Syndication, Interconnectedness, and Systemic Risk*

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Abstract

This paper studies the interconnectedness of banks in the syndicated loan market as a major source of systemic risk. We develop a set of novel measures to describe the "distance" (similarity) between two banks' syndicated loan portfolios and find that such distance explains how banks are interconnected in this market. As lead arrangers choose to work with those that have a similar focus in terms of lending expertise, there is a high propensity of bank lenders to concentrate syndicate partners rather than to diversify them. We find some evidence of potential benefits of this behavior as to lower costs of screening and monitoring, for example, higher shares of the loan taken by more connected lenders and lower loan spreads if syndicated lenders are more connected. Lastly, we find that the most heavily interconnected lenders in the syndicated loan market are also the greatest contributors to systemic risk, suggesting important negative externalities associated with the syndication process.

Keywords: Interconnectedness, syndicated loans, systemic risk

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1 Introduction

In summer 2007, the global financial system entered a crisis that became truly systemic after Lehman Brothers' default in September 2008. Since then, academics and regulators have developed different concepts and proposals as to how to measure systemic risk, classify systemically important financial institutions (SIFIs), and trace the determinants of systemic risk.[1] Two important measures of systemic risk are "Systemic Expected Shortfall" (SES) developed in Acharya et al. (2010) and "CoVarR" in Adrian and Brunnermeier (2010). Brunnermeier et al. (2011) analyze the determinants of systemic risk and identify noninterest income as a main source of systemic risk.

One overlooked possible factor in explaining systemic risk is the propensity of bank lenders to concentrate syndicate partners rather than to diversify them. Syndication is one particular example as to how financial institutions are interconnected. These networks are beneficial to the financial system under normal conditions providing lenders the possibility to diversify risks and borrowers access to a larger pool of capital. During crises, however, this interconnectedness can lead to systemic risk if all banks hold similar portfolios and might turn the failure of one institution into a full-blown systemic crisis.

Federal Reserve Chairman Ben Bernanke highlighted during his speech at the Conference on Bank Structure and Competition in May 2010 in Chicago:

> "We have initiated new efforts to better measure large institutions' counterparty credit risk and interconnectedness, sensitivity to market risk, and funding and liquidity exposures. These efforts will help us focus not only on risks to individual firms, but also on concentrations of risk that may arise through common exposures or sensitivity to common shocks. For example, we are now collecting additional data in a manner that will allow for the more timely and consistent measurement of individual bank and systemic exposures to syndicated corporate loans."

[1] For example, the G-20 has just released the names of 29 globally systemic institutions that will be required to hold an additional capital buffer. In Europe, regulators require 70 European banks to increase their core capital ratio to 9% until June 2012 and hold a temporary capital buffer against additional write-downs of their sovereign debt holdings.

In this paper we study the issue by examining the organizational form of loan syndicates.[2] During the last decade, a fast growing literature has looked at various aspects of the syndicated loan market.[3] None of these papers, however, compares the portfolio holdings of syndicate lenders and studies the implications of their interconnectedness, particularly with respect to systemic risk. This is the main contribution of our paper.

We develop a set of novel measures to describe the "distance" (similarity) between two banks' syndicated loan portfolios and explore how this distance relates to interconnectedness. Banks' asset portfolios are inherently complex, which means that we cannot infer that two banks are similar to each other because they both invest in the same industry or market. The extent and depth of their investment matters, as well as other types of investments and their relative weights. We thus focus on the similarity in lending expertise between two banks in the syndicated loan market as data pertaining to this market are fairly complete to provide us a comprehensive view of the banks' entire loan portfolios. This is essential to properly assess how distant/close the banks are along various dimensions such as industry specialization or physical market presence. Using DealScan's loan origination data, we compute banks' portfolio weights based on loan amounts they arranged in each area of specialization and measure the distance between two banks as the Euclidean distance based on these portfolios weights.[4] Such distance is a *direct* measure of interconnectedness: the closer two banks are, the more similar their loan portfolios are, and thus, the higher exposure they have to common shocks.

[2] Loan syndicates are ideal for the purpose of our paper. A syndicate consists of: (i) one or multiple lead arrangers that are delegated to screen/monitor the borrower and administer the loan/syndicate, and (ii) participant lenders whose main role is often just funding part of the loan. Lead arrangers choose whom to invite to participate in the loan and may delegate certain tasks to the senior members of the syndicate, e.g., co-agents. Thus, loan syndicates provide rich content about the interrelationships among lenders.

[3] Among others, Chowdhry and Nanda (1996), Pichler and Wilhelm (2001), and Tykvová (2007) theoretically analyze the rationale for syndication and find that syndicates are formed for reasons such as risk sharing, knowledge transfer, and regulation circumventing. Empirical papers on syndicated loans have examined syndicate structure from the perspectives of information asymmetry [e.g., Lee and Mullineaux (2004), Jones, Lang and Nigro (2005), and Sufi (2007)], lenders' reputation [e.g., Dennis and Mullineaux (2000) and Gopalan, Nanda and Yerramilli (2011)], and liquidity management [e.g., Gatev and Strahan (2009)]. The effect of information asymmetry and liquidity has also been studied in syndicated loan pricing [e.g., Gupta, Singh and Zebedee (2008) and Ivashina (2009)].

[4] Giannetti and Yafeh (2009) also use the Euclidean distance, yet in a two-dimension space, to measure cultural differences between lead arrangers and borrowers and within member banks in loan syndicates.

Using the distance measure, we first analyze how banks connect with each other through loan participation. More precisely, we study the effect of distance on the syndicate structure. Do lead arrangers choose syndicate members that are more or less distant based on their specializations in a borrower's industry as well as a borrower's geographic location? Choosing close syndicate members can be beneficial for efficiency reasons. A lead arranger can profit from other lenders' degree of specialization and delegate some of the syndicate functions to them [e.g., François and Missonier-Piera (2007)] such that the cost of, for example, screening and monitoring the borrower can be reduced. On the downside, however, this strategy can also bring the corporate borrower and competing lenders closer together, eventually at the cost of future lending business. Whether the costs outweigh the benefits is ultimately an empirical question that is addressed by the first part of our paper. Overall, we find strong evidence that lead arrangers choose lenders that are closer in terms of specialization, i.e., those that are already more connected through similar loan portfolios as lead arrangers themselves. It is an important result. Even though this behavior can benefit both syndicate lenders and borrowers under normal circumstances, it may as well create negative externalities during crises as banks become more systemic. Our distance measure is thus also an *indirect* measure of interconnectedness: the closer two banks are, the more likely they will be involved with each other's loan portfolio and thereafter become further interconnected.

We then examine the possible reasons for and consequences of banks' choosing close syndicate members. Syndicate lenders can be broadly classified into three categories: (i) lead arrangers or co-leads if multiple lead arrangers exist, (ii) co-agents, and (iii) participants. While participants expand the pool of funds available for providing loans to borrowers, co-leads and co-agents can be chosen to take on some administrative responsibilities. We find that lenders that are closer, more connected with the lead arrangers are more likely to be given senior role functions in the syndicate, i.e., co-leads and co-agents. If responsibilities are indeed delegated to these lenders, they have incentives to shirk on their screening and monitoring effort [e.g., Holmstrom (1982), Diamond (1984), and Holmstrom and Tirole (1997)].[5] In order to ensure proper incentives to screen and monitor, they need to have larger stakes in the loan. We find that the loan share held by a syndicate lender increases significantly the closer it is to the lead arranger. These results are consistent with lead arrangers delegating responsibilities among syndicate members. The *incremental* effect of distance between two banks on their collaboration over and above the effects of prior bank-borrower relationships provides another layer of understanding how banks collaborate in the corporate loan market which, to the best of our knowledge, is new to the literature.[6]

Next, we ask how borrowers are affected by the way banks are interconnected in the syndicated loan market. To analyze this, we measure the impact of lender distance in the syndicate on loan spread charged to the borrower.[7] We find that the *net* effect of lender distance on loan pricing is that the borrower is charged a lower loan spread if the syndicate consists of lenders that are closer to one another in terms of specialization. This is consistent with the interpretation that borrowers are able to internalize part of the benefits from lenders' potential collaboration on screening and/or monitoring. It provides further support to the hypothesis that syndicate members close to lead arrangers can help reduce the overall loan syndication costs. We also ask whether greater interconnectedness among syndicate members, measured by lender distance, eventually reduces default rates. Interestingly, after controlling for borrower quality and creditworthiness, we do not find that the benefits of interconnectedness extend to loan default.

Lastly, we analyze the implication of concentrating syndicate lenders on systemic risk. More specifically, we ask whether banks that are strongly connected with other banks as a result of this syndication process also contributed most to systemic risk during the

[5] Strausz (1997) argues that delegation is positive as it has both incentive and commitment effects.

[6] We carefully control for prior relationships between banks as well as between borrowers and potential lenders in our regressions as lead arrangers may choose participant lenders based on their familiarity with borrowers when facing a high degree of information asymmetry [Sufi (2007)].

[7] Theoretically, the effect may be ambiguous. On the one hand, a borrower might benefit from savings in screening and monitoring costs as the lead arranger delegates tasks to syndicate members that are similar to itself. On the other hand, lenders that would initially compete for the same business might collude and charge a higher spread to extract more rents from the borrower as described in Sharpe (1990) and Rajan (1992).

2007-2009 financial crisis. Acharya et al. (2010) measure systemic risk as the amount by which a bank is undercapitalized in a systemic event in which the entire financial system is undercapitalized, and they call this concept the systemic expected shortfall (SES). Defined as the amount of equity capital a bank drops below its target value conditional on the aggregate capital falling below a target value, SES can be explained by two factors: (i) the marginal expected shortfall (MES) that measures the performance of the bank when the market experiences its worst, for example, 5% days within a specific time period (that is, the downside exposure of a bank to systemic shocks), and (ii) leverage (a more leveraged bank has, ceteris paribus, a larger shortfall in a systemic crisis). The banks with the largest capital shortfall are the greatest contributors to a financial crisis. Acharya et al. (2010) and Brownlees and Engle (2010) develop the systemic risk index $SRISK\%_i$ which measures the percentage contribution of bank i to the overall shortfall risk. Here, we relate distance, which is our measure of interconnectedness, to MES and $SRISK\%_i$. We find that based on MES as of June 2007, which is before the crisis hit, a bank's interconnectedness explains a significant portion of the variation in its shortfall risk. Moreover, we find that banks with the highest interconnectedness index as of 2007 are also the greatest contributors to the capital shortfall during the period from July 2007 to December 2008. We then explore this relationship in a multivariate setting using monthly $SRISK\%$ data over the period from January 2000 to November 2011 and find consistent results.

