicial system, the law enforcement is moderately homogenous across the U.S. (Glaeser & Saks, 2006; Smith, 2016).

Within each firm, loan issuance could be correlated with each other. Therefore, I cluster the standard errors by firm in each regression (Cameron & Miller, 2015); loans issued to the same firm contain less corruption related information than loans issued to different firms although unreported tables show that results still hold as I cluster errors by state and year as Smith (2016) does. To control for the systematic differences across industries and years, I include industry dummies and year dummies. I also include state dummies to control for unobservable state-level factors correlated to corruption, such as integrity or financial sophistication of state legislators (Butler et al., 2009). Moreover, I also include president dummy into regressions to control for law enforcement. Untabulated findings show that the baseline results still hold.

4.1. Multivariate analysis for loan spreads

I use the following model specifications to test the empirical implications of my hypotheses:

$$Spread = f(Corruption, firm\ characterisitcs,$$
$$loan\ characterisitcs, industry, year\ and\ location\ fixed\ effects,$$
$$loan\ type\ and\ purpose\ fixed\ effects)\ , \quad (1)$$

where spread is the all-in spread drawn (*allindrawn*) in the Dealscan database. I follow the literature on bank-lending (Bharath, Dahiya, Saunders, & Srinivasan, 2009; Ertugrul et al., 2017; Graham et al., 2008) to control for relevant firm and loan characteristics. I also include industry, year and state dummies into regression models to control for unobservable variations across industries, years and states, respectively.

Table 3 presents the estimates of previous equations using ordinary least square (OLS) regressions with firm level clustered standard errors. Results show that, consistent with the "prudent bank" hypothesis, borrowers in more corrupt areas need to pay higher spreads than less corrupt areas; the coefficients of loan spread variables, *ln(allindrawn)* and *allindrawn*, are positive and significant at 0.001 level. Specifically, one increase in the standard deviation of *Regional Corruption Rate* increases *ln(allindrawn)* by 0.022 and *allindrawn* by 4.4 bps. Most signs of the coefficients of controls are expected except that the coefficient of cash ratio is not significant. I also include president dummy into regressions to control for law enforcement. Untabulated results indicate that the findings still hold.

To illustrate the economic significance of these results, I calculate the difference of loan spread (*allindrawn*) between Alabama Southern (a corrupt district) and Wisconsin Eastern (a non-corrupt district), for the difference of the median value of the *Regional corruption rate* between these two districts is 0.498, approximating the standard deviation of *Regional Corruption Rate*. Using the coefficient of *Regional Corruption Rate* in Table 3, I find the loan spread (*allindrawn*) in Alabama Southern, *ceteris paribus*, is 2.19 bps higher than that in Wisconsin Eastern, 0.1% of the median value of loan spread (*allindrawn*).

4.2. Multivariate analysis for non-price terms

To analyze the impact of corruption on maturity and collateral requirements, I use OLS regressions with firm level clustered standard errors to estimate the following models:

$$\begin{aligned} non-price\ terms \ &= f(Corruption, firm\ characterisitcs, \\ &\quad loan\ characterisitcs, \\ &\quad industry, year\ and\ location\ fixed\ effects, \\ &\quad loan\ type\ and\ purpose\ fixed\ effects)\ , \end{aligned} \tag{2}$$

Table 4 presents results of the baseline models: the coefficients for maturity and collateral are not significantly different from zero, failed to reject the null hypothesis indicating that corruption has no impact on non-price terms.

<Insert Table 4 about here>

4.3. Address the endogeneity

Omitted variable bias could drive a spurious relationship between corruption and loan spreads. local geographic and cultural factors, such as social networks, facilitate information flow and decrease information asymmetry (Dimant & Tosato, 2018; Ertugrul et al., 2017). This decrease in information asymmetry could lower corruption levels and loan costs simultaneously (cut from a long sentence). Measurement errors will also occur if corruption takes place beyond judicial district lines. Meanwhile, corporate headquarter locations will be endogenous if firms have discretion over their headquarter location choices. Finally, the impact of local economic conditions, such as unemployment rates, could intervene in the impact of corruption on loan spreads.

To allay concerns about omitted variable bias and measurement errors, I use two instrumental variable (IV) analyses (Kennedy, 2008) and the propensity score matching technique to allay these concerns. To disentangle the impacts of local economic conditions on the cost of bank loans, I add demographic and economics characteristics, such as unemployment rates, per capita income, and population into the baseline regressions and re-estimate the models respectively. I use two instrumental variable (IV) analyses and the propensity score matching technique to allay these concerns. To disentangle the impacts of local economic conditions on the cost of bank loans, I add demographic and economics characteristics, such as unemployment rates, per capita income, and population into the baseline regressions and re-estimate the models respectively.

4.3.1 Additional control variables

Local demographic and economic conditions, such as county-level per capita income, county-level unemployment rates, state-level population, could affect the cost of bank loans. An increase in the local spending associates with faster expansion of local economy, improving the firm performance and decreasing loan costs in those areas.

<Insert Table 5 about here>

I re-estimate the regressions after adding these omitted variables into the baseline models.

Table 5, Column 1 and 3, shows that after controlling for these variables, results are barely changed: the relationship between *Regional Corruption Rate* and loan spreads remains positive and statistically significant at 0.001 level. This result suggests that the local economic condition will not affect the impact of the corruption on the loan spreads.

4.3.2 Instrumental variables method

I use two IVs for state-level corruption. The first one is the mean value of the natural log of the distance between the population and state capital (*AvgLogDistance*), and the second one is the score of public interest in corruption at the state level (*Interest by State*) (Enestor Dos Santos, 2018). In my setting, valid instrumental variables should correlate with corruption and loan costs only through corruption, and both these two instrumental variables satisfy this requirement.

Like Campante and Do (2014), I use *AvgLogDistance* to measure the degree of the isolation of the state capital in terms of its population. This spatial concentration variable is an index ranging from 0 to 1, and the higher the index, the more isolated the state capital. For instance, *AvgLogDistance* equals zero if all people live close to the state capital. Campante and Do (2014) advocate that the less concentrated the population around a state capital, the more corrupt the state. They find that isolated state capitals associate with low accountability since this isolation reduces media coverage on political issues, as well as voters' interest and knowledge in these issues, resulting in high levels of corruption.

Although positively associated with state-level corruption, *AvgLogDistance* and loan costs have an ambiguous relationship with each other because loan issuance decisions appear not to relate to how isolated the state capital is. Therefore, *AvgLogDistance* affects loan costs only through the relationship with state-level corruption (*State corruption convictions*), satisfying the exclusion restriction in instrumental variables.

The second instrumental variable, the score of public interest in state-level corruption (*Interest by state*), also satisfies this exclusion restriction. Sourced from Google Trends, I first calculate the ratio of search volume of the term "corruption" within one state to total search volume of "corruption" on Google Trends, ranging from 0 to 100. Then I adjust this ratio of local searches of "corruption" to general searches by its corresponding state-level population (Interest by State). *Interest by state* measures public attention to state-level corruption. Enestor Dos Santos (2018) observes that a higher score indicates more attention paid to the corruption in one state, and usually associates with higher corruption occurrences there.

Complementing *AvgLogDistance*, one objective measure, *Interest by state,* indicates the public's evaluation of the local government in terms of corruption. Thus, a higher score usually associates with a high level of corruption. Bank lending decisions, however, do not seem to relate to public attention to state-level corruption. Therefore, *Interest by State* affects the cost of bank loans only through state-level corruption (*State corruption convictions*).

