Peer Information in the Cost of Debt*

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Abstract

This paper studies how peer information impacts bank lending behavior and firms' cost of debt. Using syndicated loan data, I find that firms obtain lower loan rates when borrowing from banks that lent to their peers in previous years. The benefit in loan rates increases with firm and peer group similarity and with firm opacity. To establish a causal interpretation of peer effects in loan pricing, I use class action litigation records and find the benefit diminishes when peers in bank portfolio committed financial misconduct, conditional on a wide cross-section of firm characteristics. The increased loan rates concentrate on firms that are harder to switch banks, indicating the possibility that banks take the advantage of peer information deterioration to extract rent.

Keywords: Peer Information, Cost of Debt, Bank Lending, Financial Misconduct

JEL Classification: G14, G21, G32

*I am particularly grateful to Martin Goetz, for his guidance and support. This paper also benefited greatly from Cheung Ying Lun, Casey Dougal, Jie Cai, Rainer Haselmann, Jan Pieter Krahnen, Chunbo Liu, Michelle Lowry, Thomas Mosk, Tobin Hanspal, Gregory Nini, and participants at Finance Brown Bag in Goethe University Frankfurt, Drexel University, China Meeting of the Econometric Society, Econometric Society Australasian Meeting and Greater China Area Finance Conference. Financial support from the Center of Excellence SAFE, funded by the State of Hessen initiative for research LOEWE is gratefully acknowledged.

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1. Introduction

Peer firms share economic proximity and common prospects. They have an active impact on corporate policies (Leary and Roberts, 2014; Foucault and Fresard, 2014; Bustamante and Fresard, 2017; Grennan, 2018), which is known as peer effects, since managers tend to learn from peer firms' corporate decisions and adjust their own. Meanwhile, investors may also value peer information and alter expectations about firms[1], which could influence the cost of debt firms obtain. Understanding the effect of peers in firm financing costs through the views of investors is both interesting and important, however, it remains less explored.

In this paper, I explore the peer effects in bank lending and loan pricing terms. Specifically, I examine whether and how firms' cost of loans are influenced by the peer firms banks previously lent to. Banks are considered to be diligent in information acquisition and acquire information from various sources in the course of designing loan contracts (Sharpe, 1990; Botsch and Vanasco, 2018). As opposed to other types of investors, they have private peer information collected from previous lending, which allows them to form a more precise perspective about current (similar) borrowers' projects.

Whether loan rates would differ if banks lent to firms' peers before is ambiguous. First of all, as stated above, lending to similar firms provides banks with an informational advantage. While more information is generally favorable to banks, it is unclear whether it can translate to lower loan rates. An extensive banking literature has documented the benefit in loan rates for relationship borrowers (Petersen and Rajan, 1994; Berger and Udell, 1995; Berlin and Mester, 1999; Boot, 2000; Elyasiani and Goldberg, 2004; Bharath, Dahiya, Saunders, and Srinivasan, 2011; Engelberg, Gao, and Parsons, 2012; Karolyi, 2018). Banks are willing to offer a beneficial loan terms following good project realizations, as it is welfare enhancing (Boot and Thakor, 1994). Another strand of literature suggest this information monopolies

[1] Recent studies provide evidence that disclosure or restatement of financial reports can generate externalities among firms in the same industry (see e.g., Guiso, Sapienza, and Zingales (2008); Gleason, Jenkins, and Johnson (2008); Durnev and Mangen (2009); Chen, Young, and Zhuang (2013); Shroff, Verdi, and Yost (2017)), supporting that investors value peer information when evaluating firm performance.

may result in hold-up problems and allow informed banks to charge at non-competitive rates (Sharpe, 1990; Hauswald and Marquez, 2003; von Thadden, 2004; Ioannidou and Ongena, 2010). Besides, banks may have other considerations when lending to similar firms. For example, having many similar firms in banks' portfolios can be undesirable from a diversification standpoint and may cause them to demand higher loan rates (Diamond, 1984; Boyd and Prescott, 1986). Additionally, banks would also take peer competition environment into consideration, charging a higher loan rates when there is higher competition (Valta, 2012).

I examine how banks lend to peer firms of their previous borrowers empirically in the syndicated loan market. With a firm-bank matched loan dataset, I identify the relationships of firms and their peers that banks lent in previous periods. Peers are defined as firms operating in the same product markets based on the Text-based Network Industry Classifications (TNIC) developed by (Hoberg and Phillips, 2016). This classification captures an up-to-date and dynamic relationship between firm-pairs, who are competitors operating in the same business and product market, therefore sharing relevant information. Moreover, it contains a firm-pair similarity measure that allows me to measure peer information by considering similarities between the current borrower and similar firms to which banks had previously lent. More similar peers should contain more relevant information that is valuable for banks to evaluate.

My results show that a firm obtains a lower loan rate when borrowing from a bank that lent to similar peers in the past. These results hold after controlling for a wide cross-section of firm characteristics that affect loan rates including distance-to-default, leverage, profitability, etc. I also make use of the panel structure and compare loan rates that a firm receives from banks with different levels of peer information. The results are consistent and robust to controlling for time-varying bank-specific factors. The information premium in loan rates could be due to the fact that the syndicated loan market is competitive and banks as well as firms are typically large, hence firms are less likely to be "informational captured", especially when the information is from peers. Moreover, contrary to the information monopolies explanation, I find that the benefit mainly comes from firms with less analyst coverage, suggesting that banks are more likely to rely on their previously collected information when the public information about firms is limited.

To identify the role of peer information in loan pricing, I utilize peer financial misconduct shocks at bank-firm level and examine for bank reaction in pricing terms. Peer financial misconduct deteriorates the quality of peer information, which should be reflected in loan pricing if peers play a role in bank loan decision making. Using records in Securities Class Action Clearinghouse (SCAC) as proxies for firm misreporting and fraud behavior (hereafter I use the term fraud and misconduct interchangeably), I find that fraud behavior of firm peers to which banks lent have an impact on firms' cost of credit. Within the loans of which borrowers are peers of firms that banks lent to, loan rates are more expensive if the peers in bank portfolio committed fraud in the previous year. In fact, the benefit for peer firms almost disappears. This finding suggests that banks adjust their loan terms when peer information environment changes and hence peer information plays a role in bank loan decision making.

I rule out several confounding explanations of the increased loan rates. First, although financial misconduct is mostly firm-specific misbehavior, it is likely to spill over to the same or related industries, causing a negative effect on current borrowers. However, the effect should be transformed into firm and peer fundamentals, in line with the finding that conditional on firm and peer credit riskiness and profitability, banks do not react to peer fraud cases if the fraudulent peers are not in their loan portfolio. In addition, I also restrict my sample to only firms that never committed fraud and continue to find an increase in loan rates when firm peers committed fraud. Second, having fraudulent firms in portfolio may cause negative impact on banks. For instance, banks may write tighter contract terms after suffering payment defaults[2] to all borrowers (Murfin, 2012). It is also likely that banks suffer from reputation loss as firms committed fraud under their supervision, and have an impact on loan rates (Lindahl and Paravisini, 2011). I control for these time-varying bank-specific

[2]Most of the financial fraud cases do not necessarily lead to default, but some big fraud cases can go along with (technical) default, such as the cases of Enron and WorldCome.

factors by comparing loan rates banks lent within a year.

In addition, I conduct a within-firm analysis to further identify the peer effect. The ideal analysis would compare loan rates offered to the *same firm-year* borrowing from two banks that differ in whether there exist any fraudulent peers in their portfolios, similar to the empirical strategy of Khwaja and Mian (2008). Due to the limited number of firms borrowing from two banks simultaneously, I use propensity score matching techniques to find loans with similar features and confirm that loan rates are more expensive when borrowing from banks with fraudulent peers, while there is no significant difference when fraudulent firms in banks portfolio are non-peers. This evidence provides a clear identification toward the role of peers. The economic magnitude is non-trivial: borrowing from a bank that lent to similar non-fraudulent peers results in 8-10 bps lower in loan rates, which is around $455,000$ $ for an average sized syndicated loan.

Why would banks react to peer financial misconduct by charging a higher loan rates? There are two possible explanations. First, peer firms' financial misrepresentation deteriorates banks' posterior belief about similar projects. It makes banks less able to rely on the formerly collected peer information, as firms misreport financial numbers. More importantly, it may also affect banks' overall suspicion or distrust, reducing the precision of former belief formed from peer firms. They become less certain about the peer information and no longer rely on it, which should reduce the benefit in loan rates from peer information. Second, as financial misconduct is public and contains negative information, it may worsens all investors' beliefs (Guiso et al., 2008). Banks that lent to fraudulent peers, however, have more private information and hence may be less uncertain than other banks. They may take advantage of the information monopolies and charge higher loan rates to hold-up a similar firm, when public information environment about a firm's environment is unfavorable. To exam this more, I explore the heterogeneity in the increased loan rates and find that the increase in loan rates are concentrated in relationship loans and firms without public debt issuance, which are more likely to be held up.

Finally, I provide evidence that financial misconduct not only poses negative externalities on costs of credit, but also affects firms' credit availability. Banks tend to reduce lending to similar firms after their peers had any financial misconduct behavior, given the firm never committed any wrongdoings. The results are robust after controlling for any credit supply or demand side (at industry level) factors.

This paper contributes to several strands of literature. First, it provides novel evidence that peer information can have an impact on costs of debt based on syndicated loans. Previous studies document investors tend to value peer information which has an impact on stock market (Gleason, Jenkins, and Johnson, 2008; Durnev and Mangen, 2009; Shroff, Verdi, and Yost, 2017), I provide evidence that banks also value peer information in making lending decisions. Closest to this finding is a recent paper by Shroff, Verdi, and Yost (2017), who also provide evidence that peer information has externalities on the cost of capital. Shroff et al. (2017) focus on the private firms that raise public capital (debt or equity) for the first time and examine how public peer information in financial market affects the cost of capital. I provide direct evidence that banks value private peer information they collected and adjust their lending behavior, which affects the cost of debt firms obtain. This may provide some implications for firms to choose which lenders to borrow. Borrowing from banks that lent to similar peers with good performance can provide firms with a beneficial loan contract in a competitive lending market.