Taken together, syndication provides some benefits to banks and firms. Supposedly, banks can diversify their risks through syndication under normal conditions. However, our analysis shows that the syndication process has increased interconnectedness of banks over the last two decades. In other words, at the same time as banks diversify their individual loan portfolios, overall risk is contained within this network, and the increasing interconnectedness of banks has elevated the exposure of these banks to systemic shocks.

This article relates to the literature on systemic risk. Recent papers that proposed measures of systemic risk are Acharya et al. (2010), Brunnermeier and Adrian (2010), Allen, Bali and Tang (2010), Billio et al. (2010), Brownlees and Engle (2010), Chan-Lau (2010), Huang, Zhou and Zhu (2010), and Tarashev, Bori and Tsatsaronis (2010). There are also papers analyzing factors that contribute to systemic risk. For example, Brunnermeier, Dong and Palia (2011) find that banks' noninterest income explains some of the variation in their systemic risk proxies.

More broadly, our paper relates to the growing literature that studies networks in financial markets.[8] This literature analyzes, among others, contagion effects [e.g., Allen and Gale (2000)], interbank markets [e.g., Freixas, Parigi and Rochet (2000)], social networks and investment decisions [e.g., Cohen, Frazzini and Malloy (2007)], and investment banking networks [e.g., Morrison and Wilhelm (2007) and Hochberg, Ljungqvist and Lu (2007)]. Our paper contributes to this literature by analyzing the interconnectedness of banks in commercial lending networks.

The paper proceeds as follows. In Section 2, we lay out our empirical methodology, in particular, derive our measures of distance in specialization. Data are described in Section 3 with summary statistics for both our sample of syndicated loan facilities and various distance measures. Sections 4-6 examines empirical results on how banks interconnect in loan syndication, what the implications of such interconnectedness are, and how this relates to systemic risk, respectively. We conclude in Section 7.

2 Empirical Methodology

In this section, we develop our key explanatory variables, *distance measures*, and how they are used in the empirical analyses. First, we describe how distance is measured between two banks based on lending specializations reflected in their syndicated loan portfolios. Then, we explain how lender distance is measured at the syndicated loan facility level and what is the distance maintained by each lead arranger from its partners. Distance is viewed as a *direct* measure of interconnectedness in this section, and we will show that it is also an

[8] See Allen and Babus (2008) for a survey.

indirect measure of interconnectedness later.

2.1 Distance between Two Lenders

We focus our analyses on the U.S. syndicated loan market, that is, syndicated loans extended to U.S. firms. Five proxies of specializations are employed to measure a bank's lending expertise in this market related to borrower industry and borrower geographic location. More specifically, we use the 1-digit, 2-digit, and 3-digit borrower SIC industry, the state where the borrower is located, and the 3-digit borrower zip code to examine in which area(s) each bank has heavily invested and thus possesses good knowledge.[9, 10, 11] We then compute the distance between two banks by quantifying the similarity of their loan portfolios. The detailed construction of our distance measures is as follows.

First, based on DealScan's loan origination data, we rank lead arrangers by the total loan facility amount originated in the U.S. market during each of the years from 1988 to 2010.[12] There are a total of 3,144 unique lead arranger-years. In order to make the data and computations more manageable, we limit our interest to the top 100 lead arrangers of each year who held an aggregated share of 99.7-100% of the total market.[13] As a result, the number of unique lead arranger-years is reduced to 1,708 in our study. Then, we compute portfolio weights for each of the top 100 lead arrangers in each specialization category (e.g., 2-digit borrower SIC industry). Let $w_{i,j,t}$ be the weight lead arranger i invests in specialization (i.e., industry or location) j in year t. Note that for all pairs of i and t, $\sum_{j=1}^{J} w_{i,j,t} = 1$, where J is the number of industries or locations the lender can be specialized

[9] We also examine lenders' concentration in the 4-digit borrower SIC industry and find similar results.

[10] The 3-digit zip code refers to the first three digits of the U.S. zip code, which designate a sectional center facility, the mail-sorting and -distribution center for an area. With the first digit of the zip code representing a group of U.S. states and the second and third digits together representing a region or a large city in that group, these three digits combined pinpoint a more specific geographic location than states.

[11] Borrower geographic location is determined by the address of the borrowing firm's headquarter. As financing decisions, especially those related to issuing large amounts of debt such as syndicated loans, are made by a firm's finance department typically located at its headquarter, it is reasonable to assume that banks develop relationships with their clients' headquarters instead of satellite offices at other locations.

[12] Loan amount is split equally over all lead arrangers for loans with multiple leads.

[13] According to Cai (2009), banks commonly rotate their roles as lead arrangers and participant lenders in loan syndicates. Such reciprocal arrangements make it feasible to analyze the interrelationships among the top 100 lead arrangers since they are also heavily involved in loan participation.

in. For example, for the 2-digit borrower SIC industry, J can be as many as 100.

Next, we compute the distance between two banks (that are among the top 100 lead arrangers) as the Euclidean distance between them in this J-dimension space.[14] Let $d_{m,n,t}$ be the distance between banks m and n in year t, where $m \neq n$. Then

$$d_{m,n,t} = \sqrt{\sum_{j=1}^{J} (w_{m,j,t} - w_{n,j,t})^2}. \qquad (1)$$

Appendix 1 provides examples on how to compute distance between two banks as specified in (1). We show computation of distance among three lead arrangers that have ranked the top three since 2001 – JPMorgan Chase, Bank of America, and Citigroup. Two particular years are chosen here: the pre-crisis year of 2006 and the post-crisis year of 2010. We can easily observe that Citigroup invested in a loan portfolio that was more similar to those of JPMorgan Chase and Bank of America in 2010 compared to 2006, and consequently, its distance from the other two top banks became smaller. However, it was not the case if we look at how the distance between JPMorgan Chase and Bank of America changed during the same period.

Appendix 2 summarizes the pairwise distance among the top ten lead arrangers in both 2006 and 2010. First, distance was in general smaller in 2010 compared to 2006. Second, distance between a U.S. bank and a non-U.S. bank was often larger than between two U.S. banks or between two non-U.S. banks.

Distance is defined such that the more similar two banks' loan portfolios are, the closer they are. With similar investments, banks are vulnerable to the same kinds of common shocks. Thus, distance is a *direct* measure of interconnectedness.

We examine the effect of this distance between two banks, $d_{m,n,t}$, on: (i) the likelihood of one bank being chosen as a syndicate member by the other, (ii) the frequency and depth of the relationships between these two banks, and (iii) the loan share held by one bank who takes a role, either as a co-lead, a co-agent, or a participant in the syndicate arranged by

[14] The Euclidean distance is the square root of the sum of the squared differences in portfolio weights across all dimensions of lending specializations.

the other. Note that we use the distance in year $t-1$ to explain (i)-(iii) in year t. Empirical results on (i) and (ii) are in Section 4 and (iii) in Section 5.2.

2.2 Lender Distance in Syndicated Loans

There is substantial variation as to how distant syndicate members are across different loans in our sample. To analyze how this affects loan pricing and borrower performance, we need an overall measure for each syndicated loan facility. We compute the lender distance at the loan facility level as follows.

Suppose that there are X_k pairs of lead arranger(s) and other members in syndicate k. The lender distance for the loan is the *average* distance of these X_k pairs of lenders in the *previous* year. Let $D_{k,t}$ be the lender distance in syndicate k that is arranged in year t. Then

$$D_{k,t} = \left(\sum_{x=1}^{X_k} d_{m^x, n^x, t-1} \right) \div X_k, \tag{2}$$

where $d_{m^x,n^x,t-1}$ denotes the distance between the x^{th} pair of lead arranger (m^x) and syndicate member (n^x) in year $t-1$, where $m^x \neq n^x$.

We use the lender distance in a loan syndicate, $D_{k,t}$, to define whether it is a close or distant syndicate (Section 5.1). Furthermore, we use $D_{k,t}$ as a key explanatory variable for the interest spread charged to the borrower (Section 5.3) and loan default (Section 5.4).

2.3 Distance Maintained by Lead Arrangers

Each lead arranger may choose its own optimal level of distance from all the other lenders it works with via loan syndication. To see how such an implementation of distance relates to a bank's contribution and exposure to systemic risk, we compute the following measure of distance maintained by the lead arranger.

Suppose that lead arranger i originated $Y_{i,t}$ syndicated loans during year t. The distance maintained by the lead arranger in year t is the *average* distance for all these $Y_{i,t}$ loans. Let

$L_{i,t}$ be the distance maintained by lead arranger i in year t. Then

$$L_{i,t} = \left(\sum_{y=1}^{Y_{i,t}} D_{y,t} \right) \div Y_t. \tag{3}$$

We discuss the relation between a bank's systemic risk measures and the level of distance the bank maintains as a lead arranger during year t, $L_{i,t}$, in Section 6 where $L_{i,t}$ serves as the interconnectedness index.

3 Data and Summary Statistics

In this section, we first briefly describe our data sources. Then we provide summary statistics regarding lenders, borrowers, syndicated loan facilities, and the various distance measures we developed above.