Table 6 shows the results using these two IVs to conduct instrumental variable analyses for the relationship between *Regional Corruption Rate* and *ln(allindrawn),* as well as *allindrawn*, respectively. Regressions include all aforementioned control and dummy variables.

<Insert Table 6 about here>

I use *AvgLogDistance* to obtain exogenous errors for the first instrumental variable analysis. The data for *AvgLogDistance* is up to 1970, and two *AvgLogDistance* values are available during my sample period. I match the first one to financial variables from fiscal year 1991 to 2000 and the second one to fiscal year 2001 to 2011. To be consistent with Campante et al., (2014), I anticipate that *AvgLogDistance* is positively related to corruption.

The unreported result of the first stage regression shows that the relationship between *State corruption convictions* and *AvgLogDistance* is significantly positive at 0.01 level. Table 6 shows, while the significance level of the coefficient *of State corruption convictions* decreases from 0.001 to 0.05 in the second stage regression, the positive relationship between corruption and loan spreads still holds even in light of the restricted sample, supporting the "prudent banks" hypothesis. Particularly, one standard deviation increase in *State corruption convictions* increases *ln(allindrawn)* by 0.358 and *allindrawn* by 69.791 basis points, which corresponds to 6.98% and 31.483% of the sample means, respectively.

Then I use the public interest in state-level corruption (*Interest by state*) in the second instrumental-variable analysis. Table 6, Column 4, shows, corruption positively associates with loan spread ("prudent banks" hypothesis). Meanwhile, the unreported result of the first step test indicates that *Interest by State* is positively related to *State corruption convictions*, and the coefficient is significant at 0.01 level (see Enestor Dos Santos, 2018 for similar findings). All of the results named in this section, including the *AvgLogDistance*, also reject the null hypotheses of exogeneity and weak IV test, suggesting that both *AvgLogDistance* and *Interest by State* serve as valid instruments for corruption in terms of the cost of bank loans.

4.3.3. Propensity score matching analysis

To further test the robustness of baseline results, I use the propensity score matching (PSM) technique to address the endogeneity in a general way[5].

I assign each loan-year in the top 25% of *Regional Corruption Rate* into a treatment group and bottom 25% of *Regional Corruption Rate* into a control group. Then I match observations of each group based on lagged covariates in baseline models. The algorithm for PSM is the ten nearest neighbors with common support.

<Insert Table 7 about here>

Table 7 shows (consistent with the “prudent banks” hypothesis) corruption increases loan costs. Specifically, Specifically, Table 7, Panel A, shows that the loans spread (*allindrawn*)in corrupt areas (treated group) is higher than noncorrupt areas (control group); the average causal effect of *Regional Corruption Rate* on loan spread is 11.44bps (*allindrawn*), around 5.2% of the

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[5] Smith does similar thing in his paper " US Political Corruption and Firm Financial Policies. "

sample mean. This magnitude doubles that in baseline models. The coefficients are significant at 0.05 level.

4.4. Alternative measures for corruption

The aforementioned results give tentative evidence that corruption increases the cost of bank loans. To justify this inference, I follow Smith (2016) in using one survey measure and three alternative measures calculated based on conviction numbers to re-estimate baseline models after replacing *Regional Corruption Rate* with these measures respectively.

A commonality of the foregoing studies is the focus on examining the impact of corruption on loan costs from a quantitative perspective. An important caveat comes with these results: the multivariate analyses in this section produce conservative estimates for the impact of corruption on the cost of bank loans. *Regional Corruption Rate* only measures the actual corruption offenses that are convicted. Therefore, to add another dimension to the *Regional Corruption Rate* analysis, I use the State Integrity Investigation (*SII*) to measure the likelihood of corruption occurrences based on perceptions of government integrity experts (Smith, 2016). As a qualitative variable, *SII* provides dimensions the quantitative variable (*Regional Corruption Rate*) hardly grasps: *SII* indicates the threat of corruption (Smith, 2016) or the trend of corruption occurrences rather than the number of convicted cases only. Therefore, I use *SII* to address the concern that some corruption offenders might not be convicted. These survey data are from the State Integrity Project which was conducted by The Center for Public Integrity in 2012.

<Insert Table 8 about here>

SII grades the state-level corruption based on a range of corruption related categories. The higher the numerical grade, the less corrupt the state.

Different from Smith (2016), which uses the *SII* data compiled in 2009 for the sample period 2000 -2009, I use updated *SII* data in 2012 for the whole sample. Then I run the same regressions employed in Table 3 and Table 4 after replacing *Regional Corruption Rate* with *SII*. Table7, Column 1 and 2, show corruption premiums are imposed on loans. Specifically, an increase of one standard deviation of *SII* is associated with a decrease in *allindrawn* by 12.6 basis points, around 6.3% of the sample means and three times the magnitudeof the coefficients in the baseline models.

After I use the *SII* data to examine the relationship between the corruption and the cost of bank loans, I include three alternative measures that are also calculated based on conviction numbers into regressions to ensure the construction of *Regional Corruption Rate* has no impact on baseline results.

Butler, et al. (2009) use conviction numbers to develop an indicator variable: For each state-year, the indicator equals 1 if the observation is in the top quartile of conviction number in year t, and zero otherwise. Ithen multiply this indicator variable by its corresponding *State corruption convictions* to generate the first alternative measurement (*ConvictionsTopQuartile*). Still, the results support the "prudent banks" hypothesis. Table 7 shows that the coefficients of the *ConvictionsTopQuartile* is significantly positive at 0.05 level although the magnitude and economic significance of it is smaller than that of *Regional Corruption Rate* in baseline models.

I use weighted conviction variable (*WAC*) Garcia and Norli (2012) develop as the second alternative quantitative variable of corruption. For time t, I multiply the ratio of the number of a firm's operations in each state to the total number of the firm's operations by its corresponding *State corruption convictions*. I then sum the multiplied ratio to gain *WAC* in order to measure the overall corruption risk a firm faces rather than its corporate headquarters. Consistent with Smith (2016), who indicates the local culture of corruption isstable, *WAC* is resistant to changes in years and locations; thus, I drop state and year dummies from this adjusted regression because using the average values based on state or year dummies is meaningless.

The last alternative measure I use is the raw conviction numbers divided by 1000 as Smith (2016) does. I then match each corporate headquarters to this number, as I do in baseline models, but drop state dummies for the robustness check. The coefficients of both corruption measures are positive at 0.01 level, and the magnitudes of these coefficients are larger than the magnitudes of the coefficients of *Regional Corruption Rate* in baseline regression models.

Overall, by allaying the concern of omitted variable bias, these tests strengthen the causal relationship between corruption and loan spreads. An omitted variable, if it exists, has to correlate with unemployment rates, population, debt and equity issuances, population concentration, public interest in corruption at the state level, State Integrity Score, and three alternative corruption measures with or without local fixed effects. It is also not able to be dealt with by the propensity score matching technique.