My findings add to a large set of the literature studying information asymmetries and bank loans. While a vast studies show that relationship lending can result in beneficial loan terms (Petersen and Rajan, 1994; Boot and Thakor, 1994; Berger and Udell, 1995; Berlin and Mester, 1999; Boot, 2000; Elyasiani and Goldberg, 2004; Bharath, Dahiya, Saunders, and Srinivasan, 2011; Engelberg, Gao, and Parsons, 2012; Karolyi, 2018), I present evidence that relationship lending has externalities in that it can be shared with peers. It indicates that banks value similar information instead of the boundary of a particular firm, shedding new light on the transmission of information in bank lending behavior. On the other hand, when public information deteriorates, banks stop providing the benefit and charge a non-competing loan rates for firms that are harder to find another bank, showing hold-up costs in firm-bank relationships (von Thadden, 2004; Ioannidou and Ongena, 2010). The two findings indicate that whether information advantage can result in lower loan rates depend on the relatively bargaining power of banks and firms. In normal conditions, transparent firms may have larger bargaining power due to the competitiveness of syndicated loan market, while banks take the charge of power when information environment is unfavorable to firms.

Last, this paper contributes to the understanding of fraud on the costs of credit. Creditors are more likely to impose more restrictions on loan terms once borrowers' credit quality deteriorates (Nini, Smith, and Sufi, 2009; Bharath, Sunder, and Sunder, 2008; Murfin, 2012; Chava, Huang, and Johnson, 2017). I find that fraud behavior not only result in substantially higher loan rates, but may also raise the cost of credit for peers. Furthermore, I find that it is detrimental for firms' financing condition as banks decrease lending to this group of firms, indicating dishonest behavior can impose negative externalities on peers in terms of credit availability. The recent work by Parsons, Sulaeman, and Titman (2014) is closest to this finding that a firm's financial misconduct have a negative effect on credits to local firms. It is also in line with the literature that document distrust in the accuracy of financial statements can affect investor asset allocation (Kostovetsky, 2015; Gurun, Stoffman, and Yonker, 2018) and household choices (Guiso, Sapienza, and Zingales, 2008; Garmaise and Moskowitz, 2006; Giannetti and Wang, 2016).

The remainder of this paper is organized as follows. Section 2 describes the data source and sample construction, and discusses the empirical framework and identification. Section 3 presents the empirical results that banks provide significantly lower loan rates to previous borrowers' peers. Section 4 discusses the results when peer information deteriorates when peer firms in bank portfolio committed financial misconduct. Section 5 concludes.

2. Empirical Framework

2.1. Data source and sample construction

Data are collected from several different sources. First, loan information is obtained from Loan Pricing Corporation's (LPC) DealScan. I restrict my attention to the dollar-denominated loans whose country of syndication is the United States, and both the borrowers and lenders are located in the US to avoid different accounting rules across countries. In addition, I exclude loans to financial companies (SIC between 6000 and 6999), following the literature.

The basic unit of observation in Dealscan is a loan, also referred to as a facility. Most of the loans are offered by a group of lenders, called syndicates, consisting of one or more lead arrangers and several participants. I focus my analysis on the lead arranger(s) rather than on syndicate participants, because lead arrangers play an active role in originating loans and monitoring borrowers with primary responsibility, while participants are essentially passive investors (Ivashina, 2009; Schwert, 2018). The lead arrangers are defined following Sufi (2007) and Bharath et al. (2011): a bank is identified as a lead arranger when the field "Lead arranger credit" is "Yes", or "lender role" is one of the following: (a) Admin agent; (b) Agent; (c) Arranger; (d) Lead bank; (e) Sole lender.

Second, I add borrower and bank information for each loan. I use the DealScan-Compustat Link from Chava and Roberts (2008), which matches loan facilities from DealScan with the firm identifiers in Compustat. Then I use the lender side link table based on Schwert (2018) to link the lenders from DealScan to the identifiers in Compustat at the top holding company level. The linkage has taken bank mergers and acquisitions into account and considered lenders at the bank holding company level.[3]

Text-based Network Industry Classifications (TNIC) data are provided by Hoberg and Phillips (2016). Hoberg and Phillips (2016) use textual analysis to classify firms having

[3] I double check and add "RSSD ID" for each bank holding company using PERMCO-RSSD links from Federal Reserve Bank of New York.

similar products to be in the same industry, based on the product description sections of firms 10-K (Item 1 or Item 1A) files. Intuitively, the more common words two firms use to describe their products, the more similar these firms are in terms of the positions in product market. Firms are classified in the same TNIC when the similarity is above certain threshold. Unlike traditional industry classification such as SIC, TNIC allow more flexibility for each firm to have its own set of competitors. Moreover, it captures a dynamic and up-to-date relationship between peer firms.

I use fillings in Securities Class Action Clearinghouse (SCAC) as misconduct or fraud events, which are obtained from SCAC website, starting from 1996.[4] These events capture the federal securities class action lawsuit filings and settlements, which are generally regarded as dishonest or fraud behavior conducted by firms. It contains the information to identify firm identity and filling date for each security.

2.2. Variables

The dependent variable is the all-in-spread-drawn (AISD), which is a loan's credit spread over LIBOR plus annual fees to the lenders. It is the most comprehensive measure of borrowing costs (Bharath et al., 2011). The independent and control variables are defined as below.

2.2.1. Peer loans and information proxies

First, I use a dummy variable $PeerLoan$ to classify loans into two categories based on whether banks lent to firm peers in previous years. In the main analysis, peers are defined as firms in the same TNIC3 industry [5]. Specifically, for each observation (a bank-loan-firm facility), I check all loans issued by the bank as a lead lender in the past three years and define the dummy $PeerLoan = 1$, if the bank lent to the firm's peers and zero otherwise.

[4] `http://securities.stanford.edu/filings.html`. There are in total more than 4000 securities class action lawsuits filled in federal court after January 1, 1996.

[5] These firms share product similarities above the threshold that makes the industry as coarse as the traditional three-digit SIC.

For loans with multiple lead banks, $PeerLoan = 1$ if at least one of the lead lenders ever lent to the firm's peers in previous three years.

I then construct two other variables based on $PeerLoan$ to capture the lending frequency and similarity of peers. First, I count the number of peers a bank issued loans in the previous three years[6] and take the logarithm transformation to reduce skewness,

$$PeerLoan(N)_{b,f,t} = \log\left(1 + \sum_{k=1}^{3} n_{b,f,t-k})\right), \tag{1}$$

where $n_{b,f,t-k}$ is the number of peers bank b lent to in k year(s) prior to t. For loans with multiple lead banks, I use the average value to transform these variables into loan level.

Second, I take the similarity between peers into account. Peers should be more relevant if a new borrower is more similar to those banks once lent to. Hoberg and Phillips (2016) provide *score* which measures the pairwise similarities based on firm product descriptions in 10-K fillings. I calculate the sum of the scores for the firm and its peers the lender lent in previous three years to calculate the information proxy, specifically:

$$PeerLoan\ (score)_{b,f,t} = \sum_{k=1}^{3} \sum_{f'=1}^{n_{b,f,t-k}} score_{f,f',t}, \tag{2}$$

where $score_{f,f',t}$ is the similarity between firm f and f' at time t. $PeerLoan(N)$ can be regarded as if bank b treat firms f and its peer f' identical, while by $PeerLoan(score)$ we allow bank b to form different prior information for the borrower, based on the similarities between the firm and previous borrowers. The information set towards the new borrower is larger, if it is more similar to those banks once lent to.

In robustness checks, I use alternative definition for peers based on traditional three-digit SIC. Similarly, I count the number of peers banks lent in previous three years and take the logarithm as the lender information to the current borrower. A disadvantage of using SIC industry as peers is that we are not able to compare the similarities between firm-pairs in

[6] I also conduct robustness checks for different years.

any further step. Moreover, the static classification can be out-of-dated as firms may change their operation areas, while TNIC captures the current relationships hence a more accurate definition.

2.2.2. Fraud variables

Using SCAC filings information, I identify whether a current borrower borrow from a bank that lent to a fraudulent peers. Specifically, I define a dummy variable $PeerFraud\ (b)_{b,f,t} = 1$ if borrower f' peers in bank b's portfolio committed financial fraud and filed in SCAC in the previous year. Additionally, as financial fraud is public information, I also add a dummy variable $TNICFraud_{f,t} = 1$ if any peers in firm TNIC group committed fraud and filed in SCAC in the previous year. To illustrate, consider a firm borrows from a bank that lent to the firms' peer A in previous three years. If Peer A committed fraud in last year, both $PeerFraud\ (b)$ and $TNICFraud$ equal to one for the firm. If another peer B also committed fraud, but it is not in the bank's portfolio, then $PeerFraud\ (b) = 0$ but $TNICFraud = 1$. Firms' own fraud condition is controlled by a dummy $OwnFraud_{i,t}$, taking on the value of 1 when firm i filed in SCAC in the previous year.

2.2.3. Control variables

I control for the relationship loan (*Relloan*), a dummy taking on the value of 1 if the firm borrowed from the same bank in previous years (Bharath et al., 2011; Li et al., 2013). Note that *Peerloan* can be 0 when *Relloan* is 1, which is the case when the bank lent to the firm before but not to any of its peers.

Peer environment can also affect loan pricing. I add average peer profitability and distance-to-default to control for the economic prospects for peer firms. Additionally, I consider the environment of peer competition, measured by the Herfindahl - Hirschman Index (HHI) of peers' sales.

Other firm-level and loan level variables are described in the Appendix A. I add borrowers'

S&P long-term ratings and distance-to-default to control for their credit risk, as well as other observed characteristics, including size, leverage, ROA, tangibility and current ratio, which may have a direct or indirect effect on loan rates. I also add dummies of loan primary purposes and loan types to make sure that we are comparing the loan rates for the same type of loans. The results are also consistent when I control for loan characteristics, including maturity, loan amount and whether the loan has any collateral. All firm-level and loan-level variables are trimmed at the 0.5% level in each tail to mitigate the effect of outliers.

2.3. Sample characteristics

I match bank and firm information for each loan and restrict to loans with available firm information[7]. I then match SCAC filings in my sample as it contains the information to identify firm identity and filing date for each security. The final sample contains $19,404$ unique loans and $24,832$ firm-bank-loan observations from 1996 to 2012. I start from 1996 because TNIC and SCAC data are only available from 1996. Furthermore, the syndicated loans are also limited before 1996.