3.1 Data Sources

To analyze how banks collaborate in loan syndication networks, we construct a dataset of syndicated loans in the U.S. market over the period of 1988 through July 2011 using four data sources: *DealScan*, *Compustat*, New Generation Research Bankruptcy database, and NYU V-Lab's Systemic Risk database.[15]

3.1.1 Loan Data

Provided by Thomson Reuters LPC, *DealScan* is the primary data source on syndicated loans with fairly complete coverage, especially in the U.S. market. We first use borrower and lender information between 1988 and 2010 to compute the distance measures between any two top 100 lead arrangers within each year. We obtain detailed data on a sample of 69,805 syndicated loan facilities originated by the top 100 lead arrangers (of the prior year)

[15] The risk page of NYU's Volatility Laboratory (V-Lab) provides various risk measures of global financial institutions. The website can be found at http://vlab.stern.nyu.edu/welcome/risk.

for U.S. firms between 1989 and July 2011.[16] We collect the following: (i) loan terms and conditions such as loan amount, maturity, and pricing, (ii) information on the borrower such as its sales, whether it is a private or public firm, and whether it has an S&P or Moody's bond rating, and (iii) information on the lenders and their roles in the syndicate as well as loans shares at origination.

Our analysis is conducted on the loan facility level, and all the lending institutions are aggregated to their parent companies.

3.1.2 Firm Data and Chapter 11 Filings

In order to obtain richer financial information on individual borrowing firms, we use Roberts *DealScan-Compustat* Linking Database [Chava et al. (2008)] to match *DealScan* with *Compustat* based on firm name, ticker, and location for borrowers that are public firms, have a ticker, and/or have a credit rating.[17] We are able to retrieve financial data from *Compustat* for 32,654 loan facilities (47% of the sample).

Bankruptcy data are compiled by New Generation Research. This database contains all U.S. public companies that have $10 million or more in assets and have filed for Chapter 11 bankruptcy protection since 1988. Companies with assets over $50 million that have had a default or an exchange offer at a substantial discount to face value are also included. We consider a loan to default if the borrowing firm appears in this bankruptcy database at a time while the loan is active, i.e., after the beginning date of the loan but before its maturity date. The bankruptcy data are matched with *DealScan* first through *Compustat* based on firms' 6-digit CUSIP, i.e., the issuer code, and then directly based on firm name, location, and industry if no match is found in the first step. We are able to identify 2,140 incidents of default (6.4%) among 33,237 loans extended to public firms or firms that can be matched in *Compustat*.

[16] At least one of the syndicate members other than the lead arranger was also among the top 100 lead arrangers of the previous year.

[17] To supplement Roberts *DealScan-Compustat* Linking Database, we manually matched the two databases to obtain information on new borrowers that entered the syndicated loan market since May 2011.

3.1.3 Systemic Risk

We obtain information about the systemic risk contribution of our lenders to the financial system from NYU V-Lab's Systemic Risk database. The database calculates various risk measures for about 95 U.S. financial firms including volatility and firm beta. More importantly, they construct systemic risk measures based on the theoretical analysis in Acharya et al. (2010). Systemic risk is measured as the percentage contribution of each bank to the overall capital shortfall during a systemic crisis. They are constructed based on a firm's downside exposure to shocks (marginal expected shortfall or MES) and a market value based version of leverage. These measures are appealing as they rely on market data. Short run MES are measured using volatility and correlation models, and simulations are used to extrapolate short run MES to shortfalls in a crisis period based on the analysis in Brownlees and Engle (2011).

3.2 Classifications of Lender Roles

We classify lenders into three categories based on their roles provided in *DealScan*: (i) lead arranger, (ii) co-agent, and (iii) participant lender.[18] A lender is classified as a lead arranger if its "LeadArrangerCredit" field indicates "Yes." If no lead arranger is identified using this approach, we define a lender as a lead arranger if its "LenderRole" falls into the following: administrative agent, agent, arranger, bookrunner, coordinating arranger, lead arranger, lead bank, lead manager, mandated arranger, and mandated lead arranger.[19] If two or more lead arrangers are identified, they are then co-leads to one another.

We identify a lender as a co-agent if it is not in a lead position *and* its "LenderRole" falls into the following: co-agent, co-arranger, co-lead arranger, co-lead manager, documentation agent, managing agent, senior arranger, and syndications agent. In addition, a lender is considered a co-agent if it is not a lead arranger based on the "LeadArrangerCredit" field but its "LenderRole" is in the list of titles for lead arrangers.

[18] See Standard & Poor's *A Guide to the Loan Market* (2011) for descriptions of lender roles.

[19] The "LeadArrangerCredit" and "LenderRole" fields generate similar classifications of lead arrangers.

Lenders with neither lead nor co-agent roles are classified as participant lenders.

3.3 Summary Statistics

3.3.1 Loan and Borrower Characteristics

Table 1 presents the characteristics of lenders, borrowers and loans based on the 69,805 syndicated loan facilities in our sample. *Panel A* of *Table 1* reports lead arranger characteristics. We have 1,708 unique lead arranger-years. An average lead arranger has a market share of 1.3% and arranges 53 loan facilities, which correspond to a total volume of $18.4 billion, during one year.

Panel B of *Table 1* reports borrower characteristics. An average borrowing firm in our sample has sales of $3.23 billion at loan closing. Sixty-five percent had previously borrowed from the syndicated loan market at least once, and the average number of previous syndicated loans among all the borrowers is 3 loan facilities. Among borrowers whose firm type is known, 38% are identified as private firms, whereas 24% are public firms without bond ratings and 38% are public firms with bond ratings.[20] Among borrowers who have *Compustat* data available, the average book value of total assets is $12.3 billion, the average book leverage ratio is 37%, the average earnings to assets ratio is 7%, and 55% have S&P debt ratings of which 56% have an investment-grade rating.

Panel C of *Table 1* shows characteristics of syndicated loan facilities in our sample. An average syndicated loan facility has a size (loan amount) of $278 million and maturity of 49 months. The average interest spread on drawn funds is 224 basis points over LIBOR. About one-third (31%) of the facilities are classified as term loans. On average, there are 7 lenders in one syndicate, and the lead arrangers retains 32% of the loan.[21] The most common reason for borrowing is working capital or corporate purposes (62%), followed by

[20] The firm type indicated in *DealScan* is the most current status for the borrower at the end of the sample period and hence does not reflect the change between public and private, nor between rated and unrated, over time. Thus, we cross-check the firm type with *Compustat* data, i.e., whether a borrower can be found in *Compustat* at the time the loan was originated and whether a credit rating was available then.

[21] The share retained by the lead arranger is available for only 16,529 loan facilities (24% of the sample). Thus, there may be some sample selection bias in spite of the fact that this is a widely used variable in the empirical literature on syndicated loans.

acquisitions (24%), refinancing (21%), and backup lines (7%).[22] Default occurred in 6% of the loan facilities in the sample.

3.3.2 Distance Measures

Table 2 reports summary statistics of the distance measures we described in section 2 across the 5 specialization categories, i.e., the 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code . *Panel A* of *Table 2* summarizes the distance between any two lenders that were among the top 100 lead arrangers in each year from 1988 to 2010, whereas *Panel B* and *Panel C* of *Table 2* summarizes lender distance at the syndicated loan facility level and distance maintained by lead arrangers each year, respectively, from 1989 to 2011. A number of important points are worth making here. First, based on the definition of Euclidean distance, all distance measures must lie within the range of 0 to $\sqrt{2}$. Second, the average lender distance at the syndicated loan facility level is in the range of 0.43-0.47 and the average distance maintained by lead arrangers is in the range of 0.63-0.70, which are both smaller than the average distance between two randomly selected lenders (a range of 0.84-0.90). This is consistent with banks intentionally choosing syndicate members with similar lending expertise. Third, the standard deviations of these distance measures – 0.3 for distance between two randomly selected lenders and 0.2 at the loan as well as lead arranger level – imply that there is sufficient variation in the data for empirical tests. Fourth, the distributions of distance measures across different specialization categories are similar to one another, which indicates that our measures capture the distance in a persistent way.

Figure 1 plots the time series of these various distance measures by year. *Part A*, *Part B*, and *Part C* of *Figure 1* again show distance between any two lenders, lender distance at the loan level, and distance maintained by lead arrangers, respectively. The time-series results indicate that in general distance has declined over time, that is, banks have become increasingly interconnected: the most significant drop occurring during 1993-1995 when

[22] A loan facility can state more than one purpose for borrowing.

syndicated lending began to surge. There were also two small rises in lender distance during 2001-2002 and 2007-2010. However, overall, the distance between any two randomly selected lenders declined by 16-20% during our sample period, whereas lender distance declined by 45-59% at the loan level and 35-45% at the lead arranger level. Interestingly, after some increases in lender distance during the crisis period, there was another sharp decrease in distance in the most recent year. It should be noted that given this time trend displayed in our distance measures, we carefully control for year or loan facility fixed effects in all our empirical tests.

4 Interconnectedness of Banks in Loan Markets

In this section, we show empirically that lead arrangers tend to invite to their syndicates lenders that are closer to themselves in terms of specialization. They are also more likely to give lenders more senior role functions in the syndicate, i.e., co-leads and co-agents, if these lenders have a similar specialization focus. Furthermore, the closer two lenders are in lending expertise, the more frequently they will collaborate, and the deeper the degree of collaboration will be. Thus, smaller distance infers stronger interconnectedness through more collaboration. This is over and above higher exposure to common shocks, and distance hence can be viewed as an *indirect* measure of interconnectedness.