4.5. Adjust for geographic concentration

It's easier for politicians to extort a firm with more operation branches in their judicial districts.That firms compete for government permissions such as licenses (Krueger, 1974) grants politicians bargaining power to seek rents; this bargaining power is strongest when the firm only operates in their jurisdiction districts, maximizing the firm's exposure to corruption risks (Lee, Oh, & Eden, 2010). Therefore, banks could demanddiversification premiums on the borrower: the more geographically concentrated the borrower is, the higher "corruption premiums" banks charge. One caveat, in terms of the interpretations of the outputs in this session, is that the geographic concentration of corporate headquarters could be an outcome variable as firms could shift to non-corrupt districts to avoid expropriation from corrupt officials (Smith, 2016).

I use the geographic operation data from Garcia and Norli (2012) to generate the geographic concentration variable at the firm level (*GC*). Using 10k files, Garcia and Norli (2012) count the number of the appearances of the states in which the firm locates in 10k files. Like Smith (2016), I divide the counts of the firm's headquarter-state by the counts of all other states in which the firm's branch operations locate to get *GC*. The higher the *GC*, the more geographically concentrated the firm. For instance, if *GC* equals 1, the firm only operates in one state. The sample period (1993-2008) of the data on geographic concentration restricts my final sample size to 6908 loan-year observations

<Insert Table 9 about here>

Table 9 shows the results of regressions including the interaction term of *GC* and *Regional Corruption Rate*. It also include interaction terms of *GC* and firm characteristics since *GC* affects firms' financial performances (Smith, 2016). That the significance of the coefficients of the *Regional Corruption rate* disappear is rational since a borrower does not need to pay a corruption premium if none of its operations are in the state where itsheadquarters is located. The positive signs of the coefficient of the interaction term of *GC* and *Regional Corruption Rate* are consistent with the prediction that a decrease in risk diversification results in higher loan spreads; the better the firm diversifies its corruption risk geographically, the lower the corruption premium the firm need to pay. The statistical insignificance of this coefficient could result from the large standard errors driven by the restricted sample size that shrinks from around 22,000 observations for baselinemodels to around 7,000 observations for the models including *GC*.

The unreported tests also show that the geographic diversification of the firm barely changes the relationship between corruption and non-price terms. This is consistent with the aforementioned results, although we should be cautious about interpreting the findings because of the restricted sample size and the simultaneity between the firm's headquarters location choice and corruption.

4.6. Bank-firm relationship

I further explore whether banks impose the corruption premiums merely out of low animal spirits (Akerlof & Shiller, 2010) or based on the rational calculation of corruption-related uncertainty. These findings are consistent with information asymmetry theory (Akerlof, 1970): the amelioration of information asymmetry decreases corruption premiums; banks impose the corruption premiums as rational utility maximizers (Akerlof, 1970).

I use the *loan-to-asset* ratio as a proxy for the borrower-lender relationship as Dass and Massa (2009) do. This variable is the ratio of the natural log of loan size (*loan size*) to the natural log of lagged asset averaged over loan tenor (*Asset_tenor*). The higher the *loan-to-asset ratio* of the borrowers, the more important the loan for the firms, resulting in a stronger borrower-lender relationship that facilitates banks' information-gathering process, and reducing the information asymmetry between lenders and borrowers accordingly. All controls have also been averaged by *Asset_tenor*. To compare the results with those of baseline models, I use the same corruption measurement (*Regional Corruption Rate*) and include all of the control and dummy variables that are used in baseline regressions. In addition to this, in an unreported table, I average the conviction rates over loan tenor as an alternative measurement for the *Regional Corruption Rate* and re-estimate the regressions, and the results are nearly unchanged.

<Insert Table 10 about here>

Table 10, shows the significance of the coefficients of *Regional Corruption Rate* disappears; the coefficient of the interaction term of *Regional Corruption Rate* and *loan-to-asset ratio* are not significant while the signs of *loan-to-asset ratio* are significantly negative at 0.01

level. This indicates that, consistent with the “prudent hypothesis” and echoed the established fact that strong lender-borrower relationship decreases the information asymmetry and loan rates accordingly (Dell’Ariccia & Marquez, 2004). The results also suggest the resultant low loan rates are caused by the reduction of information asymmetry associated with corruption. Therefore, it is the uncertainty related to corruption, rather than “animal spirits”, that drives up the loan costs; banks act as rational utility maximizers (Akerlof, 1970) in response to political corruption.

Table 10, shows the significance of the coefficients of *Regional Corruption Rate* disappears; the coefficient of the interaction term of *Regional Corruption Rate* and *loan-to-asset ratio* are not significant, while the signs of *loan-to- asset ratio* are significantly negative at 0.01 level. As a result, these findings are consistent with the “prudent hypothesis” and echoed by the established fact that strong lender-borrower relationship decreases the information asymmetry and loan rates accordingly (Dell’Ariccia & Marquez, 2004). The results also suggest the resultant low loan rates are caused by the reduction of information asymmetry associated with corruption. Therefore, it is the uncertainty related to corruption, rather than “animal spirits”, that drives up the loan costs; banks act as rational utility maximizers (Akerlof, 1970) in response to political corruption.

5. Conclusions

Combating corruption has centered on law enforcement instead of relying on market discipline. By establishing the stylized fact that corruption causes spillover effects on loans, this paper, however, suggests that market discipline could complement law enforcement to reduce the potential negative impact of corruption on lending markets.

Ceteris paribus, firms in corrupt areas pay higher loan spreads than firms in non-corrupt areas. This relationship is robust and consistently indicative from both quantitative and qualitative perspectives: results hold including additional variables related to macroeconomic conditions to two instrumental variable analyses, as well as propensity score matching technique and regressions with one survey and three alternative measures of corruption.

Specifically, I use IV analysis to address omitted variable bias plus propensity score matching technique to address the endogeneity in general, respectively. The first IV I use is the mean value of the natural log of the distance between the population and capital in the state (Campante & others, 2014) and the second one is the public interest in state-level corruption, calculated based on Google Trend data.

All results support the “prudent hypothesis." Particularly, the effect sizes of the impacts of corruption on the cost of bank loans in IV analyses are larger than they are in baseline models. These impacts diminish after including *loan-to-asset ratio* that proxies for lender-borrower relationship into regressions, indicating the uncertainty associated with corruption, rather than sheer “animal spirits”, engenders the corruption premium. Banks act as rational expected utility maximizers in response to corruption: the amount of this premium is based on the extent to which firms manage to mitigate their information asymmetry in specific ways - such as building strong relationships with banks.

Overall, on the one hand, these results suggest that corruption “sands the wheel of economy growth”(Méon & Sekkat, 2005) in a twofold manner: corruption erects obstacles for firms to borrow from banks by increasing loan spreads, and in turn, constrains the economic expansion given the prominent role banks play in the local economy development. That banks count on the relationship with borrowers to mitigate the information asymmetry of the borrowers in corrupt areas increases the likelihood for the establishment of an oligarchy or even monopoly in these areas, impeding the effective competition in local markets.

On the other hand, these results suggest that lender-borrowers relationships produce information as other studies do (Prilmeier, 2017); rather than contract with a firm while knowing about nepotism and cronyism, banks collect the information to make loan decisions in order to pursue their self-interests. This characteristic information-gathering of the banking industry is more likely to lead to an efficient resource allocation.

Thus, to reduce the potential negative impact of corruption on the economy, financial disclosure policies in mitigating the information asymmetry between borrowers and lenders are in demand.

Since bank loans transmit information to the capital market (Lummer & McConnell, 1989), further research could focus on the stock market reactions to the ripple effects of the corruption premiums that banks impose on loans. Policy implications will also be enriched by exploring whether the spillover effects on loan costs discipline local corruption, ex post.