Table 1 shows the summary statistics of the main variables for $PeerLoan$ and non-$PeerLoan$ separately. About 70% of the loans in the sample are $PeerLoan$s. Differences in loan- and firm- characteristics can be observed in these two groups of loans. T-tests indicate the differences are significant at the 1% level, except for Tobin's Q and coverage ratio. First, as summarized in Panel A, a $PeerLoan$ has a lower credit spread (AISD) compared to non-$PeerLoan$. The average facility amount is much higher for $PeerLoan$, while the collateral is lower, suggesting banks have more trust towards these borrowers and demand less collateral. The main types of loans are revolving line of credit and term loans[8] for both type of loans,

[7] The matching results in good coverage of the Dealscan-compustat sample, which includes 76.4% loans and 82.7% loan amount. The primary cause of lost observations is the borrowers' missing data in Compustat. The final sample covers 51.1% of loan number and 61.7% of loan amount in Dealscan-compustat sample.

[8] Revolving credit works like credit cards: a borrower is charged a commitment fee on the entire loan amount, but only pay the interest on actual drawn amount. In contrast, a term loan is more like a bond: the borrower receives the entire amount of the loan and pays off the principal and interest by the maturity date.

while relatively more revolving loans are offered to *PeerLoan*. Second, differences in the firms' features are present at firm-quarter level for the two groups, as displayed in Panel B. In total, there are $4,032$ firms in the sample. Firms in *PeerLoan* group are much larger and have better credit ratings. However, as stated above, Tobin's Q and coverage ratio are insignificantly different in the two groups of firms. Panel C shows the summary statistics for other interested variables at unique loan-quarter observations. About half of the loans are relationship loans. Within *PeerLoa*s, the average (median) number of peers a bank lent in previous three years is 6.6 (4).

In total, there are 671 filing cases used in the sample, which are listed in Panel B of Table 2 by year and sector.[9] A majority of the fraud cases happened in Services and Technology sectors. Many firms obtain syndicated loans after filling in SCAC. On average, 2.82% of loans of which the borrowers obtain syndicated loans within a year after filings, and around 8.85% whose peers (the same bank once lent in last three years) committed fraud in previous year. Panel A of Table 2 lists the annual numbers and ratios of loans whose borrowers (or borrowers' peers) filed in SCAC in the last four quarters prior to the loan issuance.

2.4. Empirical Framework

As a benchmark model, I estimate the following regression to examine whether loan rates offered to previous borrowers' peers are cheaper:

$$AISD_{l,t} = \beta_1 PeerLoan_{l,t} + \mathbf{X'}\boldsymbol{\gamma} + \delta_b + (\delta_{b,t}) + \delta_f + \epsilon_{l,t}, \tag{3}$$

where $AISD_{l,t}$ is the all-in-spread-drawn for each loan l, originated by bank b for borrower f at time t, and *PeerLoan* are proxy variables measuring banks' previous lending to firm peers. $\mathbf{X}$ are control variables that characterize loan and firm features and peer environment.

[9] The sector definition is directly obtained from case summary in SCAC website. Though I exclude firms from financial and utilities industry, it appears that there are peers in the two industries. Excluding these cases does not change the results.

δ_b, $\delta_{b,t}$, and δ_f are bank, bank-year and borrower fixed effects. Standard errors are clustered at the three-digit SIC level to allow for correlation in loan rates within industries[10].

Borrower fixed effect remove time-invariant firm features, such as industry and location. Bank-year fixed effect accounts for any time varying bank factors at the bank level, such as size and loan portfolio risk. β_1 then shows whether banks offer lower loan rates to firms that are similar to those they once lend to.

Establishing a causal interpretation of peer effect on loan rates is challenging. The endogenous matching between banks and firms is likely to be correlated with the peer proxies, leading to a bias estimation. For example, banks develop certain expertise in selecting better firms after multiple interactions with similar firms. To identify the role of peer firms, I use shocks a bank-peer level, specifically, peer firms' financial misconduct. Peer information deteriorates when peer firms committed financial misconduct. This is a shock to (public) peer information, and banks should react to the change in peer information environment if peers play a role.

Using a difference-in-difference (DiD) design, I divide $PeerLoan$s into two groups based on whether peers committed fraud prior to the current loan and test whether loan rates are different in the two groups. Specifically,

$$AISD_{l,t} = \rho_1 PeerFraud\ (b) \times PeerLoan_{l,t} + \rho_2 PeerLoan_{l,t} + \mathbf{X}'\boldsymbol{\gamma} + \delta_{b,t} + \epsilon_{l,t}, \qquad (4)$$

where $PeerFraud\ (b)$ is a dummy variable indicating whether any peer firms banks lent to committed fraud prior to the current $PeerLoan$.[11] Control variables are the same as before. I additionally add $TNICFraud$ and $OwnFraud$, which is a dummy taking on the value of one if any TNIC peers of firm f or firm f itself committed any fraud in the previous year to control for adverse effects from a firm's peers or own fraud behavior. Standard errors are clustered at industry level. ρ_1 measures the average difference in loan rates between the two

[10] I aslo tried to cluster at firm or bank level, and the results are robust.

[11] The interaction term of $PeerFraud\ (b)$ and $PeerLoan$ is just $PeerFraud\ (b)$, as $PeerFraud\ (b)$ is a subset of $PeerLoan$.

groups.

Ideally, one should compare the loan rates offered to the same *firm-year* borrowing from banks that differ in whether there exists any fraudulent peers in bank portfolio. In particular, I restrict the sample to firms that have fraudulent peers and borrow from (at least) two banks. Both of the banks lend to firms' peers before, but one of them lent to a fraudulent peer while the other not. Hence, although both of them may have the above concern, the bank with fraudulent peers should offer a higher loan rate, since it is less able to re-use the collected information than the other. Due to the limited firms satisfying the above conditions, I use propensity score matching to find similar firms and compare the average loan rates in the two groups.

3. Lending to Borrowers' Peers

In this section, I provide the empirical evidence that firms obtain lower loan rates when borrowing from banks that lent to their peers before. In addition, the effect is stronger with firm and peer group similarity. In a cross-sectional analysis, I show that the effect mainly comes from firms that have relatively limited own information.

3.1. Baseline results

The multivariate regression results are presented in Table 3. I add firm characteristics variables affecting loan rates and year fixed effect controlling for national variations in loan rates. Loan type dummies are also added to make sure that we are comparing loan rates in similar categories. Column (1) shows the baseline result of the average difference in loan rates between $PeerLoan$ and non-$Peerloan$. The coefficient is significantly negative, implying $PeerLoan$ are on average 6.598 basis points cheaper, other things equal. In column (2), I additionally add peer environment controls. Specifically, I control for peer profitability, credit riskiness and competition. The significant coefficients indicate that banks take peer environment into consideration when making loan decisions. Consistent with Valta (2012), I find more competition associated with higher loan costs. Lending to more peers indicates the industry is more competitive (Corr(Peer HHI, $PeerLoan$) = -0.35), therefore omitting the competition variable underestimates the effect of peer information. Indeed, the coefficient increases and becomes more significant when peer competition is conditioned.

Most of the firms in the sample borrowed loans several times, with an average of nine loans and around 90% of firms in the sample borrowed more than one loan. This allows me to add firm fixed effects to remove time-invariant firm features in column (3). Moreover, the banks in the sample are typically large and lend to many firms in each year, which allows me to add bank-year fixed effect to account for any time varying bank specific factors, largely alleviate the matching concerns. Moreover, it gives us an identification towards peer information channel, as portfolio diversification concerns is washed out. The results are reported in column (4), with a consistent and robust estimate.

I construct two additional variables to proxy peer information based on bank previous lending activities. First, I count the number of peers banks lent in preceding three years to borrowers' peers ($PeerLoan$ (N)), as banks should accumulate more knowledge after more frequently lending to similar firms. Second, I take the similarities between these peers into considerations ($PeerLoan$ $(score)$): the more similar a new borrower is compared with the previous firms, the more relevant information the banks can reuse for screening or monitoring. Column (5) and (6) show significantly negative coefficients, consistent with previous hypothesis.

To sum up, the OLS results show that loan rates are on average cheaper if banks have more peer information, after controlling for loan and firm characteristics and bank-year fixed effect.

3.2. Peer and firm own information: substitutes?

Next I explore the effect of peer information cross-sectionally: where does the previous benefit come from?

Peer information should be more relevant when firm own information is limited, in which case banks are more likely to rely on their previously collected peer information, if we think firm and peer information are substitutes. Although firms involved in syndicated loans are typically large firms with relatively transparent information, they still differ in terms of own information.

I use analyst coverage as a proxy for own information. Information asymmetry is reduced when a firm is covered by more analysts. The numbers of analysts are obtained from I/B/E/S database. I construct a dummy when analyst coverage is below the median and term it as "Opaque". The results are consistent with the hypothesis. Interestingly, the coefficients of the interaction terms show that the benefit mainly comes from firms with less analyst coverage and thus limited own information.

3.3. Robustness tests

I consider several potential issues in this section and check the robustness for the previous finding. A potential concern is the numerous existence of relationship loans, as half of the observations in the sample are loans with relationship. The effect of relationship should be controlled by adding the dummy *Relloan* in the above columns. To further check it, I exclude loans with relationship and re-run the above regression. Hence, the sub-sample only contains the loans that firms borrow from the banks for the first time. Interestingly, with a substantial decrease in the sample size, I still observe a significantly negative effect in columns (1) to (3), indicating firms can obtain beneficial loan rates from a bank that lent to its peers even without prior relationship with the bank.

Syndicate loans are grouped into packages or deals and many of them consist of more than one loan. Typically, a package can contain two loans: a term loan and a revolving line of credit. Since the loans are made for the same bank and firm at the same time, it may complex the estimation with fewer variations in variables. Hence, I try to re-do the analysis at package level by only keeping the largest loan in a package. Column (4) and (6) report the robust results.