We first examine whether banks choose close competitors, i.e. lenders with a similar focus in lending, as syndicate partners. As outlined in the Introduction, choosing a close competitor can have both negative effects (e.g., increased competition for future business with the same borrower) and positive effects (e.g., screening and monitoring responsibilities can be delegated to this chosen, similar lender). To understand the *net* effect, we estimate the following regression:

$$Member_{m,n,k,t} = \alpha + \beta_1 \cdot d_{m,n,t-1} + \beta_2 \cdot RELL_{m,n,t-1} + \beta_3 \cdot RELB_{n,k} + \beta_4 \cdot MS_{n,t-1} + F_k' + \epsilon_{m,n,k,t}, \quad (4)$$

where the dependent variable $Member_{m,n,k,t}$ is an indicator variable that equals one if lead arranger m chooses lender n as a member in loan syndicate k that is originated in year t and zero otherwise. The key independent variable $d_{m,n,t-1}$ measures the distance between lead arranger m and lender n in year $t-1$. $RELL_{m,n,t-1}$ is a proxy for bank-bank relationships and measured as the number of syndicated loans lead arranger m syndicated with lender n prior to the current loan (no matter what roles the two lenders took). $RELB_{n,k}$ is a proxy for bank-firm relationships and measured as the number of syndicated loans that were made to the borrower prior to loan syndicate k in which lender n participated (no matter what role it took). By including $RELL_{m,n,t-1}$ and $RELB_{n,k}$ in the regression, we control for the effects of prior relationships between the two lenders and prior relationships between the borrower and lender n on the construction of the syndicate, that is, who are invited to join the syndicate. $MS_{n,t-1}$ is the market share of lender n as a lead arranger one year before the loan was issued, i.e., year $t-1$. We use $MS_{n,t-1}$ to proxy for lender n's reputation and market size or power. F_k is a vector of loan facility fixed effects, which are included to rule out any facility-specific effects, including the effects from the borrower, the lead arranger, the time trend in a particular year, and any loan characteristics. Standard errors are heteroscedasticity robust and clustered at the year level. The regression size is $\sum_{k=1}^{K} M_k \times (100-1)$ observations, where K is the total number of syndicated loan facilities in the sample and M_k is the number of lead arrangers in syndicate k. The resulting sample size is nearly 11 million pairs of lenders in unique loan facilities.

The results are reported in *Panel A* of *Table 3*. Five types of distance measures are used in *Columns (I)* to *(V)*, based on the 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and the 3-digit borrower zip code, respectively. In all regressions, our distance measures show negative coefficients that are significant at the 1% level. That is, the larger the distance in lending specialization between a lender and the lead arranger, the smaller the likelihood that the lender is chosen as a syndicate member. In other words, lead arrangers seek to collaborate with *close* competitors. Thus, our initial results support the view that lead arrangers structure syndicates in order to delegate some screening and monitoring to other syndicate members. We also find that a lender's prior relationships with either the lead arranger ($RELL_{m,n,t-1}$) or the borrower ($RELB_{n,k}$) have significantly positive influences on the likelihood of being chosen as a syndicate member. The effect is especially strong for prior lender-borrower relationships, which confirms the findings in Sufi (2007). Interestingly, lender n's previous-year market share ($MS_{n,t-1}$) reduces its likelihood to be included in the syndicate. This may imply a subtle balance in partner choice: banks prefer to work with close competitors who they or the borrower worked with before *and* who are not big enough to threaten future loan syndication business.[23]

We then analyze the effect of distance on the depth of collaboration so as to seek supporting evidence that lead arrangers collaborate to delegate screening and monitoring responsibilities within the syndicate. We measure the depth of collaboration using the syndicate role lenders are assigned to (typically by the lead arrangers). Based on the lender role classifications described in Section 3.2, we generate a discrete variable, $Role_{m,n,k,t}$, that takes the value 0 if lender n is not a member of the syndicate, 1 if it is a participant, 2 if it is a co-agent, and 3 if it is a co-lead. While pure participants only contribute capital to the syndicate, more senior roles such as co-leads and co-agents often have managerial functions within the syndicate. A higher number for $Role_{m,n,k,t}$ can therefore be associated with a greater depth of collaboration. To test this, we estimate the following regression model:

$$Role_{m,n,k,t} = \alpha + \beta_1 \cdot d_{m,n,t-1} + \beta_2 \cdot RELL_{m,n,t-1} + \beta_3 \cdot RELB_{n,k} + \beta_4 \cdot MS_{n,t-1} + F'_k + \epsilon_{m,n,k,t}. \tag{5}$$

The results are reported in *Panel B* of *Table 3*. We find a significantly negative relationship between distance and syndicated role depth at the 1% level. That is, the greater the distance from the lead arranger in terms of lending specialization, the smaller the like-

[23] As a robustness check, we use probit and logit specifications with the same independent variables except loan facility fixed effects and find the same distance effect. A large number of fixed effects are inappropriate for probit and logit specifications due to concerns of the "incidental parameters problem" [e.g., Green (2004)]. The probit and logit results are available from the authors on request.

lihood that a lender will be chosen as a senior member of the syndicate, consistent with the view that lead arrangers structure their syndicates to delegate screening and monitoring responsibilities to members with a similar focus and expertise in lending.[24]

We provide more evidence as to the importance of common lending expertise in *Table 4*, aggregating participation and syndicated role depth for each pair of lenders on a yearly basis. We find that the frequency and depth of lender relationships decreases in distance. In other words, collaboration is more frequent and deeper among lenders that are more similar in lending specializations.

Specifically, *Panel A* of *Table 4* estimates the following regression:

$$Freq_{m,n,t} = \alpha + \beta_1 \cdot d_{m,n,t-1} + \beta_2 \cdot Freq_{m,n,t-1} + \beta_3 \cdot MS_{n,t-1} + L'_m + Y'_t + \epsilon_{m,n,t}, \quad (6)$$

where $Freq_{m,n,t}$ is the number of times that lead arranger m chooses lender n in syndicates it leads in year t (no matter what role lender n took) and $d_{m,n,t-1}$ measures the distance between lead arranger m and lender n in year $t-1$, which is our key independent variable of interest. $Freq_{m,n,t-1}$ is the lagged value of $Freq_{m,n,t}$, included in the regression to control for the relationships between lenders m and n in the previous year so that their current collaboration is not a simple continuation of their prior relationships. $MS_{n,t-1}$ is lender n's previous-year market share as a lead arranger. L_m is a vector of lead arranger fixed effects and Y_t is a vector of year fixed effects. Note that prior lender-borrower relationships cannot be controlled for in this regression as banks may collaborate on lending to more than one borrower and the collaboration frequency variable is not borrower-specific. Regression (6) includes approximately $100 \times (100-1) \times T$ observations, where T is the number of years in the sample. The resulting sample size is close to 220,000 pairs of lenders over the sample period of 1989-2011. The coefficients on our distance measures across all five specialization categories are consistently negative and significant at the 1% level. That is, the closer

[24] As a robustness check, we find similar evidence based on ordered probit and logit specifications, again without loan facility fixed effects. The ordered probit and logit results are available from authors on request.

two lenders are in terms of their lending specializations, the more frequently they work together in loan syndication. In addition, the coefficients on $Freq_{m,n,t-1}$ and $MS_{n,t-1}$ are significantly positive, which indicates a positive impact from these two variables on lender collaboration.

Panel B of *Table 4* estimates a similar regression with the dependent variable now measuring the aggregate depth of relationships between two banks:

$$Depth_{m,n,t} = \alpha + \beta_1 \cdot d_{m,n,t-1} + \beta_2 \cdot Depth_{m,n,t-1} + \beta_3 \cdot MS_{n,t-1} + L'_m + Y'_t + \epsilon_{m,n,t}, \quad (7)$$

where $Depth_{m,n,t}$ is the depth of all the relationships between lead arranger m and lender n in year t, computed as the sum of the ordinal variable, $Role_{m,n,k,t}$, for all the loans originated by lead arranger m. That is, $Depth_{m,n,t} = \sum_{k_m=1}^{K_{m,t}} Role_{m,n,k_m,t}$, where $K_{m,t}$ is the number of loans originated by lead arranger m during year t. Recall that $Role_{m,n,k,t}$ equals 0 if lender n is not a member of the syndicate k_m arranged by m, 1 if it is a participant, 2 if it is a co-agent, and 3 if it is a co-lead. We regress the depth of relationships between lead arranger m and lender n on their lagged distance as well as the previous-year relationship depth between them ($Depth_{m,n,t-1}$) and lender n's previous-year market share as a lead arranger ($MS_{n,t-1}$). Lead arranger and year fixed effects are also included in regression (7). All coefficients on our distance measures are significantly negative at the 5% level or better. That is, the closer two lenders are with respect to their lending expertise, the deeper their collaboration in the syndicated loan market. In addition, the coefficients on $Depth_{m,n,t-1}$ and $MS_{n,t-1}$ are again significantly positive as expected.

One possible argument is that our distance effect is driven by the size of large banks. Large banks typically invest in more industries and/or locations, that is, they are more diversified with regards to their loan portfolios. Consequently, on average the distance between two large banks will be smaller than the distance between two smaller banks or the distance between one large bank and one small bank. Thus, since large banks frequently work with other large banks, some of our results may simply be driven by the mechanical effects of bank size rather than the *true* organizational form of loan syndicates. To examine this, we control for bank size by including each bank's syndicated loan market share in the regressions specified above. In addition, to further show that bank size is not a concern, we exclude the top three to ten lead arrangers of each sample year from all regressions and obtain qualitatively similar results.[25] In other words, distance is an important factor when banks choose partners, regardless of the bank size.

Taken together, we find a propensity of bank lenders to concentrate syndicate partners rather than to diversify them. In the next section, we provide evidence as to the benefits of this strategy.

5 Efficiency Gains in Screening and Monitoring

Section 4 provides important insights into how banks choose partners in loan syndicates. The question still arises as to why the organizational structure matters. To address this question, we examine in this section what different strategies mean to borrowers and lenders.

5.1 Close versus Distant Syndicates

A possible benefit of inviting similar lenders in syndicates is efficiency gains, for example, with respect to screening and monitoring [Strausz (1997)]. To explore this, we first use the lender distance at the loan facility level [as defined in Equation (2)] to group our sample of syndicated loans into close and distant syndicates. The sub-sample of close syndicates consists of syndicates in which lender distance is below the median lender distance in the originating year, whereas the sub-sample of distant syndicates consists of the remaining syndicates, i.e., those with lender distance above the median. We then look into the differences between close and distant syndicates.[26]

Table 5 reports the mean differences for key borrower and loan characteristics between the two sub-samples, i.e., $\mu_{Close} - \mu_{Distant}$. We find that on average borrowers of close syn-

[25] Results are available from the authors on request.