References

Addoum, J. M., Kumar, A., Le, N., & Niessen-Ruenzi, A. (2019). Local bankruptcy and geographic contagion in the bank loan market. *Available at SSRN 2637026*.

A., & Di Tella, R. (1999). Rents, competition, and corruption. American Economic Review, 89(4), 982–993.

Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics, 84(3), 488–500.

Akerlof, G. A., & Shiller, R. J. (2010). Animal spirits: How human psychology drives the economy, and why it matters for global capitalism. Princeton university press.

Bai, J., Jayachandran, S., Malesky, E. J., & Olken, B. A. (2013). Does economic growth reduce corruption? Theory and evidence from Vietnam.

Berger, A. N., & Udell, G. F. (1990). Collateral, loan quality and bank risk. Journal of Monetary Economics, 25(1), 21–42.

Bharath, S. T., Dahiya, S., Saunders, A., & Srinivasan, A. (2009). Lending relationships and loan contract terms. The Review of Financial Studies, 24(4), 1141–1203.

Blackwell, D. W., & Winters, D. B. (1997). Banking relationships and the effect of monitoring on loan pricing. Journal of Financial Research, 20(2), 275–289.

Butler, A. W., Fauver, L., & Mortal, S. (2009). Corruption, political connections, and municipal finance. The Review of Financial Studies, 22(7), 2873–2905.

Cameron, A. C., & Miller, D. L. (2015). A practitioner’s guide to cluster-robust inference. Journal of Human Resources, 50(2), 317–372.

Campante, F. R., & others. (2014). Isolated capital cities, accountability, and corruption: Evidence from US states. The American Economic Review, 104(8), 2456–2481.

Christos Lycos. (2015). The Spanish Real Estate Crisis: A Historical Perspective. In Working Paper. Retrieved from https://www.academia.edu/11371302/The_Spanish_Real_Estate_Crisis_A_Historical_Perspective

Dass, N., & Massa, M. (2011). The impact of a strong bank-firm relationship on the borrowing firm. The Review of Financial Studies, 24(4), 1204–1260.

Dell’Ariccia, G., & Marquez, R. (2004). Information and bank credit allocation. Journal of Financial Economics, 72(1), 185–214.

Dhaliwal, D. S., Lee, K. J., & Fargher, N. L. (1991). The association between unexpected earnings and abnormal security returns in the presence of financial leverage. Contemporary Accounting Research, 8(1), 20–41.

Dimant, E., & Tosato, G. (2018). Causes and effects of corruption: what has past decade's empirical research taught us? A survey. Journal of Economic Surveys, 32(2), 335–356.

Ding, H., Fang, H., Lin, S., & Shi, K. (2017). Equilibrium consequences of corruption on firms: Evidence from China's anti-corruption campaign.

Dischinger, M., Knoll, B., & Riedel, N. (2014). The role of headquarters in multinational profit shifting strategies. International Tax and Public Finance, 21(2), 248–271.

Durnev, A., & Fauver, L. (2008). Stealing from thieves: Firm governance and performance when states are predatory.

Edwards, F. R., & Heggestad, A. A. (1973). Uncertainty, market structure, and performance: The Galbraith-Caves hypothesis and managerial motives in banking. The Quarterly Journal of Economics, 87(3), 455–473.

Enestor Dos Santos. (2018). Guest Post–Assessing Corruption with Big Data. Retrieved from https://globalanticorruptionblog.com/2018/07/12/guest-post-assessing-corruption-with-big-data/ website: https://globalanticorruptionblog.com/2018/07/12/guest-post-assessing-corruption-with-big-data/

Ertugrul, M., Lei, J., Qiu, J., & Wan, C. (2017). Annual report readability, tone ambiguity, and the cost of borrowing. Journal of Financial and Quantitative Analysis, 52(2), 811–836.

Fisman, R., & Gatti, R. (2002). Decentralization and Corruption. Public Choice, 113(1), 25–35.

Garcia, D., & Norli, Ø. (2012). Geographic dispersion and stock returns. Journal of Financial Economics, 106(3), 547–565.

Graham, J. R., Li, S., & Qiu, J. (2008). Corporate misreporting and bank loan contracting. Journal of Financial Economics, 89(1), 44–61.

Guriev, S. (2004). Red tape and corruption. Journal of Development Economics, 73(2), 489–504.

Harford, J., Klasa, S., & Maxwell, W. F. (2014). Refinancing risk and cash holdings. The Journal of Finance, 69(3), 975–1012.

Houston, J. F., Jiang, L., Lin, C., & Ma, Y. (2014). Political connections and the cost of bank loans. Journal of Accounting Research, 52(1), 193–243.

Inderst, R., & Mueller, H. M. (2007). A lender-based theory of collateral. Journal of Financial

Economics, 84(3), 826–859.

Jain, P. K., Kuvvet, E., & Pagano, M. S. (2014). Corruption's impact on liquidity, investment flows, and cost of capital. Investment Flows, and Cost of Capital (February 14, 2014).

Kennedy, P. (2008). A guide to econometrics. Malden, MA: Blackwell Pub.

Keynes, J. M. (1937). The general theory of employment. The Quarterly Journal of Economics, 51(2), 209–223.

Leff, N. H. (1964). Economic development through bureaucratic corruption. American Behavioral Scientist, 8(3), 8–14.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. American Economic Review, 90(2), 426–432.

Méon, P.-G., & Sekkat, K. (2005). Does corruption grease or sand the wheels of growth? Public Choice, 122(1–2), 69–97.

Pavel, C. A., Phillis, D., & others. (1987). Why commercial banks sell loans: An empirical analysis. Federal Reserve Bank of Chicago Proceedings, (152).

Prilmeier, R. (2017). Why do loans contain covenants? Evidence from lending relationships. Journal of Financial Economics, 123(3), 558–579.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. The Journal of Finance, 47(4), 1367–1400.

Ruccio, D. F., Amariglio, J., & Amariglio, J. J. (2003). Postmodern moments in modern economics. Princeton University Press.

Schenone, C. (2010). Lending Relationships and Information Rents: Do Banks Exploit Their Information Advantages? The Review of Financial Studies, 23(3), 1149–1199.

Smith, J. D. (2016). US political corruption and firm financial policies. Journal of Financial Economics, 121(2), 350–367.

Stigler, G. J. (1971). The theory of economic regulation. The Bell Journal of Economics and Management Science, 3–21.

Stulz, R. M. (2005). The limits of financial globalization. The Journal of Finance, 60(4), 1595–1638.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. The Journal of Finance, 62(2), 629–668.

Sun, C., Xu, J., Weill, L., Fungacova, Z., Solanko, L., Hasan, I., … Aisen, A. (2018). Anti-

Corruption and Bank Lending. Working Paper.

Taleb, N. (2005). Fooled by randomness: The hidden role of chance in life and in the markets (Vol. 1). Random House Incorporated.

Vashishtha, R. (2014). The role of bank monitoring in borrowersʹ discretionary disclosure: Evidence from covenant violations. Journal of Accounting and Economics, 57(2), 176–195.

Wittenberg-Moerman, R. (2008). The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market. Journal of Accounting and Economics, 46(2–3), 240–260.

tates. *The American Economic Review*, *104*(8), 2456–2481.

Ding, H., Fang, H., Lin, S., & Shi, K. (2017). *Equilibrium consequences of corruption on firms: Evidence from China's anti-corruption campaign*.