Finally, I use alternative definitions for peers based on traditional three-digit SIC. Contrary to time varying groups of TNIC, SIC classification is static. Similarly, I use a dummy and count the number of firms in the same three digit SIC banks lent in preceding three years to construct the proxies as previously. The results are reported in column (7) and (8), with a significant negative effect. A disadvantage of this classification is that I cannot construct the proxy based on firm-pairwise similarity.

4. Peer Information Deterioration

In this section, I use the financial misconduct records of peers as shocks to peer information to establish a casual interpretation of peer effects in loan pricing. I first examine how the loan rates differ for $PeerLoan$s with fraudulent peers and find higher loan rates if peers committed fraud. I discuss two possible explanations and shed light on bank rent extraction behavior. In addition, I provide evidence that peer financial misconduct can impose negative externalities on firm credit availability.

4.1. Preliminary: Corporate fraud and loan rates

4.1.1. Corporate fraud and SCAC fillings

Corporate fraud and financial misconduct refers to illegal activities or dishonest behavior performed by managers or companies, typically involving false favorable statements about business and concealing or obscuring negative information. Two of the largest corporate fraud events ever happened in U.S. corporate history are the cases of Enron and WorldCom during October 2001 and June 2002. In both cases, the firms committed accounting manipulations to cover liabilities, hide expenses and create the appearance of profit. After the investigations conducted by the SEC, their top executives stepped down and were charged with criminal and civil convictions. The firms also became bankrupt subsequently after the frauds. Firms can survive from frauds, but they committed reputation losses (Karpoff et al., 2008), and investors would suspect the credibility of their accounting numbers and other information. Besides accounting fraud, there are other forms of dishonesty, such as fraudulent transfers in mergers and acquisitions, misrepresentations, and insider trading, which can result in lawsuits and complaints.

The Securities Class Action Clearinghouse (SCAC) filings contain the information about federal civil securities class action lawsuits, when there is a violation of the federal securities laws, and firms were sued in multiple class action complaints. The complaints generally contain allegations that the company and/or its officers and directors violated certain federal or state securities laws. It starts to track securities class actions filed in Federal Court after the Private Securities Litigation Reform Act of 1995 came into effect. As the firms in my sample engaged in financial misconduct and filed in SCAC in different times, I utilize the variations to examine how loan rates differ if banks have fraudulent peers or not.

4.1.2. The effect of corporate fraud on loan rates

Banks react to corporate financial misconduct behavior by posing a negative effect on loan terms, as it deteriorates borrowers' credit quality, making it harder for banks to judge the credibility of firm accounting numbers and repayment ability (Francis et al., 2005; Bharath et al., 2008; Chava et al., 2017).

I examine the evolution of loan rates when borrowers are subject to financial misconduct and file in SCAC. To start with, I first identify the quarter (T) a firm commits fraud and create a series of dummy variables taking on the value of 1 in one to ten quarters prior to the fraud ($T-1, T-2, \ldots, T-9, T-10$) and similarly one to ten quarters subsequent the fraud $(T+1, T+2, \ldots, T+9, T+10)$.[12] I then merge the information with syndicated loan sample and estimate the following regression:

$$
\begin{aligned}
AISD_{l,t} = {} & \beta_{-10} Fraud_{t-10} + \beta_{-9} Fraud_{t-9} + \cdots + \beta_{9} Fraud_{t+9} + \beta_{10} Fraud_{t+10} \\
& + \delta_{b,t} + \delta_{f} + \epsilon_{l,t},
\end{aligned} \tag{5}
$$

where $Fraud_{t-j}$ equals one in the jth quarter before a firm files in SCAC, $Fraud_{t+j}$ equals one in the jth quarter after a firm files in SCAC. Standard errors are clustered at industry level.

Figure 1 plots the coefficients of time dummies. I use one quarter before fillings as the reference year, as one can observe the loan rates become more expansive since then. The one-quarter time lag could due to the lags in filling SCAC settlement which typically lag the public announcement of lawsuits Karpoff et al. (2017). The figure shows an evidence of the arising financing costs due to fraud. The magnitude is quite large, especially after half a year, around 50 bps higher. It indicates that dishonest behavior would result in a higher financing costs, consistent with previous literature.

4.2. Peer financial misconduct and loans rates

Peer financial misconduct deteriorates peer information, which should be reflected in the loan pricing if peers play a role in bank loan decision making. Utilizing the shocks at bank-peer level, I analyze whether loan rates are any different when borrowing from banks that have fraudulent peers or not. Specifically, I separate loans into two groups by identifying whether any peers (bank lent to in past three years) committed fraud prior to the current loan ($PeerFraud$) in the previous year.

Table 6 shows the results. Year and industry fixed effects are added in each column. In column (1), I control for firm own fraud behavior by adding a dummy indicating whether

[12] One complication arises when a firm commits fraud more than once within two years when constructing these time dummies. In that case, I assign the dummies to be one regarding to the closest fraud event to time t.

the firm committed fraud in the previous year. The coefficient of $OwnFraud$ is significantly positive, with a large economic magnitude of 39.269 bps. I also add two dummy variables indicating whether firm peer committed fraud ($PeerFraud$) and if the fraudulent peers are in bank portfolio ($PeerFraud$ (b)). Both of the two coefficients are significantly positive, showing a more expensive credit costs. In column (2), I add firm as well as TNIC group profitability and credit riskiness, additional on other controls. Interestingly, the coefficient for $PeerFraud$ becomes insignificant and small, indicating peer financial misconduct behavior have little impact on loan pricing after controlling for firm and peer characteristics. However, the coefficient of $PeerFraud$ (b), which is the fraudulent peers are *in bank loan portfolio*, is still significantly positive, showing a bank-peer specific factors in loan pricing. The magnitude is comparable with the average benefit in $PeerLoan$, suggesting the previous benefit in $PeerLoan$s disappears if peers committed fraud and in banks' portfolio.

Firm and bank-year fixed effects are added in column (3). Bank-year fixed effect can address the concern that banks raise loan rates to all borrowers instead of mere peers due to the potential default loss (Murfin, 2012), which absorbs this bank-specific effect. This also applies to the bank reputation concern raised by Lindahl and Paravisini (2011) that banks subject to a reputation loss as firms committed fraud under their monitoring. The adverse effect in reputation results in higher loan rates for firms borrow from these banks. These bank-specific factors can also be washed away by bank-year fixed effect.

The fraud behavior of peers may unveil some fundamental problems within an industry, or have a negative impact on the current borrower. For example, the fraud behavior shakes the entire industry, passing negative shocks to firms. The observed positive effect may be not due to information deterioration, but banks' rational expectation for the potential risks. However, these factors should be transformed into firm specific risk and profitability. This is in line with the fact that we do not find significant reactions from fraudulent peers outside bank portfolio, once we condition on firm profitability and credit riskiness. Additionally, I drop firms that ever committed fraud in the sample and re-do the analysis in column (4), and find a consistent and robust result. These firms never committed fraud and hence the increased loan rates reflects a bias of banks in reusing peer information. In column (5) and (6), I use the two other measures of peer information to examine the sensitivity in each subgroup. The results are consistent, showing firms with fraudulent peers have lower benefit in loan rates.

4.3. Within-firm analysis: Propensity score matching

Ideally, one should compare loan rates offered to the same firm-year from (at least) two banks that differ in whether they have fraudulent peers in their portfolio ($PeerFraud$ loans). This can give us a cleaner identification, since banks should form similar view to the same firm, however one of them has less peer information to use due to peer fraud behavior. Due to the limited firms that satisfy the conditions, I use propensity score matching to find firm-year pairs that are the same in all aspects except whether there are fraudulent peers in bank portfolio.

I first restrict the sample to firms whose peers committed fraud in last year prior to current loans. I also only keep $PeerLoan$, so banks have peer information. Then I separate the sample into two groups based on whether the banks have lent to any fraudulent peers. The hypothesis is that the one lent to fraudulent peers (*treated*) have destroyed information and thus should charge a higher loan rates. I run a probit regression based on firm- and loan- characteristics as before to obtain the propensity score of being in each group. In addition, I control for time trend by adding the Default Spread, which is the spread between BAA and AAA corporate bond yield prevailing at that quarter. I then match loans in two groups based on the closest propensity score and obtain the arithmetic average of the nearest neighbor (n=10 and 50) to compare the mean AISD difference between the two groups.

Figure 2 compares firm and loan features for the two groups before and after matching, which shows the standardized percentage bias[13] of covariates. As observed, significant differ-

[13]It is calculated as the percentage difference of the sample means in the treated and control sub-samples

ences exist between these borrowers and loans. In the *treated* group, that is when banks lend to firms with fraudulent peers, the loans are typically larger, with relationship and better credit rating, which are likely to have lower credit costs. After matching, the differences are largely reduced.

The estimated results of the difference in AISD are displayed in Table 7. The standard errors are robust, based on Abadie and Imbens (2016). Column (1) and (2) reports the average treated effect. Contrary to the above notion that larger and relationship loans should have lower costs, the coefficient shows a significant *higher* of loan spreads for the treated group after matching. The exercise shows a robust estimate of higher borrowing costs, around 8-11 bps, when firms borrow from banks that have fraudulent peer loans in their portfolio, consistent with the idea that fraud behavior destroys bank information set and results in higher lending costs.

To rule out bank-level factors like bank reputation, I also conduct a similar matching exercise where non-peers committed fraud. I drop fraudulent peers and find a similar firm borrowing from a bank experienced fraud from non-peers. The results are shown in column (3)-(4), suggesting no evidence that non-peers fraud can have any impact on current firms.

4.4. Discussion: bank belief deterioration or rent extraction

Previous results indicate that banks only react to fraudulent peer firms in their loan portfolio by charging a higher loan rate for current similar firms. I discuss two possible explanations in this section. First, peer financial misconduct deteriorates peer information banks collected. Not only banks cannot rely on peer financial reports, but also it is likely that banks suffer from belief or trust ruination. They suspect the authenticity of formerly collected peer information, and therefore cannot use it to judge the current borrower. They need more effort in screening and monitoring just like other banks, which increase the lending costs and make the previous benefit diminished. Second, as financial misconduct is public

over the percentage of the square root of the average of the sample variances in the treated and control groups Rosenbaum and Rubin (1985).

and bad information, it may worsens all investors' belief. Banks that lent to fraudulent peers, however, have more private information and take the advantage of the information monopolies to extract rent from firms. They are aware that firms cannot get a more appealing loan rate from elsewhere and charge a non-competing loan rates. The two explanations are hard to disentangle as they are both at bank-peer level. I explore some heterogeneities in the increased loan rates to provide more insights.