[26] The main differences remain qualitatively the same even if we split the sample into more groups.

dicates are less likely to be private firms but more likely to be rated, have S&P investment-grade ratings, have borrowed previously from the syndicated loan market, and show higher sales at loan closing. In addition, close syndicates tend to have larger loan size, shorter maturity, and fewer term loans. In other words, close syndicates seem to have safer borrowers and safer loans. All these differences are statistically significant at the 1% level.

Furthermore, the average loan share retained by lead arrangers is about 0.4-1.7% lower among close syndicates. The differences are significant at the 10% level or better across all five specialization categories except the 3-digit borrower zip code. With respects to loan pricing and loan default rates, we find that close syndicates: (1) offer on average lower interest spreads on drawn funds over LIBOR by 15-35 basis points and (ii) result in a lower default rate of 0.5-1.4% in all cases except measured by borrower state. These differences are significant at the 5% level or better. Such results from bivariate tests are in general consistent with efficiency gains from screening and monitoring.

In Sections 5.2-5.4 below we examine the effect of distance on syndicate structure, loan pricing, and loan default in a more formal regression framework.

5.2 Distance and Syndicate Structure

If lead arrangers choose their syndicate partners to delegate some screening and monitoring responsibilities, they must give these lenders incentives to fulfill these tasks diligently. Such incentives arise from the shares of a loan these lenders hold. The closer a lender is to the lead arranger, the more likely it will be delegated responsibilities to, then the stronger the need for incentives through a higher share of the loan. Thus, we expect that the distance in specialization between a lead arranger and a syndicate lender is negatively related to the share of the loan this lender holds. Consequently, we test the following empirical specification:

$$Share_{m,n,k,t} = \alpha + \beta_1 \cdot d_{m,n,t-1} + \beta_2 \cdot RELL_{m,n,t-1} + \beta_3 \cdot RELB_{n,k} + \beta_4 \cdot MS_{n,t-1} + F_k' + \epsilon_{m,n,k,t}, \tag{8}$$

where $Share_{m,n,k,t}$ is the share of loan syndicate k held by lender n, and $d_{m,n,t-1}$ measures the distance between lead arranger m and lender n in year $t-1$. $RELL_{m,n,t-1}$, $RELB_{n,k}$, $MS_{n,t-1}$, and F_k are the same as defined in Equations (4) and (5) above. That is, we regress loan share taken by lender n in syndicate k on its lagged distance from lead arranger m as well as control variables such as lender n's prior relationships with lead arranger m and the borrower, lender n's previous-year market share as a lead arranger itself, and loan facility fixed effects. This regression includes close to 160,000 pairs of syndicate lenders on unique loan facilities. Note that the effect of distance on $Share_{m,n,k,t}$ in Equation (8) is estimated conditional on the fact that lender n is a member lender of the syndicate, i.e., was chosen by the lead arranger. Based on our results in Section 4, this group of lenders are relatively closer to the lead arranger compared to those who were not selected at all. Thus, variation in distance among this particular group is smaller compared to the whole sample.

Table 6 shows results for our distance measures across five specialization categories. Having controlled for prior relationships (i.e., $RELL_{m,n,t-1}$ and $RELB_{n,k}$,) and lender size/reputation (i.e., $MS_{n,t-1}$), we find that the coefficients on our distance measures are consistently negative and significant at the 1% level. These results are consistent with syndicate lenders holding significantly larger loan shares if they have similar lending specializations as the lead arranger, i.e., distance is smaller. We also find that a lender's loan share more significantly increases with its prior relationship with the borrower than with the lead arranger. In addition, a lender's market share has a significantly positive impact on its loan share, which may be related to larger players in the market having more funds to invest.

5.3 Distance and Loan Pricing

There exist potentially two possible effects of pricing from lender distance. First, borrowers might benefit from smaller lender distance because lead arrangers can pass on some savings from screening and monitoring costs to borrowers. However, collaboration among close competitors might also lead to extraction of rents (higher spreads) from borrowers. Our bivariate tests show that close loan syndicates are associated with lower spreads, suggesting that borrowers can internalize some of the efficiency gains. To examine the *net* effect of distance on loan pricing more formally, we run the following regression:

$$Spread_{k,l,s,t} = \alpha + \beta_1 \cdot D_{k,t} + \beta_2 L'_{l,t} + \beta_3 M'_k + I'_s + Y'_t + \epsilon_{k,l,s,t}, \tag{9}$$

where $Spread_{k,l,s,t}$ is the interest spread over LIBOR on drawn funds. As defined in Equation (2), $D_{k,t}$ is the lender distance in syndicated loan k issued to borrower l. $L_{l,t}$ is a vector of borrower control variables as of year t, including whether borrower l is a private firm, whether it has a publicly available rating, whether it has an S&P investment-grade rating, the number of syndicated loan previously borrowed, and sales at closing. M_k is a vector of loan control variables, including loan amount, maturity, whether it is a term loan, loan purpose, and interest rate type (i.e., fixed vs. floating). I_s is a vector of borrower two-digit SIC industry fixed effects and Y_t is a vector of year fixed effects. The unit of observation is a loan facility.

The results are reported in *Table 7*. Our distance measures are all positive and significant at the 1% level except distance based on borrower state. Thus, on a net basis, borrowers actually benefit from working with close loan syndicates by paying lower loan spreads. The saving is 7-13 basis points for a reduction of one standard deviation in lender distance based on borrower industry and zip code. This result is consistent with lenders sharing some benefits from low lender distance with their borrowers. In addition, coefficients on the other control variables show that (i) loan spreads decrease in loan amount and increase in maturity, (ii) loans are cheaper for borrowers with S&P investment-grade ratings as well as higher sales, and (iii) term loans pay higher spreads of about 71 basis points on average.

Taken together, these results are consistent with the view that close syndicate members can help with screening and monitoring so as to reduce the overall loan syndication costs.

5.4 Distance and Loan Default

We next examine whether potential efficiency gains from constructing close syndicates extend to lower default rates. We estimate the following regression:

$$Default_{k,l,s,t} = \alpha + \beta_1 \cdot D_{k,t} + \beta_2 L'_{l,t} + \beta_3 M'_k + I'_s + Y'_t + \epsilon_{k,l,s,t}, \tag{10}$$

where $Default_{k,l,s,t}$ is an indicator variable that equals one if the loan is in default and zero otherwise. $L_{l,t}$, M_k, I_s and Y_t are the same control variables and fixed effects as in the regression of loan interest spread [i.e., Equation (9)]. That is, we regress loan default on lender distance, loan and borrower characteristics, and industry and year fixed effects. Since the independent variables include whether the borrower is rated, whether its rating is of an investment grade, and its sales at loan closing, we control for *ex-ante* borrower quality and creditworthiness and hence the coefficient on lender distance indicates the effect of distance on subsequent loan default. The regression is estimated at the loan facility level. *Table 8* reports the regression results from a linear probability model. We find *no* evidence that closer distance reduces loan default rates.[27]

6 Interconnectedness and Systemic Risk

The previous sections demonstrate that the syndication process has made the loan portfolios of banks increasingly similar over the last two decades. In other words, it increased the

[27] As a robustness check, we use probit and logit specifications with the same independent variables and find no distance effect on default rates. The probit and logit results are available from the authors on request.

interconnectedness of banks that were active in the loan syndicate network. While there are benefits to syndication (some of which we have analyzed earlier in this paper), it also creates systemic risk because problems of some banks can spread throughout this network for different reasons: banks are exposed to each other, exposed to similar assets, and exposed to the same type of investors who eventually run on some banks because of problems that surfaced at other banks (and the inherent opaqueness of the banking sector).

In our empirical analysis, we follow the definition of systemic risk as outlined in Acharya et al. (2010) as the contribution of each individual bank to the aggregate capital shortfall during a systemic crisis when there is an aggregate shortage of capital in the financial sector. Systemic risk occurs if the financial sector is undercapitalized because the reduction in lending by one institution cannot be offset by other financial institutions and might cause a credit crunch. Acharya et al. (2010) measure systemic risk as the amount by which a bank is undercapitalized in a systemic event in which the entire financial system is undercapitalized, and they term it the systemic expected shortfall or SES. This concept is appealing as it uses market data that are readily available to regulators and market participants. They show that SES is the bank's level of undercapitalization assuming a target leverage ratio (for example, 8%). They demonstrate that SES can be explained by two factors. The first is the *ex-ante* market-leverage ratio of the bank, and the second captures the downside exposure to systemic shocks which they call the marginal expected shortfall (MES). MES is the expected equity loss of one bank when the market declines beyond a specific threshold over a given period. Acharya et al. (2010) and Brownlees and Engle (2010) develop a systemic risk index $SRISK\%_i$ which is the capital shortfall of one bank relative to the financial sector. The concept is very intuitive. Suppose that k is the prudential capital ratio, say 8%, $D_{i,1}$ is firm's i debt in period 1, and $W_{i,1}$ ($W_{i,2}$) is the firm's equity in period 1 (period 2). The expected capital shortfall of this firm in period 1 is then

$$
\begin{aligned}
CS_{i,1} &= E_1\left[k(D_{i,1}+W_{i,2})-W_{i,2}|Crisis\right] \\
&= kD_{i,1}-(1-k)W_{i,1}MES_{i,1}
\end{aligned} \tag{11}
$$

The firm experiences a capital shortfall only if $CS_{i,1}>0$, i.e.

$$
\begin{aligned}
SRISK_{i,1} &= \min(0, CS_{i,1}) \\
SRISK\%_{i,1} &= \frac{SRISK_{i,1}}{\sum\limits_{i} SRISK_{i,1}}
\end{aligned} \tag{12}
$$

where $SRISK\%$ is the percentage version. MES is measured dynamically using asymmetric GARCH models and DCC.

NYU's Volatility Laboratory (V-Lab) Global Systemic Risk Database ("SRISK") provides systemic risk measures for about 1,200 publicly traded financial institutions worldwide. We can match 53 of our top 100 lead arrangers to SRISK. *Appendix 3* shows a list of these institutions. Interestingly, 24 of these institutions are also part of the FSB's list of Global-SIFIs which more stresses the interconnectedness of the global financial institutions even in the U.S. syndicated loan market.[28]

We start analyzing the impact of interconnectedness on systemic risk graphically using the top lead arrangers as of June 2007. Forty international institutions were responsible for 96% of the syndicated loan origination as of that date. Twenty-two of them were U.S. firms, among which were Wachovia, Lehman Brothers, and Bear Sterns. All three belonged to the top 15 originators that year.