Enestor Dos Santos. (2018). Guest Post–Assessing Corruption with Big Data.

Garcia, D., & Norli, Ø. (2012). Geographic dispersion and stock returns. *Journal of Financial Economics*, *106*(3), 547–565.

Graham, J. R., Li, S., & Qiu, J. (2008). Corporate misreporting and bank loan contracting. *Journal of Financial Economics*, *89*(1), 44–61.

Houston, J. F., Jiang, L., Lin, C., & Ma, Y. (2014). Political connections and the cost of bank loans. *Journal of Accounting Research*, *52*(1), 193–243.

Leff, N. H. (1964). Economic development through bureaucratic corruption. *American Behavioral Scientist*, *8*(3), 8–14.

Stigler, G. J. (1971). The theory of economic regulation. *The Bell Journal of Economics and Management Science*, 3–21.

Sufi, A. (2007). Information asymmetry and financing arrangements: Evidence from syndicated loans. *The Journal of Finance*, *62*(2), 629–668.

Sun, C., Xu, J., Weill, L., Fungacova, Z., Solanko, L., Hasan, I., … Aisen, A. (2018). Anti-Corruption and Bank Lending. *Working Paper*.

Appendix : Variable Definitions

Corruption variables	**Definitions**
Regional corruption rate (Conviction per 100,000):	The ratio of the conviction number to the population on zip code level times 100,000
State corruption convcitions	The ratio of the conviction number to the population at the state level
Corruption perception measure (Butler et al. (2009)):	The score measures house reporter's perceptions toward state level corruption from the survey conducted in 1999. A high score indicates higher corruption in the state from house reports' perspetives.
Raw convictions	On district level, the raw conviction number *1000 to avert tabulate extreme magnitude for coefficients.
Weighted corruption measure (Garcia and Norli, 2012)	Defined as $\sum_{1}^{i}$ (A firm's operation ratio in each state i *conviction number in state i)
SII	The score in State integrity investigation complied by Center for Public Integrity, Global Integrity and Public Radio International in 2012. The higher the score, the less corrupted the state.
Geography concentration variable	
RO	The number of the firm's operations in each state (judicial district) over the total number of the firm's operations
GC	Defined as the ratio of the operations in the state where the firm's headquarter located(Garcia & Norli, 2012). The higher the ratio, the more geography concentrated the firm.
Instrumental variables	
Gravity-based Centered Index for Spatial Concentration (GCISC)	The variable measures the population distribution around the state capital. Specifically, the measure is defined as $\varpi * \sum$ (the inverse of the squared distance from any point in the state to state capital), where ϖ is the weight. In the paper, the measurement is normalized by state size (Campante and Do, 2009). Specifically, higher the GCISC value, the closer the population distribution to the capital in the state.
AveLogDistance	$1 -$GCISC(Campante & others, 2014)
State of Interest	The ratio of search volume of corruption to total search volume on google, sourced from google trend.
The cost of bank loans variables	
The price term for the cost of bank loans	
allindrawn	The total cost of a drawn loan in bps
ln(allindrawn)	The natural logarithm of the total cost for a drawn loan in bps

The non-price terms for the cost of bank loans	
ln(maturity)	The natural logarithm of loan maturity in months
Security	A dummy variable indicating whether the loan is required of collateral or not. Specifically, the dummy variable equals one if the loan is secured by collaterals and 0 otherwise
Firm level control variables	
Log(at)	The natural logarithm of a firm's total asset
M/B	Market value of equity divided by book value of equity on firm level
Leverage	Defined as (A firm's book value of long-term debt/ A firm's total assets)
Profitability	Defined as [A firm's PP&E(plants property and equipment/ A firm's total assets at book value)](Campello and Giambona (2013)).
Cash ratio	Defined as (A firm's cash and cash equivalents/ A firm's total assets)
Spregrade	A dummy variable indicating whether a firm's bond is rated as investment grade (credit rating is above BBB-by Standard & Poor's Financial Services) or not. Specifically, the dummy variable equals one if the firm's bond is rated as non-investment grade and zero otherwise.
Control variables for bank loan characteristics	
Loan size($millions)	The quantity of a loan measured in millions of dollars
Additional control variables	
Net debt issuance	Defined as (dltis-dltr). Both of two variables are from Compustat
Net equity issuance	Defined as (sstk-prstkc). Both of two variables are from Compustat
ln(per capita income)	Defined as ln(per capita income on county level). The county-level per capita income data is from U.S. census.
ln(population)	Defined as ln(population on state level). The state population data is from U.S. census.
Unemployment rate	Unemployment rate on county level
Bank-firm relationship variable	
loan-to-asset ratio	Loan size/at.The borrower’s asset is the preloan average of its asset. Loan size is from Dealscan database and at is from Compustat.

Table A.1. Summary statistics for *Regional Corruption Rate* by U.S. federal judicial districts
This table shows the summary statistics of *Regional Corruption Rate* at federal judicial district level. The sample covers period 1990-2014 and data are sorted by median value of *Regional Corruption Rate*.

DISTRICT	Median	Mean	Standard Deviaiton	Minimum	Maximum
DISTRICT OF COLUMBIA	6.874	7.418	4.056	1.973	15.782
LOUISIANA MIDDLE	4.275	4.527	3.398	0.138	10.551
ALABAMA MIDDLE	4.122	4.157	2.766	0.101	7.764
SOUTH DAKOTA	3.782	4.879	3.991	0.145	11.941
FLORIDA NORTHERN	3.205	3.056	1.649	0.220	6.381
ILLINOIS SOUTHERN	3.142	2.893	1.974	0.080	6.368
MISSISSIPPI NORTHERN	2.978	3.471	2.676	0.097	7.658
WEST VIRGINIA	2.856	3.162	2.321	0.097	8.341
NORTH DAKOTA	2.838	4.896	3.836	0.135	12.906
NEW MEXICO	2.696	2.367	1.589	0.058	5.050
TENNESSEE EASTERN	2.426	2.174	1.193	0.049	3.962
MAINE	2.343	2.474	1.891	0.077	6.152
ALABAMA SOUTHERN	2.263	2.799	3.058	0.119	10.554
ALASKA	2.231	3.290	3.636	0.151	11.487
GEORGIA SOUTHERN	2.162	2.129	2.087	0.071	7.154
DELAWARE	2.143	3.344	3.573	0.107	10.865
HAWAII	2.104	2.483	2.043	0.071	6.985
IDAHO	2.084	2.094	1.945	0.064	6.009
MISSOURI WESTERN	2.063	1.616	1.128	0.032	3.291
OKLAHOMA NORTHER	2.047	2.554	1.913	0.104	8.115
KENTUCKY WESTERN	1.903	1.692	1.185	0.049	3.827
MONTANA	1.875	2.802	2.789	0.104	8.032
RHODE ISLAND	1.824	2.928	2.378	0.093	7.224
ARKANSAS EASTERN	1.769	2.043	1.642	0.065	4.858
TENNESSEE MIDDLE	1.699	1.666	1.490	0.042	3.893
INDIANA NORTHERN	1.561	1.662	1.143	0.118	3.596
NEVADA	1.558	1.672	1.497	0.038	4.532
WISCONSIN EASTERN	1.514	1.420	0.883	0.065	2.456
GEORGIA MIDDLE	1.463	1.702	1.418	0.050	4.082
LOUISIANA WESTERN	1.456	1.882	1.446	0.097	4.047
LOUISIANA EASTERN	1.386	1.493	0.790	0.181	3.690
CALIFORNIA SOUTHERN	1.375	1.286	0.851	0.030	2.546
ILLINOIS CENTRAL	1.339	1.452	1.243	0.045	3.532
INDIANA SOUTHERN	1.326	1.218	0.672	0.057	2.231
NORTH CAROLINA MIDDLE	1.313	1.263	1.036	0.034	3.251
PENNSYLVANIA WESTERN	1.309	1.061	0.718	0.050	2.063
TEXAS EASTERN	1.223	1.261	0.892	0.027	3.523