The results are shown in Table 8. I first separate the $PeerFraud\ (b)$ loans into two groups by the median of the following attributes: the similarity between the current borrower and the fraudulent peers, the size of the fraudulent peers, the credit riskiness and current ratio of the borrower. I find the effect mainly exist when the fraudulent cases are more relevant and bigger, and when firm performance are weaker. These findings are in line with both two channels, as these features both increase the hold-up probability and deteriorate bank belief more.

In the last three columns, however, I find evidence supporting the rent extraction channel. First, I find the increased loan rates concentrates on relationship loans. Banks should know these firms more, and thus peer fraud events should have less impact on them. Meanwhile, these firms may find it harder to switch a bank given the existing relationship and more likely to be hold-up with the current banks. The observed increased loan rates support the rent extraction channel. Second, I consider whether the firm has any other sources of debt financing, and find the effect mainly comes from firms without net debt issuance. Third, I find the increased loan rates are mainly from syndicate loans with less members, in which cases the banks should be more diligence in information collection (Sufi, 2007) and less affected by peer information deterioration. Hence this also points to rent extraction channel as they may have more bargaining power.

4.5. Negative spillover in lending: quantities

In previous sections, I show that peer fraud behavior affects loan prices. Does the adverse information of peers also affect bank lending quantities? The hypothesis is that banks would decrease lending when peers committed fraud.

To test this hypothesis, I first construct the data at bank-firm level. That is, for each bank, I expand all firm-year for firms borrowed from the bank. Detailed construction is in Appendix C. In this way, I can check the change in loan amount from the bank after firm peers that bank once lent committed fraud. Specifically, I estimate the following regression,

$$\mathbf{1}(N_{b,f,t} < 0) = \beta_1 \Delta PeerFraud\ (b)_{b,f,t-1} + \delta_{b,f} + \delta_{b,t} + \delta_{k,t} \varepsilon_{b,f,t}, \tag{6}$$

where $\mathbf{1}(N_{b,f,t} < 0)$ is a dummy equals 1 if bank b reduces loan amount to firm f in year t. $PeerFraud\ ()_{b,f,t-1}$ is a dummy equals 1 if firm peers in bank b's portfolio committed fraud in last year. $\delta_{b,f}$, $\delta_{b,t}$ and $\delta_{k,t}$ are the bank-firm pair, bank-year and industry-year fixed effects. I drop firms that ever committd fraud in the sample.

The results are in Table 9. In the first two columns, I estimate a logistic estimation. The coefficient of $PeerFraud\ (b)$ is significant positive, showing a higher probability that banks reduce to lending to firms when there are fraudulent peers in banks' portfolio. In column (2), I estimate a fixed-effect logistics model to examine the effect within bank-firm group and obtain consistent result. The effect is insignificant if fraudulent peers are not in banks' portfolio. In column (3), I estimate a fixed-effect OLS model, which allows me to conditional on more factors. Specifically, I add bank-year fixed effect to absorb any supply side factors, and industry-year fixed effect to control for demand side factors as the fraud behavior of their competitors may affect their demand of credit. The overall results suggest that fraud behavior of firms can pose negative externalities to peer firms in terms of credit availability.

5. Conclusion

Peers have an active impact on firms' financing and investment decisions, as managers tend to learn from peer information. In this paper, I present the evidence that banks also use peer information in loan contract designing. Using syndicated loans data, I find that loan rates are lower for firms that borrow from banks with a prior lending relationship to the firms' peer. Moreover, the benefit in loan rates is larger if the current borrower is more similar to its peers and with limited own information. The effect is robust after controlling for large cross-section of firm characteristics and peer environment. To further validate the role of peer effect, I use the fraud records of firms' peers as shocks and find that the benefit in loan rates diminishes. I provide two possible explanations for the finding, either banks belief or trust gained from peers destroyed by the dishonest behavior or banks are extracting the rents when other investors in the market are uncertain. The findings that the higher costs in loan rates concentrate on relationship loan and firms without debt issuance suggest that banks may take the advantage of information and hold up the firms that not easy to switch lenders. Moreover, banks also reduce lending activities to firms when their peers committed fraud. The findings suggest whether information advantage can result in lower loan rates depend on the relatively bargaining power of banks and firms. In normal conditions, transparent firms may have larger bargaining power due to the competitiveness of syndicated loan market, while banks take the charge of power when information environment is unfavorable to firms. To sum up, the paper provides evidence that banks value peer information when making lending decisions.

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Fig. 1. **Loan rates before and after filing in SCAC**

This figure plots the evolution of loan rates around filings in SCAC. The specification is $AISD_{l,t} = \beta_{-10}Fraud_{t-10} + \beta_{-9}Fraud_{t-9} + \cdots + \beta_9 Fraud_{t+9} + \beta_{10}Fraud_{t+10} + \delta_{b,t} + +\delta_f + \epsilon_{l,t}$, where $Fraud_{t-j}$ equals one in the jth quarter before the firm files in SCAC, $Fraud_{t+j}$ equals one in the jth quarter after the firm files in SCAC, using a quarter before fraud as the reference year. Bank-industry, firm and bank-year fixed effects are added. The dashed lines plot the 95% confidence interval.

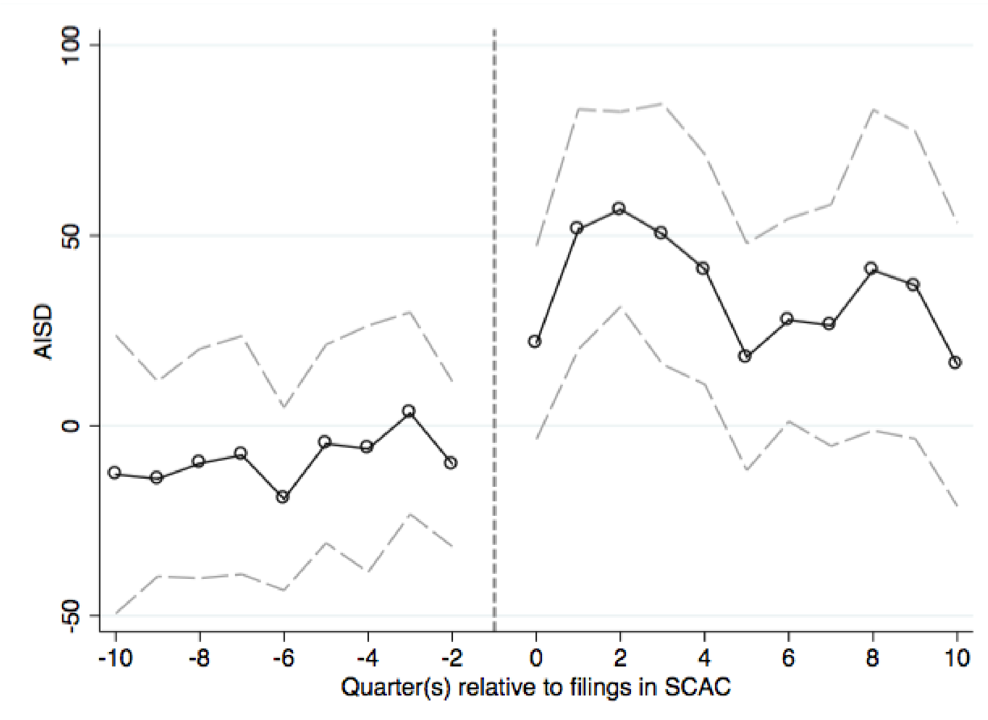

Fig. 2. **Covariates before and after matching**

This figure plots the standardized percent bias across covariates before and after matching. The sample only consists $PeerLoan$ whose borrowers have fraudulent peers in last four quarters. The treated group is $FraudPeer$ loans of which the borrower borrow from a bank that have lent to fraudulent peers. The matching is conducted using the nearest-neighbor (n=10).

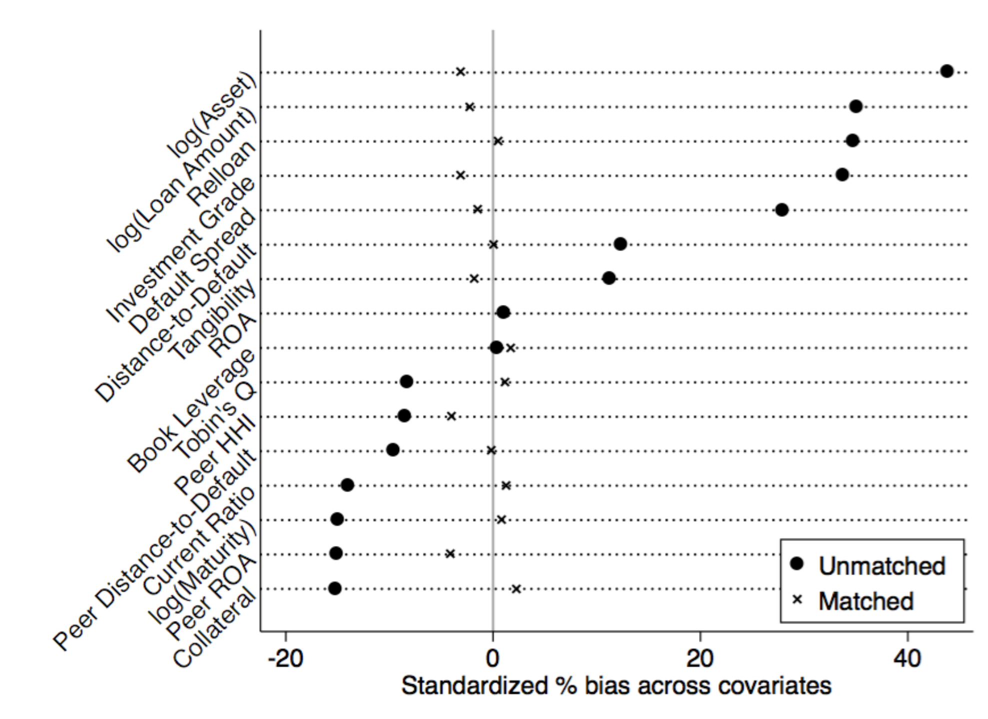

Table 1: **Summary Statistics**

This table reports the summary statistics for the main variables used in the analysis. The time spans from 1996 to 2012. Panel A and C reports loan characteristics and other vriables at loan-quarter level, and Panel B reports firm characteristics at firm-quarter level. See Appendix A for variable definitions.