We analyze whether the distance maintained by a bank [as defined in Equation (3)] can predict its contribution to the capital shortfall of the financial sector during a systemic crisis. We collect monthly $SRISK\%_i$ measures from SRISK and calculate an average relative shortfall measure for each bank during the period from July 2007 to December 2008. We

[28] The list of the Global-SIFIs can be accessed at http://www.financialstabilityboard.org/publications/r_111104bb.pdf.

plot this measure against our distance measure in *Figure 2*, of which *Part A* shows U.S. financial institutions, *Part B* shows European institutions, and *Part C* includes the full sample. We find that distance explains a major part of the variation of $SRISK\%_i$ (R^2 is above 50%). As distance is our measure of interconnectedness, this is equivalent to say that the most interconnected banks are also the greatest contributors to systemic risk.

In a next step, we test this interconnectedness-systemic risk relation in a multivariate setting using monthly $SRISK\%$ data for the period from January 2000 to November 2011. As not all firms survived the financial crisis or had publicly traded equity throughout this time period, the panel is unbalanced with 4,998 bank-month observations. Our dependent variable is *Ln* [$SRISK\%$] which is the natural logarithm of $SRISK\%$ to account for the skewness of the variable. $SRISK\%$ is left censored at 0 and our sample has 1,506 left-censored observations. That is, *Ln* [$SRISK\%$] is available for 3,492 bank-month observations.[29] We construct an indicator variable *European* which equals 1 if the institution is headquartered in Europe. To account for differences between Europe and the U.S. we introduce the interaction term *Distance* × *European*. We also include as control variables (i) the natural logarithm of the quasi-market leverage ratio which is calculated as book total assets minus book value of equity plus market value of equity, scaled by market value of equity, and (ii) the natural logarithm of market value of equity. Both leverage and market value of equity come from SRISK. All regressions further include year-quarter fixed effects. We assess the effect of *Distance* on *Ln* [$SRISK\%$] using OLS regressions. The results are reported in *Table 9*.

Model (I) of *Table 9* shows that more interconnected lenders contribute more to systemic risk. The effect is significant at the 1% level and the R^2 is 15.94%. In *Models (II)* and *(III)*, we introduce *European* and *Distance* × *European*. European financial institutions have a higher systemic risk index. We control for leverage in *Model (IV)*. As we are interested in the change in the contribution to systemic risk of one bank relative to

[29] We perform additional robustness tests using $SRISK\%$ as dependent variable and tobit regressions explicitly controlling for left-censoring at 0. All results remain unchanged.

the other banks if interconnectedness changes, we estimate a between effects model. The results are reported in *Model (V)* of *Table 9*. The nature of the coefficient on our distance measure is unchanged. We then include *Ln* [*market value*] as control for bank size in *Models (VI)* and *(VII)*. Due to high correlation between *European* and *Ln* [*market value*], we exclude *European* and its interaction term with distance in these two models. The results for distance, however, remain unchanged. We test different model specifications introducing interaction terms between *European*, *Ln* [*leverage*] and *Ln* [*market value*] to account for the elevated correlation without any effect on our results. We omit these tests for brevity.

Taken together, we find strong supporting evidence to our conjecture that the most interconnected banks are also the greatest contributor to systemic risk.

7 Conclusion

This paper studies interconnectedness of banks in the syndicated loan market as a major source of systemic risk. We develop a set of novel measures to describe how banks are interconnected based on the similarity of their loan portfolios. We use a dataset of newly originated syndicated loans for the period from 1988 to July 2011 and analyze which banks are invited to join the syndicates and how this is influenced by their existing loan portfolios. We find a propensity of banks to concentrate syndicate lenders rather than to diversify them. We analyze potential benefits of this behavior and find evidence consistent with the view that close syndicate members can help with screening and monitoring so as to reduce the overall loan syndication costs. More specifically, we find that lead arrangers assign more responsibilities to banks they are already connected with and have these banks take on higher shares of the loan as incentive. We also find significantly lower loan spreads for closer syndicates, which suggest that cost savings exist and borrowers can internalize a fraction of these savings.

Subsequently and more importantly, we analyze potential negative externalities associated with syndication. Using data for the most systemically important lenders in this market, we find that interconnectedness of banks can explain the downside exposure of these banks to systemic shocks. Moreover, we find that the most interconnected banks are also the greatest contributors to systemic risk.

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Appendix 1: Examples of Computing Distance between Lead Arrangers

This appendix shows how distance is computed by examples. Distance between two lenders is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on 1-digit borrower SIC industry. We show below the computation of such distance among JPMorgan Chase (JPM), Bank of America (BAC), and Citigroup (C), which have been the top three lead arrangers since 2001. Panels A and B covers the pre-crisis year of 2006 and post-crisis year of 2010, respectively.

A. Top Three Lead Arrangers in 2006 (Pre-crisis)

1-digit SIC	JPM	BAC	C	$(\text{JPM-BAC})^2$	$(\text{JPM-C})^2$	$(\text{BAC-C})^2$
Agriculture (0)	0.0288%	0.1695%	0.0000%	0.00000198	0.00000008	0.00000287
Construction (1)	7.4369%	10.0986%	5.0807%	0.00070846	0.00055518	0.00251795
Manufacturing (2)	16.2823%	10.2499%	15.6509%	0.00363902	0.00003987	0.00291710
Manufacturing (3)	12.4032%	13.0988%	19.6492%	0.00004840	0.00525054	0.00429076
Transportation (4)	12.2990%	12.0246%	20.1229%	0.00000753	0.00612126	0.00655812
Wholesale/Retail (5)	9.2723%	11.1839%	3.7299%	0.00036544	0.00307180	0.00555624
Finance (6)	29.1845%	30.7133%	18.4803%	0.00023371	0.01145801	0.01496453
Services (7)	7.2318%	6.1904%	11.2364%	0.00010845	0.00160371	0.00254622
Services (8)	5.8613%	6.2484%	5.9401%	0.00001499	0.00000062	0.00000951
Public Admin (9)	0.0000%	0.0226%	0.1096%	0.00000005	0.00000120	0.00000076
Total	100%	100%	100%	0.00512802	0.02810227	0.03936406
			Distance:	0.07161021	0.16763731	0.19840379

B. Top Three Lead Arrangers in 2010 (Post-crisis)

1-digit SIC	JPM	BAC	C	$(\text{JPM-BAC})^2$	$(\text{JPM-C})^2$	$(\text{BAC-C})^2$
Agriculture (0)	0.0000%	0.5199%	0.0000%	0.00002703	0.00000000	0.00002703
Construction (1)	9.5212%	7.4029%	3.6260%	0.00044870	0.00347535	0.00142654
Manufacturing (2)	18.0379%	11.4444%	20.9279%	0.00434732	0.00083523	0.00899358
Manufacturing (3)	17.1886%	11.9594%	13.0201%	0.00273446	0.00173761	0.00011252
Transportation (4)	11.5772%	16.0003%	16.7372%	0.00195636	0.00266263	0.00005432
Wholesale/Retail (5)	10.6755%	12.1554%	8.9399%	0.00021899	0.00030126	0.00103394
Finance (6)	21.5120%	23.7368%	26.5538%	0.00049496	0.00254196	0.00079355
Services (7)	7.9820%	9.4324%	5.5891%	0.00021038	0.00057260	0.00147715
Services (8)	3.3892%	7.1262%	4.6060%	0.00139656	0.00014807	0.00063515
Public Admin (9)	0.1165%	0.2222%	0.0000%	0.00000112	0.00000136	0.00000494
Total	100%	100%	100%	0.01183589	0.01227608	0.01455872
			Distance:	0.10879289	0.11079746	0.12065953

Appendix 2: Distance among Top Ten Lead Arrangers

This appendix shows distance between any two top ten lead arrangers in the pre-crisis year of 2006 (Panel A) and post-crisis year of 2010 (Panel B). Distance between two lenders is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specialization in this appendix is based on 1-digit borrower SIC industry. The top ten lead arrangers in 2006 were: JPMorgan Chase (JPM), Bank of America (BAC), Citigroup (C), Wachovia Bank (WB), Credit Suisse (CSGN), Deutsche Bank (DB), Royal Bank of Scotland (RBS), Goldman Sachs (GS), Barclays (BARC), and UBS (UBSN). The top ten lead arrangers in 2010 were: Bank of America (BAC), JPMorgan Chase (JPM), Citigroup (C), Wells Fargo (WFC), Barclays (BARC), BNP Paribas (BNP), Deutsche Bank (DB), Credit Suisse (CSGN), Royal Bank of Scotland (RBS), and PNC Bank (PNC).

A. Top Ten Lead Arrangers in 2006 (Pre-crisis)

	JPM	BAC	C	WB	CSGN	DB	RBS	GS	BARC	UBSN
JPM	-									
BAC	0.0716	-								
C	0.1676	0.1984	-							
WB	0.2186	0.2190	0.2091	-						
CSGN	0.3466	0.3431	0.2890	0.2974	-					
DB	0.1927	0.2128	0.1581	0.1496	0.2737	-				
RBS	0.3604	0.4114	0.3200	0.3154	0.3627	0.2778	-			
GS	0.2586	0.2804	0.1355	0.1624	0.2604	0.1723	0.2797	-		
BARC	0.4421	0.4624	0.3466	0.3064	0.4642	0.3858	0.4048	0.2481	-	
UBSN	0.3913	0.3772	0.3757	0.3648	0.1477	0.3767	0.4409	0.3555	0.5342	-

B. Top Ten Lead Arrangers in 2010 (Post-crisis)

	BAC	JPM	C	WFC	BARC	BNP	DB	CSGN	RBS	PNC
BAC	-									
JPM	0.1088	-								
C	0.1207	0.1108	-							
WFC	0.1245	0.1651	0.2039	-						
BARC	0.2493	0.2731	0.2716	0.3012	-					
BNP	0.4168	0.3997	0.4621	0.3530	0.4392	-				
DB	0.2223	0.1822	0.1804	0.3010	0.1806	0.4492	-			
CSGN	0.1807	0.2062	0.2320	0.2241	0.1368	0.4328	0.2017	-		
RBS	0.2802	0.2777	0.2833	0.2895	0.1437	0.3700	0.2101	0.2113	-	
PNC	0.1068	0.1223	0.1947	0.1421	0.2595	0.3736	0.2427	0.1750	0.2820	-

Appendix 3: Financial Institutions with Systemic Risk Measures

This appendix lists the 53 financial institutions available in NYU's Volatility Laboratory (V-Lab) Global Systemic Risk Database ("SRISK") that provides systemic risk measures.