KANSAS	1.121	1.247	0.943	0.036	2.857
CONNECTICUT	1.118	1.165	0.832	0.028	2.328
MINNESOTA	1.107	1.018	0.554	0.019	1.946
NORTH CAROLINA EASTERN	1.078	1.079	0.794	0.032	2.846
KENTUCKY EASTERN	1.021	1.424	1.314	0.108	4.366
TENNESSEE WESTERN	1.013	1.990	1.785	0.193	5.036
IOWA SOUTHERN	1.011	1.266	1.568	0.062	4.890
NEBRASKA	0.977	1.001	1.094	0.057	4.265
MISSISSIPPI SOUTHERN	0.976	1.890	1.682	0.053	5.113
OKLAHOMA EASTERN	0.937	2.884	3.538	0.137	10.976
SOUTH CAROLINA	0.904	0.942	0.656	0.023	2.001
VIRGINIA WESTERN	0.892	1.306	1.100	0.044	3.737
OKLAHOMA WESTERN	0.806	1.436	1.479	0.055	4.110
UTAH	0.786	1.078	1.138	0.041	3.469
WISCONSIN WESTERN	0.775	0.986	1.034	0.044	2.978
OREGON	0.767	0.763	0.658	0.028	1.910
PENNSYLVANIA MIDDLE	0.725	1.210	0.985	0.030	2.751
NEW YORK SOUTHERN	0.689	0.840	0.509	0.177	1.905
VIRGINIA EASTERN	0.673	0.739	0.446	0.154	1.743
NORTH CAROLINA WESTERN	0.658	1.030	0.978	0.033	3.392
NEW YORK NORTHER	0.623	1.017	0.922	0.029	2.470
NEW YORK WESTERN	0.603	1.057	0.863	0.106	2.497
ALABAMA NORTHERN	0.561	0.859	0.773	0.042	3.148
WASHINGTON WESTERN	0.559	0.714	0.612	0.040	1.798
MISSOURI EASTERN	0.556	0.923	0.904	0.075	2.851
ARIZONA	0.519	0.773	0.620	0.038	2.020
ILLINOIS NORTHER	0.510	0.527	0.244	0.171	0.966
PENNSYLVANIA EASTERN	0.494	0.510	0.243	0.059	1.088
MARYLAND	0.487	0.600	0.408	0.020	1.431
OHIO NORTHERN	0.477	0.560	0.319	0.122	1.416
COLORADO	0.474	0.720	0.727	0.026	2.514
WYOMING	0.426	3.099	4.144	0.171	15.013
FLORIDA SOUTHERN	0.420	0.589	0.405	0.093	1.422
GEORGIA NORTHERN	0.412	0.590	0.523	0.043	1.944
TEXAS SOUTHERN	0.402	0.453	0.309	0.041	1.473
TEXAS WESTERN	0.395	0.634	0.554	0.060	1.908
TEXAS NORTHERN	0.373	0.482	0.385	0.020	1.461
CALIFORNIA NORTH	0.372	0.490	0.315	0.148	1.139
NEW JERSEY	0.369	0.430	0.197	0.128	0.976
OHIO SOUTHERN	0.363	0.504	0.467	0.017	1.480
MICHIGAN WESTERN	0.355	0.844	0.891	0.029	2.631

VERMONT	0.345	2.077	2.494	0.161	8.212
MASSACHUSETTS	0.324	0.443	0.381	0.033	1.452
CALIFORNIA EASTERN	0.273	0.330	0.204	0.038	1.103
NEW YORK EASTERN	0.261	0.358	0.290	0.037	0.991
FLORIDA MIDDLE	0.260	0.319	0.266	0.031	1.139
WEST VIRGINIA NORTHERN	0.257	1.863	2.278	0.121	8.063
CALIFORNIA CENTRAL	0.238	0.271	0.119	0.089	0.536
MICHIGAN EASTERN	0.233	0.377	0.371	0.031	1.200
ARKANSAS WESTERN	0.173	0.840	1.201	0.076	4.621
IOWA NORTHERN	0.167	1.258	1.452	0.082	5.070
WASHINGTON EASTERN	0.157	1.598	2.270	0.065	7.570
NEW HAMPSHIRE	0.152	0.639	1.063	0.075	4.012

Table A.2. Summary statistics for *Regional Corruption Rate* by fiscal year
This table shows the summary statistics of *C Regional Corruption Rate* from fisical year 1990 to 2014.
Data are sorted by median value of *Regional Corruption Rate*.

Year	Median	Mean	Standard Deviation	Minimum	Maximum
2008	1.272	1.997	2.480	0.038	11.355
1999	1.259	1.801	1.954	0.047	11.753
2000	1.258	1.747	1.694	0.032	8.220
2003	1.041	1.523	1.462	0.037	7.643
2007	1.006	1.646	1.887	0.051	9.401
2002	0.994	1.808	2.145	0.041	8.705
2011	0.949	1.710	2.153	0.028	9.380
1998	0.948	1.924	2.589	0.031	13.808
1990	0.933	1.791	2.322	0.020	11.941
2013	0.930	1.570	1.794	0.029	8.063
1997	0.923	1.798	2.160	0.026	10.554
2006	0.856	1.565	1.977	0.036	8.659
2005	0.813	1.719	2.497	0.023	15.013
2012	0.754	1.730	2.231	0.019	10.976
2001	0.733	1.470	2.012	0.038	9.564
2010	0.712	1.609	2.278	0.017	11.487
2009	0.709	1.297	1.621	0.068	9.516
1995	0.683	1.697	2.398	0.020	15.782
1994	0.678	1.562	2.346	0.049	13.629
1993	0.665	1.688	2.056	0.028	10.865
1991	0.664	1.344	1.465	0.020	6.152
2014	0.616	1.315	1.607	0.029	8.480
2004	0.570	1.373	1.782	0.028	8.015
1996	0.561	1.602	2.093	0.026	10.551
1992	0.533	1.361	2.173	0.038	14.893

Table 1. Summary statistics

This table shows the summary statistics of *Regional Corruption Rate* and main control variables that have positive asset value. The sample contains 22816 loan-year observations during 1991-2014. Financial services firms (SIC 6000-6999) and utility firms (SIC 4900-4999) are excluded. Missing values of firm-level control variables reduce the sample size. All variables are defined in Appendix A.