	PeerLoan				non - *PeerLoan*			
	N	Mean	Std.dev	Median	N	Mean	Std.dev	Median
Panel A: Loan characteristics (loan-quarter level)								
AISD	13,488	174.8	119.4	150	5,764	201.4	122.2	200
Loan amount ($ millions)	13,584	455.4	929.9	200	5,818	193.6	508.1	75
Loan maturity (months)	13,085	46.06	23.43	53	5,576	43.45	23.16	42
Collateral	13,584	0.493	0.500	0	5,818	0.617	0.486	1
Revolving facility	13,584	0.743	0.437	1	5,818	0.704	0.456	1
Term loan	13,584	0.226	0.418	0	5,818	0.263	0.441	0
Panel B: Firm characteristics (firm-quarter level)								
Book assets (million)	9,803	6,963	24,514	1,505	4,047	3,042	21,584	389.9
ROA	9,134	3.267	2.692	3.201	3,620	3.150	2.889	3.194
Distance-to-default	8,564	6.879	5.415	5.602	3,343	6.09	5.086	4.781
Tobin's Q	9,323	1.414	0.918	1.132	3,801	1.461	1.008	1.143
Book leverage	9,415	0.302	0.194	0.292	3,857	0.291	0.205	0.277
Current ratio	9,326	1.826	1.094	1.566	3,795	2.049	1.141	1.814
Tangibility	9,623	0.335	0.240	0.275	3,989	0.264	0.209	0.200
Investment grade	9,803	0.321	0.467	0	4,047	0.161	0.367	0
Panel C: Other variables (loan-quarter level)								
Relloan	13,584	0.585	0.493	1	5,818	0.428	0.495	0
PeerLoan (N)	13,584	6.673	7.090	4	5,818	0	0	0
PeerLoan (sum)	14,822	0.282	0.414	0.125	6,512	0	0	0
Peer ROA	13,548	2.496	2.438	3.013	5,045	2.579	2.566	3.072
Peer Distance-to-Default	13,557	6.976	2.707	6.560	5,029	6.806	3.020	6.409
Peer HHI	13,555	0.0596	0.107	0.0181	5,135	0.211	0.300	0.0603
OwnFraud	13,584	0.0320	0.176	0	5,818	0.0193	0.137	0
PeerFraud	13,584	0.0885	0.284	0	5,818	0	0	0
PeerFraud (score)	13,584	0.00617	0.0499	0	5,818	0	0	0

Table 2: **Annual SCAC Filling**

This table shows the summary statistics of SCAC filings. Panel A displays the fraud information at loan level. The second columns gives the total number of loans in the sample in each year. Fraud N shows the annual numbers of loans whose borrowers filed in SCAC in last 4 quarters. Peer Fraud N shows the number of loans of which borrowers' peers (the lender lent in previous three years) filled in SCAC in last 4 quarters. Panel B shows the information of fraud cases used in the sample by year and sector. The sector classification is obtained from the SCAC website.

Panel A: Loan level

Year	Total Loan			Peer Loan		
	N	Fraud N	Ratio (%)	N	$PeerFraud\,N$	Ratio (%)
1996	1,408	2	0.14	751	6	0.80
1997	1,863	15	0.81	1,104	39	3.53
1998	1,591	47	2.95	990	44	4.44
1999	1,508	39	2.59	924	56	6.06
2000	1,450	43	2.97	981	53	5.40
2001	1,378	39	2.83	957	126	13.17
2002	1,322	78	5.90	984	125	12.70
2003	1,169	61	5.22	834	196	23.50
2004	1,301	44	3.38	964	83	8.61
2005	1,246	35	2.81	942	93	9.87
2006	1,042	27	2.59	836	100	11.96
2007	1,010	18	1.78	777	54	6.95
2008	589	20	3.40	442	54	12.22
2009	406	7	1.72	310	31	10.00
2010	658	36	5.47	510	40	7.84
2011	1,034	27	2.61	915	71	7.76
2012	429	9	2.10	363	31	8.54
Total	19,404	547	2.82	13,584	1,202	8.85

Panel B: Fraud case level

By year	N	Percent (%)	By Sector	N	Percent (%)
1996	16	2.38	Basic Materials	18	2.68
1997	44	6.56	Capital Goods	24	3.58
1998	46	6.86	Conglomerates	5	0.75
1999	48	7.15	Consumer Cyclical	37	5.51
2000	52	7.75	Consumer Non-Cyclical	23	3.43
2001	70	10.43	Energy	20	2.98
2002	74	11.03	Financial	14	2.09
2003	43	6.41	Healthcare	107	15.95
2004	50	7.45	Services	192	28.61
2005	38	5.66	Technology	186	27.72
2006	19	2.83	Transportation	7	1.04
2007	38	5.66	Utilities	38	5.66
2008	29	4.32			
2009	30	4.47			
2010	32	4.77			
2011	26	3.87			
2012	16	2.38			
			Total	671	100

Table 3: **Lending to Borrowers' Peers**

This table reports the multivariate regression results of loan rates lending to previous borrowers' peers. The dependent variable AISD is the All-in-spread-drawn from the LPC Dealscan database. The independent variable *PeerLoan* is a dummy equal to 1 if the bank lent to the borrower's peers in previous three years prior to the current loan, *PeerLoan* (N) is the logarithm of 1 plus the number of the borrower's peers bank lent in previous three years, *PeerLoan* (*score*) is the sum of scores between the borrower and its peers the bank lent in previous three years. Control variables include firm-, peers-, and loan- specific characteristics. See Appendix for a detailed definition of all variables. In all specifications, year and industry fixed effect are added. Borrower, and bank-year fixed effects are added as indicated. Standard errors are clustered at industry level and reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	AISD (1)	AISD (2)	AISD (3)	AISD (4)	AISD (5)	AISD (6)
PeerLoan	-6.598**	-8.508***	-10.122***	-8.299***		
	(2.548)	(3.096)	(3.013)	(2.809)		
PeerLoan (N)					-7.672***	
					(2.001)	
PeerLoan (*score*)						-11.913***
						(4.495)
Peer ROA		-3.051***	-1.998**	-1.759**	-1.813**	-1.736**
		(0.748)	(0.898)	(0.792)	(0.775)	(0.773)
Peer Distance-to-Default		-2.055***	-1.738**	-1.460*	-1.461*	-1.469*
		(0.591)	(0.746)	(0.754)	(0.748)	(0.760)
Peer HHI		-10.969*	-8.715	-6.497	-10.747	-2.302
		(5.988)	(8.327)	(7.564)	(7.730)	(6.847)
Relloan	-5.445***	-4.950**	-6.656***	-4.452**	-4.083*	-4.307**
	(2.096)	(2.177)	(2.187)	(2.148)	(2.149)	(2.141)
log(Book assets)	-21.570***	-20.664***	-22.116***	-11.119***	-11.048***	-11.099***
	(1.943)	(1.987)	(3.442)	(3.514)	(3.492)	(3.598)
Distance-to-Default	-2.589***	-2.453***	-1.248***	-0.988***	-0.963***	-0.993***
	(0.389)	(0.421)	(0.315)	(0.293)	(0.297)	(0.296)
Book leverage	86.540***	86.650***	120.223***	119.363***	118.320***	118.707***
	(9.790)	(10.073)	(13.817)	(13.494)	(13.321)	(13.444)
ROA	-6.864***	-6.358***	-3.721***	-2.589***	-2.619***	-2.636***
	(0.649)	(0.643)	(0.707)	(0.649)	(0.640)	(0.646)
Tobin's Q	-8.619***	-8.373***	-8.292***	-8.472***	-8.717***	-8.420***
	(1.954)	(1.936)	(2.036)	(1.896)	(1.879)	(1.845)
Current ratio	-7.071***	-7.907***	-5.863***	-5.393***	-5.414***	-5.356***
	(1.237)	(1.287)	(1.710)	(1.479)	(1.475)	(1.470)
IG	-75.102***	-75.101***	-69.340***	-55.228***	-55.194***	-55.441***
	(4.759)	(4.987)	(6.299)	(6.471)	(6.454)	(6.441)
S&P Long-term Rating	36.850***	37.427***	25.054***	16.950***	17.510***	17.807***
	(5.248)	(5.532)	(7.236)	(6.513)	(6.469)	(6.346)
log(Loan maturity)				2.194	2.228	2.255
				(1.453)	(1.448)	(1.449)
log(Loan amount)				-9.809***	-9.835***	-9.880***
				(1.336)	(1.331)	(1.331)
Collateral				35.092***	35.038***	35.192***
				(3.211)	(3.201)	(3.202)
Loan Type	✓	✓	✓	✓	✓	✓
Year and Industry FE	✓	✓	✓	✓	✓	✓
Borrower FE			✓	✓	✓	✓
Bank × Year FE				✓	✓	✓
Observations	19,199	18,566	17,852	16,974	16,974	16,974
R-squared	0.626	0.629	0.776	0.802	0.803	0.802

Table 4: **Heterogeneous Effect of Peer Information**

The table reports the cross-sectional effect of peer information on loan rates. The dependent variable AISD is the All-in-spread-drawn from the LPC Dealscan database. The independent variables are interactions of $PeerInfo$ with Opaque, which is a dummy taking on the value of 1 when a firm's analyst coverage, obtained from I/B/E/S dataset, is below the median of firms' in the sample. Control variables are added. Bank × year are added as indicated. Standard errors are clustered at industry level and reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	AISD (1)	AISD (2)	AISD (3)
Opaque × $PeerLoan$	-11.035**		
	(4.458)		
$PeerLoan$	1.504		
	(3.063)		
Opaque× $PeerLoan$ (N)		-6.222***	
		(2.185)	
$PeerLoan$ (N)		0.804	
		(1.967)	
Opaque× $PeerLoan$ $(score)$			-14.351***
			(5.467)
$PeerLoan$ $(score)$			5.121
			(4.742)
Opaque	19.350***	19.327***	14.186***
	(3.993)	(3.775)	(2.640)
Control variables	✓	✓	✓
Bank × year FE	✓	✓	✓
Observations	17,590	17,590	17,590
R-squared	0.682	0.682	0.682