	Financial Institution	Ticker		Financial Institution	Ticker
1	Allied Irish Banks	ALBK	28	Marshall & Ilsley	MI
2	Banco Bilbao Vizcaya Argentari	BBVA	29	Merrill Lynch	MER
3	Bank of America	BAC	30	Mitsubishi UFJ Financial Group	8306
4	Bank of Montreal	BMO	31	Mizuho Financial Group	8411
5	Bank of New York Mellon	BK	32	Morgan Stanley	MS
6	Barclays	BARC	33	National Bank of Canada	NA
7	BB&T Corporation	BBT	34	National City Corporation	NCC
8	Bear Stearns	BSC	35	Natixis	KN
9	BNP Paribas	BNP	36	Nordea Bank	NDA
10	Capital One Financial	COF	37	Northern Trust	NTRS
11	CIT Group	CIT	38	PNC Financial Services	PNC
12	Citigroup	C	39	Regions Financial	RF
13	CNA Financial Corp	CNA	40	Royal Bank of Canada	RY
14	Commerzbank	CBK	41	Royal Bank of Scotland	RBS
15	Credit Agricole SA	ACA	42	Skandinaviska Enskilda Banken	SEBA
16	Credit Suisse	CSGN	43	Societe Generale	GLE
17	Deutsche Bank	DB	44	State Street	STT
18	Fifth Third Bancorp	FITB	45	Suntrust Banks	STI
19	Goldman Sachs	GS	46	Toronto-Dominion Bank	TD
20	HSBC	HSBA	47	UBS	UBSN
21	Huntingtons Bancshares	HBAN	48	UniCredit SpA	UCG
22	ING Groep	INGA	49	US Bancorp	USB
23	Intesa Sanpaolo SpA	ISP	50	Wachovia Bank	WB
24	JPMorgan Chase	JPM	51	Washington Mutual	WM
25	Keycorp	KEY	52	Wells Fargo	WFC
26	Lehman Brothers	LEH	53	Zions Bancorporation	ZION
27	Lloyds Banking Group	LLOY			

Figure 1: Time Series of Distance Measures

This figure shows the time series of various distance measures (by year). Distance between two lenders is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Lender specializations are measured in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code. Part A plots the mean distance between any two lenders that were among the top 100 lead arrangers of each year from 1988 to 2010. Part B shows the mean lender distance at the syndicated loan facility level, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous year, from 1989 to July 2011. Part C shows the mean distance maintained by the lender, which is the average distance on the loan facility level for all the loans arranged by the lender during the year, from 1989 to July 2011.

A. Distance between Two Lenders
(Based on 228,502 lender pair-years)

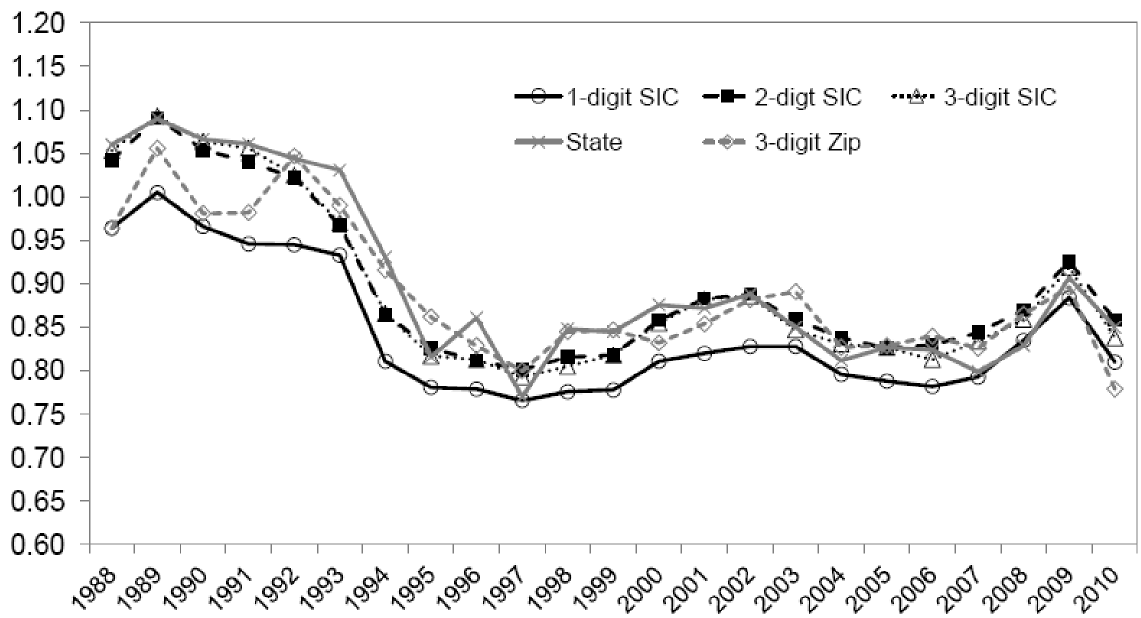
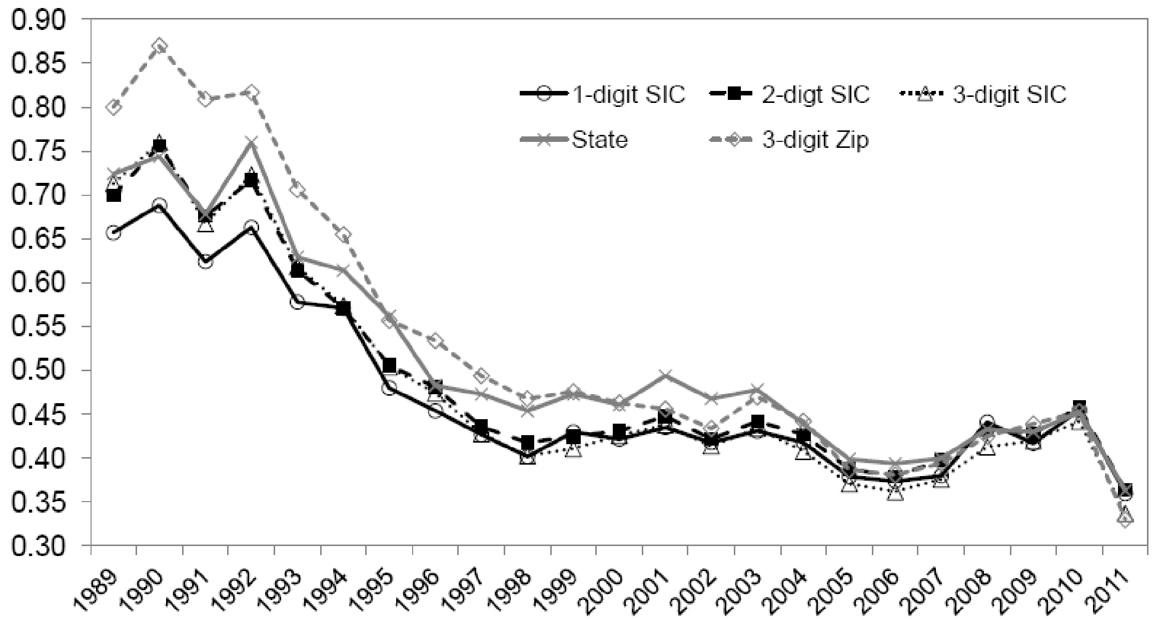


Figure 1 (continued)

B. Lender Distance in Syndicated Loans
(Based on 69,805 loan facilities)



C. Distance Maintained by Lead Arrangers
(Based on 1,708 lead arranger-years)

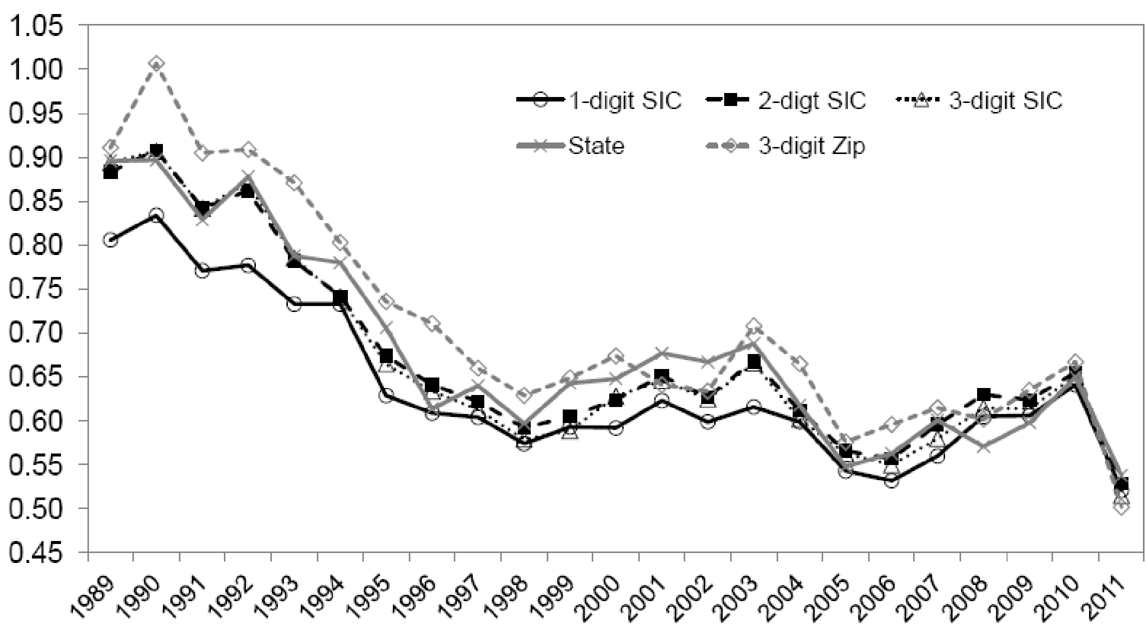


Figure 2: Distance and Systemic Risk

This figure shows the impact of interconnectedness on systemic risk among top lead arrangers as of 2007. Interconnectedness of a lead arranger is measured by the distance the lead arranger maintained, which is the average distance on the loan facility level for all the loans it arranged during the year. Distance used in this figure is based on 1-digit borrower SIC industry. SRISK%, a systemic risk index, is the average relative shortfall measure for each bank during the period from July 2007 to December 2008. During that period, 96% of the total amount of syndicated loans were originated by 40 global financial institutions, of which 22 were U.S. firms, 13 European, and 5 Canadian or Asian. Part A plots SRISK% against distance maintained by U.S. financial institutions as of June 2007, Part B includes only European institutions, and Part C uses the full sample of 40 financial institutions.