	N	Mean	Median	Standard Deviation	Minimum	Maximum
Corruption conviction	22816	0.492	0.788	1.012	0.017	13.629
allindrawn	22816	200.000	220.011	143.360	17.500	750.000
ln(allindrawn)	22816	5.298	5.128	0.819	2.862	6.620
ln(maturity)	22816	4.025	3.680	0.688	1.609	4.644
log(at)	22816	7.163	7.111	1.957	2.177	11.400
M/B	22816	1.361	1.583	0.767	0.676	5.030
Leverage	22816	0.251	0.285	0.240	0.000	1.259
Profitability	22816	0.033	0.010	0.124	-0.636	0.239
Tangibility	22816	0.226	0.298	0.241	0.009	0.922
Loan size	22816	18.603	18.390	1.758	13.816	21.822
Cash ratio	22816	0.055	0.087	0.095	0.000	0.480
Spegrade	22816	1.000	0.802	0.399	0.000	1.000
Security	22816	0.000	0.392	0.488	0.000	1.000
Day364Facility dummy	22816	0.000	0.077	0.266	0.000	1.000
TermLoan dummy	22816	0.000	0.300	0.458	0.000	1.000
RevolverTermloan dummy	22816	0.000	0.016	0.126	0.000	1.000
DebtRepay dummy	22816	0.000	0.153	0.360	0.000	1.000
Takeover dummy	22816	0.000	0.108	0.310	0.000	1.000
WorkCap dummy	22816	0.000	0.178	0.383	0.000	1.000

Table 2. Univariate Comparison between corrupt areas and non-corrupt area

This table shows the results ofunivariate tests. The sample covers period 1991-2014. Financial services firms (SIC 6000-6999) and utility firms (SIC 4900-4999) are excluded. T-statistics is calculated by firms' sample mean of each variable.The last column shows difference of means test (t-test). Firms are assigned to the corrupt (non-corrupt) group if the district median of the judical district their headquarters locate falls in the top (bottom) quartile of all district medians. The sample covers time period 1991-2014. All variables are defined in Appendix A. ***, **, * significance level at 1%, 5% and 10%, respectively.

	Corrupt	Non-corrupt	t-statistic difference in means
ln(allindrawn)	5.130	5.085	1.702*
allindrawn	220.285	214.213	1.330
ln(maturity)	3.680	3.677	0.123
Cash ratio	0.088	0.074	4.467***
log (at)	7.118	7.026	1.475
M/B	1.582	1.606	-0.983
Leverage	0.285	0.284	0.184
Profitability	0.009	0.015	-1.362
Tangibility	0.295	0.362	-8.637***

Table 3. Loan spreads and corruption

This table shows estimates from OLS regressions of the natural log of loan spreads, *ln(allindrawn)*, and loan spread, *allindrawn* on *Regional Corruption Rate*, respectively. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. Regressions include three-digit industry, year, loan type, loan purpose and state fixed dummies.The robust standard errors, values parentheses, are clustered by firm.All variables are defined in Appendix A. ***, **, * denote significance level at 1%, 5% and 10% respectively.

VARIABLES	(1) ln(allindrawn)	(2) allindrawn
Regional Corruption Rate	0.022***	4.387***
	(0.008)	(1.438)
ln(maturity)	-0.096***	-24.180***
	(0.010)	(2.358)
Security	0.363***	60.900***
	(0.014)	(2.678)
Cash ratio	-0.043	25.160
	(0.084)	(15.730)
log(at)	-0.064***	-9.382***
	(0.007)	(1.200)
M/B	-0.052***	-4.966***
	(0.011)	-1.826
Leverage	0.248***	45.990***
	(0.035)	(7.658)
Profitability	-0.117**	-47.470***
	(0.053)	(11.540)
Tangibility	-0.162***	-15.910
	(0.050)	(10.010)
Loan size	-0.071***	-11.640***
	(0.005)	(1.028)
Spegrade	0.423***	40.420***
	(0.031)	(4.304)
Constant	6.418***	446.900***
	(0.213)	(36.610)
Industry FE	YES	YES
Year FE	YES	YES
Loan type and purpose FE	YES	YES
State FE	YES	YES
Observations	22,816	22,816
Adjusted R-squared	0.527	0.399

Table 4. Non-price terms and corruption

Panel A shows estimate from OLS regressions of the natural logarithm of loan maturity on *Regional Corruption Rate*. Panel B shows estimate from probit regressions of collateral requirements on *Regional Corruption.* Collateral requirement (*Security),* is a dummy variable equaling one if the loan secured with collateral and zero otherwise. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. Regressions include the same control and dummy variables in table 3. The robust standard errors, values in parentheses, are clustered by firm. All variables are defined in Appendix A. ***, **, * denote significance level at 1%, 5% and 10% respectively.

Panel A

	ln(maturity)
Regional Corruption Rate	0.007
	(0.007)
Security	0.105***
	(0.011)
Other controls	YES
Constant	1.541***
	(0.216)
Industry FE	YES
Year FE	YES
Loan type and purpose FE	YES
State FE	YES
Observations	22,816
Adjusted R-squared	0.429

Panel B

	Security
Regional Corruption Rate	0.001
	(0.020)
ln(maturity)	0.234***
	(0.025)
Other controls	YES
Constant	-4.948***
	(0.285)
Industry FE	YES
Year FE	YES
Loan type and purpose FE	YES
State FE	YES
Observations	22,327

Table 5. Alternative loan spreads regressions --Limited sample

This table shows OLS results from regressions with additional control variables . The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. The dependent variable of coloumn (1) and (2) is the natural logarithm of loan spread, *ln(allindrawn)*. The dependent variable of coloumn (3) and (4) is loan spread, *allindrawn*. Unreported controls are all from regressions used in Table 3. All variables are defined in Appendix A. The robust standard errors, values in parentheses, are clustered by firm. ***, **, * denote significance level at 1%, 5% and 10% respectively.

	(1)	(2)	(3)	(4)
VARIABLES	ln(allindrawn)	ln(allindrawn)	allindrawn	allindrawn
Regional Corruption Rate	0.023***	0.025***	4.336***	5.001***
	(0.008)	(0.009)	(1.487)	(1.583)
ln(maturity)	-0.132***	-0.100***	-24.120***	-23.780***
	(0.010)	(0.011)	(2.372)	(2.498)
Security	0.341***	0.353***	61.010***	58.770***
	(0.014)	(0.015)	(2.700)	(2.898)
Net debt Issuance		6.95e-05***		0.002
		(0.000)		(0.001)
Net equity Issuance		6.95e-05***		0.002
		(0.000)		(0.001)
ln(per capita income)	0		1.696	
	(0.013)		(2.366)	
ln(population)	0.017		3.825	
	(0.021)		(3.312)	
Unemployment rate	-0.003*		-0.281	
	(0.002)		(0.280)	
Other controls	YES	YES	YES	YES
Constant	5.293***	5.655***	374.600***	358.700***
	(0.403)	(0.260)	(64.140)	(62.360)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Loan type and purpose FE	YES	YES	YES	YES
State fixed effects	YES	YES	YES	YES
Observations	22,470	19,983	22,470	19,983
Adjusted R-squared	0.518	0.536	0.398	0.401

Table 6. IV estimation

This table shows the second stage results of 2SLS for instrumental variable analyses (IV) that include variables instrumented for corruption conviction rate at the state level, *State corruption convictions*. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. Regressions contain the previous control variables that are unreported. Regressions include industry, year, loan type, loan purpose, state fixed effects. All variables are defined in Appendix A. The robust standard errors, values in parentheses, are clustered by firm. ***, **, * denote significance level at 1%, 5% and 10% respectively.