Table 5: **Robustness Check**

This table reports the robustness check results of loan rates lending to previous borrowers' peers. Column (1)-(3) use the sub-sample without relationship loans. In column (4)-(6), the sample is at package level and only contains the largest loan in each package. In column (7)-(8), I define three-digit SIC as peers. Control variables, bank-year and borrower fixed effects are added in all columns. Standard errors are clustered at industry level and reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	AISD	AISD	AISD	AISD	AISD	AISD	AISD	AISD
	Without Relationship			Package Level			SIC3 as Peers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PeerLoan$	-16.316***			-4.938*				
	(5.343)			(2.782)				
$PeerLoan\ (N)$		-12.743***			-4.896***			
		(2.968)			(1.810)			
$PeerLoan(score)$			-18.257***			-8.331**		
			(6.353)			(3.685)		
$PeerLoan\ (SIC3)$							-7.554***	
							(2.628)	
$PeerLoan\ (SIC3\ N)$								-6.030***
								(2.147)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,969	5,969	5,969	11,856	11,856	11,856	16,974	16,974
R-squared	0.869	0.870	0.869	0.808	0.808	0.808	0.802	0.802

Table 6: **Information Deterioration and Costs of Debt**

This table reports the multivariate regression results of the loan rates when peer committed fraud. The dependent variable AISD is the All-in-spread-drawn from the LPC Dealscan database. The independent variable $PeerFraud$ is a dummy taking on the value of 1 when peers (bank lent in previous three years) committed fraud in last four quarters. In all specifications, control variables and year fixed effects are added. Firm and bank-year fixed effects are added as indicated. Standard errors are clustered at industry level.

	AISD (1)	AISD (2)	AISD (3)	AISD (4)	AISD (5)	AISD (6)
$PeerFraud\ (b)$	8.714**	6.588*	6.304**	8.981*		
	(3.934)	(3.848)	(3.038)	(4.590)		
$TNICFraud$	-6.124*	-7.406***	-8.507***	-11.216***		
	(3.255)	(2.733)	(2.806)	(3.511)		
$PeerFraud\ (b) \times PeerLoan\ (N)$					3.622***	
					(1.081)	
$PeerLoan\ (N)$					-8.149***	
					(1.999)	
$PeerFraud\ (b) \times PeerLoan\ (score)$						12.917***
						(3.586)
$PeerLoan\ (score)$						-15.623***
						(4.716)
$PeerLoan$	9.628***	0.641	-2.306	-2.174	-2.061	-2.074
	(2.681)	(2.071)	(2.303)	(2.651)	(2.318)	(2.228)
$OwnFraud$	39.269***	35.265***	34.801***	-	34.337***	34.031***
	(9.063)	(9.785)	(10.396)		(10.324)	(10.393)
Distance-to-Default		-1.797***	-0.933***	-1.030***	-0.910***	-0.928***
		(0.357)	(0.293)	(0.314)	(0.296)	(0.297)
ROA		-4.862***	-2.535***	-1.705**	-2.568***	-2.585***
		(0.664)	(0.646)	(0.728)	(0.638)	(0.641)
Peer ROA		-2.358***	-1.708**	-1.214	-1.739**	-1.655**
		(0.705)	(0.805)	(1.006)	(0.800)	(0.803)
Peer Distance-to-Default		-1.559**	-1.580**	-1.340	-1.574**	-1.591**
		(0.618)	(0.787)	(0.908)	(0.778)	(0.794)
Other Controls	✓	✓	✓	✓	✓	✓
Year and Industry FE	✓	✓	✓	✓	✓	✓
Borrower FE			✓	✓	✓	✓
Bank × Year FE			✓	✓	✓	✓
Observations	21,516	17,549	16,796	12,079	16,796	16,796
R-squared	0.579	0.665	0.805	0.812	0.806	0.806

Table 7: **Within-Firm Analysis: Propensity Score Matching**

This table shows the average treated effect (ATE) from propensity score matching. The matching is conducted using the nearest-neighbor (n=10 and 50). In column (1)-(2), the sample only consists $PeerLoan$ whose borrowers have fraudulent peers in last four quarters. The treatment group is $PeerFraud$ loans that borrowed from a bank that lent to fraudulent peers. In column (3)-(4), the treatment group is loans that borrowed from a bank that lent to fraudulent non-peers. The standard errors are robust, based on Abadie and Imbens (2016). Standard errors are reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	(1)	(2)	(3)	(4)
Treated	$PeerFraud = 1$		non-$PeerFraud = 1$	
	n=10	n=50	n=10	n=50
ATE	8.412**	10.441***	-1.292	-1.152
	(3.889)	(3.544)	(6.307)	(5.217)
Observation				
Treated	768	768	1,537	1,537
Control	2,974	4,345	5,527	9,261

Table 8: **Trust deterioration or Rent Extraction?**

This table reports the heterogeneous effect in the costs of debt when peer committed fraud. The independent variable is the interaction term of $PeerFraud$ and different dummies as indicated. More Similar equals 1 if the score between current firm and fraudulent peers is above the median. Bigger fraudulent peers equals 1 of the fraudulent peers' book asset is above median. Higher credit riskiness equals 1 if the firm's distance-to-default is above the median, and Lower current ratio equals 1 if the firm's current ratio is below the median. w/o Debt Issuance equals 1 if the firm's net debt issuance is below 5% of book asset. Less syndicate members equals 1 if the numbers of syndicate members are below the median. In all specifications, control variables, industry and bank-year fixed effects are added. Standard errors are reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	AISD (1)	AISD (2)	AISD (3)	AISD (4)	AISD (5)	AISD (6)	AISD (7)
$PeerFraud$ $(b) \times \ldots$							
More Similarity	15.397**						
	(7.603)						
Bigger Fraudulent Peers		7.585					
		(7.841)					
Higher Credit Riskness			22.175***				
			(7.720)				
Lower Current Ratio				17.355***			
				(5.590)			
Relloan					12.377*		
					(7.108)		
Without Debt Issuance						11.994*	
						(6.804)	
Less syndicate members							14.460**
							(6.668)
$PeerFraud$ (b)	1.130	4.104	-19.118***	-15.887***	-1.006	-1.349	-14.647***
Industry FE	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓
Bank × Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	17,523	17,401	17,523	17,523	17,523	17,523	17,523
R-squared	0.680	0.680	0.680	0.680	0.680	0.682	0.680

Table 9: **Negative Spillover in Lending: quantities**

This table reports the estimates examining whether banks decrease lending to peers if they have fraudulent peers in portfolio. Column (1) and (2) reports the setimates from logit regressions, and column (3) the OLS regression. The dependent variable $\mathbf{1}(\Delta N < 0)$ is a dummy, taking on the value of 1 if Δ(Loans to Firm) < 0. $PeerFraud$ ($PeerFraud$ (b)) is a dummy taking on the value of 1 if there exists any fraudulent peers (banks lent) in last period. Bank-firm, bank-year and industry-year fixed effects are added in each specification. Standard errors clustered at bank-firm level and reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	Logit		OLS
	= 1 if Δ(Loans to Firm) < 0		
	(1)	(2)	(3)
$PeerFraud$ (b)	0.371***	0.263***	0.027***
	(0.040)	(0.046)	(0.007)
$TNICFraud$	-0.129***	-0.040	-0.002
	(0.026)	(0.035)	(0.005)
Bank-firm FE		✓	✓
Bank-year FE			✓
Industry-year FE			✓
Observations	55,527	50,525	54,649
(Pseudo) R-squared	0.0231		0.244

Appendix A. Variable Definition

Loan characteristics

AISD is the all-in-spread-drawn, as a comprehensive borrowing cost.

Loan amount ($ millions) is the loan amount, in $ millions.

Marturity (months) is the number of months between facility start and end dates.

Collateral is a dummy variable taking on the value of 1 if secured =1 and 0 otherwise.

Revolving facility is a dummy variable taking on the value of 1 if the loan is a revolving line of credit and 0 otherwise.

Term loan is a dummy variable taking on the value of 1 if the loan is term loan and 0 otherwise.

Firm and peer characteristics

Book assets ($milion) $= atq$

Book leverage $= (dlcq + dlttq)/atq$

Equity Volatility is the standard deviation of monthly returns over the 12-month period ending at the fiscal year end and annualized by multiplying it by $\sqrt{12}$.

Distance-to-default $= (log((E + F)/F) + (l.r - 0.5 * \sigma_v^2))/\sigma_v$, where r is the three month T-bill rates, $F = dlcq + 0.5 * dlttq$, $E = prccq * cshoq$, and $\sigma_v = E/(E + F) * \sigma_e + F/(E + F) * (0.05 + 0.25 * \text{Equity volatility})$.

Tobin's Q $= (atq - (atq - ltq + txditcq) + (prccq * cshoq))/atq$

Current Ratio $= actq/lctq$

Tangibility $= ppentq/atq$

ROA $= oibdpq/atq$

S&P long-term rating is a dummy taking on the value of 1 if a firm has S&P long-term rating.

Investment Grade is a dummy taking on the value of 1 if a firm has S&P long-term rating above BBB-.

Opaque is a dummy taking on the value of 1 when a firm's analyst coverage, obtained from I/B/E/S dataset, is below the median of firms' in the sample.

Peer ROA is the average of the firm's TNIC peers' ROA.

Peer Distance-to-Default is the average of the firm's TNIC peers' Distance-to-Default.

Peer HHI is the average of the firm's TNIC peers' HHI of their sales.

<u>Information related variables</u>

PeerLoan is a dummy variable taking on the value of 1 if at least one of the lead banks lent to the firm' TNIC peers in previous 3 years.

***PeerLoan* (*N*)** =log(1+number of TNIC peers banks lent in previous 3 years)

***PeerLoan* (*score*)** is the sum of the score between TNIC peers that bank lent to in previous 3 years

***PeerLoan* (*SIC*3)** is a dummy taking on the value of 1 if at least one of the lead banks lent to the firm' three-digit SIC peers in previous 3 years.

***PeerLoan* (*SIC*3 *N*)** =log(1+number of three-digit SIC peers banks lent in previous 3 years)

Δ*PeerLoan* (*N*) is the change in the number of TNIC peers banks lent in previous 3 years

Relloan is a dummy taking on the value of 1 if the firm lent from (one of the) lead banks in previous three years.

<u>Fraud variables</u>

OwnFraud is a dummy taking on the value of 1 if the firm files in SCAC in the previous year.

***PeerFraud* (*b*)** is a dummy taking on the value of 1 if peer firms (borrowed from the same bank in previous three years) committed fraud in the previous year.

TNICFraud is a dummy variable taking on the value of 1 if firm' TNIC peers committed fraud in the previous year.

***PeerFraud* (*N*)** is the number of peer firms (borrowed from the same bank in previous three years) committed fraud in the previous year.

Appendix B. Endogeneity in lending: Bank × year fixed effect

Like in any other contract choice (Ackerberg and Botticini, 2002; Chen and Song, 2013), banks and firms are not randomly matched in that banks choose firms and firms also choose banks, thus the matching result is endogenously determined. Due to unobserved or partially observed characteristics of banks and firms, the estimation of a loan spread equation is biased.

To illustrate, consider a loan spread equation that writes (I omit time index t)

$$r_{l,b,f} = \beta_1 X_b + \beta_2 Y_f + \beta_3 Z_{b,f} + \theta L_l + \varepsilon_{l,b,f}, \tag{7}$$

where $r_{l,b,f}$ is the credit rates for loan l with lender b and borrower f, and L_l are loan features like amount or maturity. X_b, Y_f are the bank and firm characteristics which we can only observe partially through $\tilde{X}_b$ and $\tilde{Y}_f$, such as size, credit rating, etc. $Z_{b,f}$ is the feature depending on bank-firm that affects loan spread. In this case, $Z_{b,f}$ is bank b's information of firm f, which is proxied by $\tilde{Z}_{b,f}$, e.g. whether bank b lent to firm f's peers in previous years,

$$X_b = \tilde{X}_b + \mu_b \tag{8}$$

$$Y_f = \tilde{Y}_f + \nu_f \tag{9}$$

$$Z_{b,f} = \tilde{Z}_{b,f} + \omega_{b,f}. \tag{10}$$

Substituting these equations into Equation (7), we can obtain

$$r_{l,b,f} = \beta_1(\tilde{X}_b + \mu_b) + \beta_2(\tilde{Y}_f + \nu_f) + \beta_3(\tilde{Z}_{b,f} + \omega_{b,f}) + \theta L_l + \varepsilon_{l,b,f}. \tag{11}$$

As banks and firms select each other based on their characteristics, $\text{Cov}(\mu_b, \tilde{Y}_f)$ is unlikely to be 0, which brings up an endogeneity problem due to omitted variables. This can biased the estimation, including our interest coefficient on $\tilde{Z}_{b,f}$.

One way to solve the problem is to add bank × year fixed effect to wash out μ_b. This can remove any time-varying bank characteristics from the loan equation and solve the issue due to

$\text{Cov}(\mu_b, \tilde{Y}_f) \neq 0$. In particular, loan portfolio risk can be washed away in this way. I am comparing loan rates bank offered in the same year, and my interest rests on testing whether peer loans would be any cheaper, other things equal.

Appendix C. Data construction

$PeerLoan$: I need a detailed network structure between firm-pair peers and firm-bank relationships in order to identify a $PeerLoan$. To illustrate, assume Firm f_1 borrowed Loan L from Bank B in 2002q2. I find all unique firms (e.g. Firm f_2) Bank b lent in previous 12 quarters (3 years) and identify which of them were peers of Firm A (in year 2002 as TNIC3 peers). I define the current Loan L as a $PeerLoan$ if there are peers Bank B lent and count the total numbers of such loans ($PeerLoan$ (N)) or score weighted numbers ($PeerLoan$ $(score)$).

$PeerFraud$ (b): I first expand quarters between current $PeerLoan$ and the loan bank lent to in preceding quarters. Continue with previous example that Bank b lent to Firm f_2 in 2000q1, so I expand quarters from 2000q1 to 2002q2 for Firm f_2 and Bank b and check whether f_2 committed fraud during this period. I define $PeerFraud = 1$ if Firm f_2 committed fraud during the time, as Bank b's information about this type of firms is considered to be deteriorated. I do it for all peers of Firm $f1$ that Bank b lent in previous 12 quarters and sum the fraud peer-quarters up (PeerFraud (N)).

$\Delta PeerLoan$ (N): I expand firm-quarter for each bank and fill the time gap. Specifically, Firm f_1 borrowed two loans from Bank B in 2002q2 and 2006q1, so there is only two bank-firm-quarter records in my original sample. I fill the time gaps for all quarters Firm f_1 and Bank B existed in the sample period and replace $PeerLoan$ $(N) = 0$ in other quarters. With the expanded firm-quarter, I can have the information about changes of $PeerLoan$s ($\Delta PeerLoan$ (N)) Bank B had with respect to Firm f_1 by calculating the first-difference of $PeerLoan$ (N).

Appendix D. Information deterioration: IV implementation

Banks decrease lending to firms when firm peers banks once lent committed fraud. Utilizing this fact, I use $PeerFraud\ (N)$ as an instrument variable for $PeerLoan\ (N)$, as it satisfied the relevance assumption. In addition, peer fraud behavior in last year should be exogenous to loan rates.

Since $PeerLoan\ (N)$ is the moving summation by construction, it is quite sticky and positively related with $PeerFraud\ (N)$ cross-sectionally. We should compare the correlation between the two variables within bank-firm group. However, in our original loan sample, it can hardly be implemented due to the limited loan records for a bank-firm pair. Hence, another way to do is to calculate the first-difference of $PeerLoan\ (N)$ in the bank-firm-year expanded sample and merge back to the loan sample. Using the first-difference value $\Delta PeerLoan\ (N)$ as an independent variable addresses the above concern and allows us to compare it cross-sectionally. The interpretation is similar, as a positive value implies an increase in peer information, and the larger the more information is available.

The IV results are displayed in Table B. 2. Column (3)-(4) show the first-stage result, with a significantly negative coefficient showing that more peer fraud leads to decreased $PeerLoan$s. This is consistent with previous findings that peer fraud behavior affect firm loan availability. Column (5)-(6) displays the reduced form results, showing that peer fraud behavior results in a more expensive loan rates, also consistent with previous findings.

Column (1) and (2) reports the second stage result from two-stage-least-square (2SLS) estimation, with a negative and significant estimates for $\Delta PeerLoan(N)$. The F-statistics is above 10, excluding the weak IV concern. The results are also robust when adding bank-industry fixed effect. Regarding to the economic magnitude, one increase in $PeerLoan$ can result in about 16-18 bps lower in loan rates.

Table B. 1: **Major Banks in the Sample**

This table lists the major banks which have more than 50 loans in our sample. Column (3) presents the total number of loans the banks lent during the first and last year in the sample. Column (4) shows the total number of $FraudLoan$ and column (5) shows the fraud ratio.

Bank	First Year	Last Year	Loans N	$FraudLoan$ N	Fraud Ratio (%)
Bank of America	1996	2012	5952	194	3.26
JP Morgan	1996	2012	5501	195	3.54
Citi	1999	2012	2246	147	6.54
Wells Fargo	1996	2012	1702	47	2.76
Wachovia	1996	2008	1288	27	2.10
Bank One	1996	2004	940	19	2.02
Fleet/FleetBoston	1996	2003	798	28	3.51
SunTrust Bank	1996	2012	635	22	3.46
PNC Financial	1996	2012	479	6	1.25
Bank of America (old)	1996	1998	427	8	1.87
US Bancorp	1996	2012	409	11	2.69
Silicon Valley Bank	1996	2012	378	23	6.08
Key Bank	1996	2012	374	10	2.67
Citi (old)	1996	1998	362	5	1.38
JP Morgan (old)	1998	2012	331	10	3.02
Morgan Stanley	1996	2000	330	13	3.94
Bank of New York	1996	2012	318	7	2.20
Bankers Trust Co	1996	1999	300	2	0.67
Goldman Sachs & Co	1999	2012	277	11	3.97
Bank Boston	1996	1999	268	8	2.99
Comerica	1996	2012	246	9	3.66
First Chicago	1996	2008	202	1	0.50
National City Bank	1996	1998	194	0	0.00
WellsFargo (old)	1996	2001	134	12	8.96
Wachovia Bank (old)	1996	2002	104	1	0.96
Mellon Bank	1996	1998	100	1	1.00
CoreStates Bank	1996	1998	56	0	0.00
AmSouth Bank	1996	2011	51	1	1.96
Fifth Third Bank	2002	2012	50	2	4.00

Table B. 2: **Peer Information and the cost of debt: IV results**

This table reports the IV results for peer information on the cost of debt. The dependent variable AISD is the All-in-drawn spread from the LPC Dealscan database. The endogenous variable Δ $PeerLoan(N)$ is the change of the number of the borrower's peers bank lent in previous three years. The instrumental variable $PeerFraud$ (N) is the number of fraudulent peer firms bank lent. Column (1)-(2) display the second-stage results, column (3)-(4) display the first-stage results, and column (5)-(6) display the reduced form results. In all specifications, control variables, bank-year, and bank-industry fixed effects are added as indicated. Standard errors are clustered at industry level and reported in parentheses. *, **, *** mean significance at ten, five, and one percent, respectively.

	Second Stage		First Stage		Reduced Form	
	AISD		$\Delta PeerLoan$ (N)		AISD	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta PeerLoan(N)$	-17.874***	-16.590***				
	(6.038)	(5.929)				
$PeerFraud(N)$			-0.145***	-0.155***	2.597***	2.565***
			(0.037)	(0.035)	(0.942)	(0.940)
Control variables	✓	✓	✓	✓	✓	✓
Bank × year FE	✓	✓	✓	✓	✓	✓
Bank × industry FE		✓		✓		✓
Observations	16,221	15,709	16,221	15,709	16,221	15,709
R-squared	0.566	0.646	0.281	0.334	0.686	0.743
F	15.71	19.70				