VARIABLES	ln(allindrawn)	ln(allindrawn)	allindrawn	allindrawn
IV estimation	(AvgLogDistance)	(Interest by state)	(AvgLogDistance)	(Interest by state)
State corruption convictions	0.358**	1.073	69.282**	394.330**
	(0.127)	(0.743)	(28.244)	(154.129)
ln(maturity)	-0.085***	-0.118***	-23.228***	-26.172***
	(0.009)	(0.010)	(2.091)	(2.029)
Security	0.385***	0.360***	68.796***	58.596***
	(0.012)	(0.011)	(2.701)	(2.286)
Other controls	YES	YES	YES	YES
Constant	7.255 ***	6.520***	548.530 ***	422.090***
	(0.157)	(0.167)	(34.929)	(34.578)
Weak IV Test	7.930***	2.310	6.010**	9.340***
Exogeneity Test	5.605**	2.600	2.867*	10.079***
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Loan type and purpose FE	YES	YES	YES	YES
State fixed effects	NO	NO	NO	NO
Observations	10,992	15,937	10,992	15,937

Table 7. Propensity matching score analysis for loan spreads
This table shows the average treatment effect of the treated (corrupt) on the loan spreads. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. The outcome variable in panel A is loan spread, *allindrawn*. The outcome variable in panel B is the natural logarithm of loan spreads, *ln(allindrawn)*. The algorithm used in the first model is ten nearest neighbors and Mahalanobis distance covariate matching. The algorithm used in the second model is local linear regression with a bandwidth of 0.05. The matching variables are all covariates from the regression used in Table 3. All variables are defined in Appendix A. ***, **, * indicate significance level at 1%, 5% and 10% respectively.

Panel A: Outcome variable is *allindrawn*

	Ten Nearest Neighbors with Common Support	Local Linear regression (bandwidth=0.05)
Average treatment effect of the treated	11.442**	-0.702

Panel B: Outcome variable is *ln(allindrawn)*

	Ten Nearest Neighbors with Common Support	Local Linear regression (bandwidth=0.05)
Average treatment effect of the treated	0.034	-0.001
Matching covariates	Firm- level, no-price term of loans, industry FEs, time FEs, State FEs, loan type and purpose FEs.	

Table 8. Alterative measurements for corruption
loan spreads regressions
This table shows OLS results of regressions with alternative measures of corruption. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. The sample covers period 1991-2014. Unreported control variables are all from regressions used in Table 3. All variables are defined in Appendix A. The robust standard errors, values in parentheses, are clustered by firm. ***, **, * indicate significance level at 1%, 5% and 10% respectively.

	Corruption Measure			
	State Integrity Investigation		Butler et al. (2009)	
	(1)	(2)	(1)	(2)
VARIABLES	ln(allindrawn)	allindrawn	ln(allindrawn)	allindrawn
Corruption measure	-0.050***	- 12.596***	4907.000	1.378e+06**
	(0.009)	(1.588)	(3568.000)	(646877.000)
ln(maturity)	-0. 097***	-24.114	-0.094***	-23.810***
	(0.01)	(2.368)	(0.010)	(2.340)
Security	0. 359***	60.267***	0.366***	61.090***
	(0.014)	(2.635)	(0.014)	(2.659)
Constant	10.134***	1335.104 ***	6.464***	454.900***
	(0.544)	(92.067)	(0.217)	(37.240)
Other controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Loan type and purpose FE	YES	YES	YES	YES
Observations	23,160	23,160	23,173	23,173
Adjusted R-squared	0.519	0.390	0.526	0.399

Continued…

	Corruption Measure			
	Raw convictions		Weighted Corruption	
	(1)	(2)	(1)	(2)
VARIABLES	ln(allindrawn)	allindrawn	ln(allindrawn)	allindrawn
Corruption measure	0.805***	202.000***	14,068.000***	202.000***
	(0.293)	(50.78)	(5357.000)	(50.780)
ln(maturity)	-0.097***	-24.10***	-0.0850***	-23.430***
	(0.010)	(2.338)	(0.0146)	(3.536)
Security	0.364***	61.150***	0.377***	68.330***
	(0.014)	(2.679)	(0.0187)	(4.007)
Constant	6.531***	461.1***	7.006***	504.2***
	(0.217)	(38.580)	(0.109)	(23.110)
Other controls	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	NO	NO
State FE	NO	NO	NO	NO
Loan type and purpose FE	YES	YES	YES	YES
Observations	23,173	23,173	10,442	10,442
Adjusted R-squared	0.526	0.399	0.425	0.329

Table 9. Regressions of loan spreads adjusted for geographic concentration--Limited sample
This table shows OLS results of regressions adjusted for geographic concentration. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded. The dependent variable of Coloumn (1) is the natural logarithmof loan spreads , *ln(allindrawn)*. The dependent variable of Column(2) is loan spread, *allindrawn*. Regressions include an interaction term between Regional Conviction rate and the geographic concentration variable, *% of operations in HQ state* Unreported variables are interaction terms of previous controls and geographic concentration variables , *% of operations in HQ stat*e. Regressions also include industry, year and loan type and purpose dummies.The robust standard errors, values in parentheses, are clustered by firm. All variables are defined in Appendix A. ***, **, * denote significance level at 1%, 5% and 10% respectively.

VARIABLES	(1) Ln(allindrawn)	(2) allindrawn
Regional Corruption Rate	0.0301	5.870
	(0.0307)	(4.957)
Corruption convictions x % of operations in HQ state	0.001	0.408
	(0.0706)	(12.790)
% of operations in HQ state	0.337	78.320
	(0.343)	(62.510)
ln_maturity	-0.126***	-26.520***
	(0.0170)	(4.361)
security_dummy	0.338***	69.59***
	(0.024)	(5.285)
Other controls	YES	YES
Constant	5.742***	472.200***
	(0.311)	(54.150)
Industry FE	YES	YES
Year FE	YES	YES
Loan type and purpose FE	YES	YES
Observations	6,908	6,908
Adjusted R-squared	0.424	0.327

Table 10. Regressions of price term adjusted for borrower-lender relationship

This table shows OLS results of regressions adjusted for borrower-lender relationship. The sample covers period 1991-2014. Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded.The dependent variable of Coloumn (1) is the natural logarithm of loan spreads, *ln(allindrawn)*.The dependent variable of Column(2) is loan spread, *allindrawn*. Regressions include interaction terms of *loan-to-asset ratio* and *Regional Corruption rate as well as*, *loan-to-asset ratio* and other control variables calculated by averaging all controls in table 3 by [t-1,t-n], where n is the loan tenor. Regressions also include industry, year, loan type and purpose dummies. The robust standard errors, values in parentheses, are clustered by firm. All variables are defined in Appendix A. ***, **, * indicate significance level at 1%, 5% and 10% respectively.

VARIABLES	(1) ln(allindrawn)	(2) allindrawn
Regional Corruption Rate	0.017	4.274
	(0.020)	(4.270)
loan-to-asset ratio* Rregional Corruption Rate	0.002	0.079
	(0.009)	(1.769)
loan-to-asset ratio	-0.103***	-16.790***
	(0.012)	(2.429)
ln(maturity)	-0.131***	-29.560***
	(0.012)	(2.881)
Security	0.366***	61.200***
	(0.015)	(2.788)
Constant	6.372***	362.400***
	(0.174)	(23.830)
Observations	20,834	20,834
Adjusted R-squared	0.528	0.403
Industry FE	YES	YES
Year FE	YES	YES
Loan type and purpose FE	YES	YES
State FE	YES	YES