A. U.S. Financial Institutions

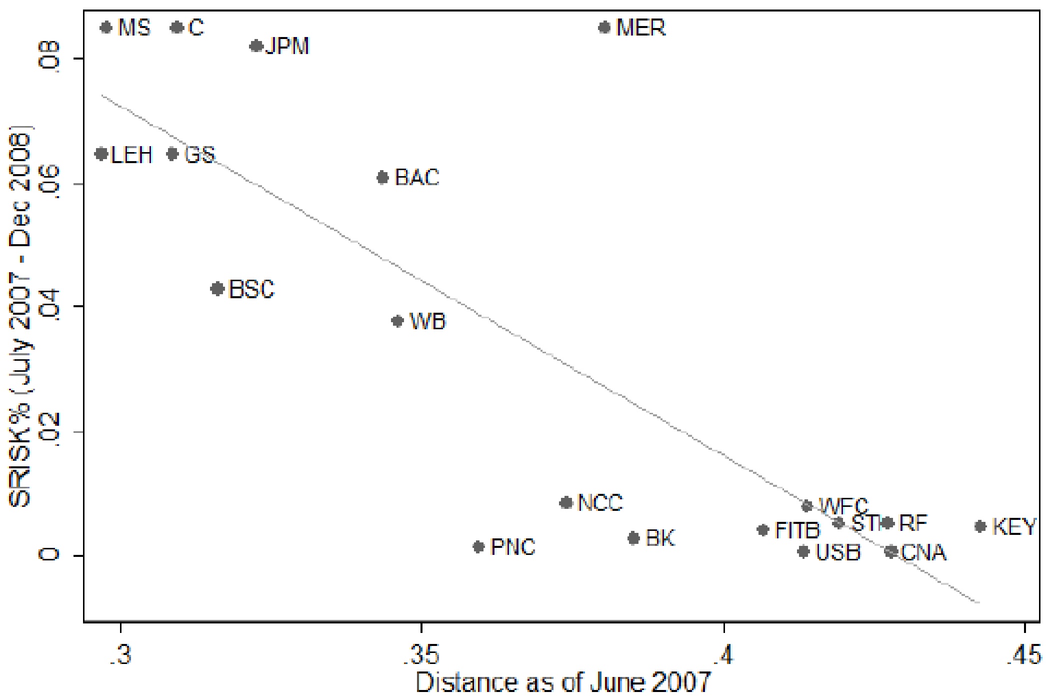
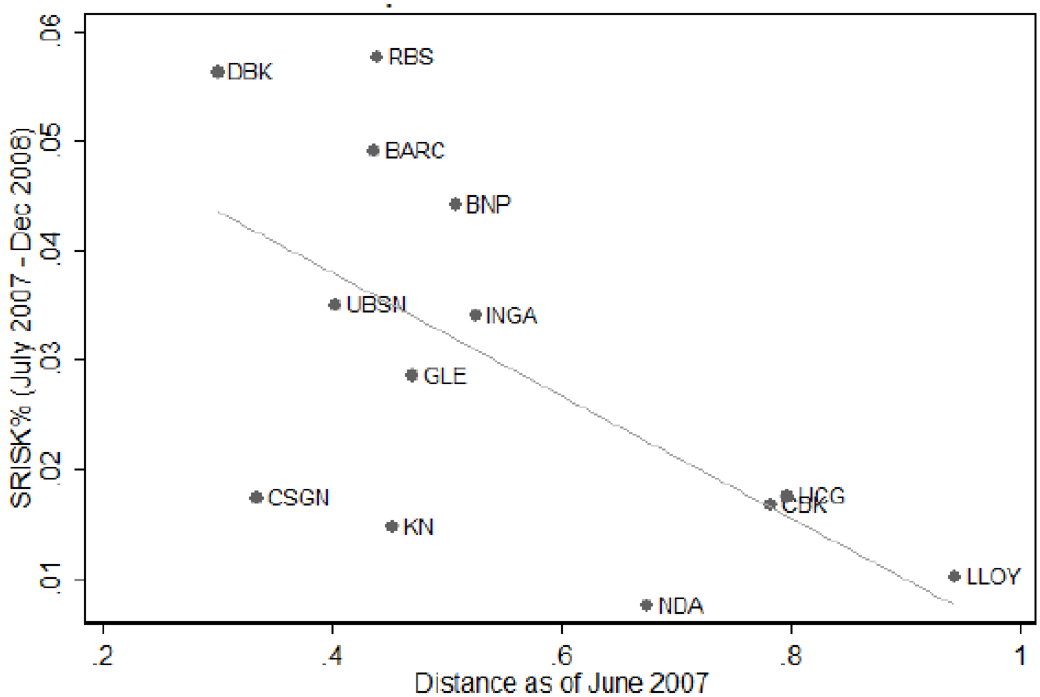


Figure 2 (continued)

B. European Financial Institutions



C. All Financial Institutions

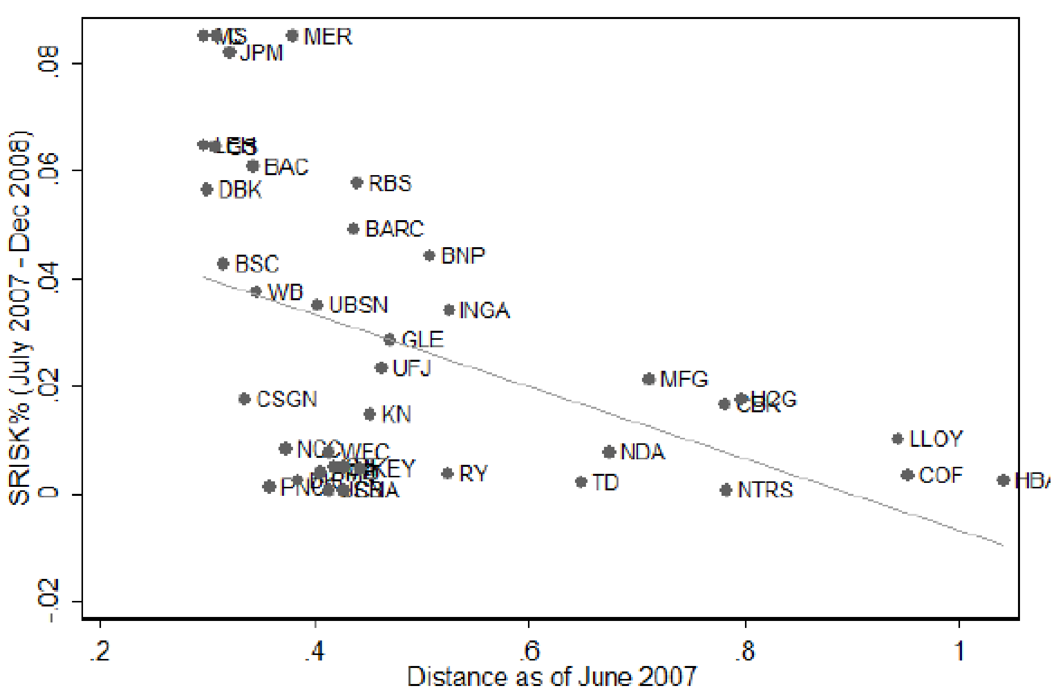


Table 1: Summary Statistics for Syndicated Loan Facilities

This table presents summary statistics for the sample of syndicated loan facilities made to U.S. firms between 1989 and July 2011. For each loan facility in the sample, at least one lead arranger and one other syndicate member were among the top 100 lead arrangers one year prior to loan origination. Lead arrangers are ranked by total loan facility amount originated, and loan amount is split equally over all lead arrangers for loans with multiple leads. Panel A reports lead arranger characteristics based on 1,708 unique lead arranger-years. Panels B and C report borrower and loan characteristics, respectively, based on 69,805 loan facilities.

A. Lead Arranger Characteristics

(Based on 1,708 lead arranger-years)

	$N =$	Mean	SD	10^{th}	50^{th}	90^{th}
Market share (%), previous year	1,708	1.29	3.63	0.01	0.17	2.52
# of loans as lead arranger	1,708	53	131	1	11	128
$ of loans as lead arranger ($mm)	1,708	18,400	64,400	100	1,760	35,500

B. Borrower Characteristics

(Based on 69,805 loan facilities)

	$N =$	Mean	SD	10^{th}	50^{th}	90^{th}
All Borrowers:						
Sales at closing ($mm)	46,796	3,230	13,600	69	527	6,710
# of previous syndicated loans	69,805	2.65	4.32	0	1	7
Private firm indicator	56,950	0.38	0.49	0	0	1
Public, unrated firm indicator	56,950	0.24	0.43	0	0	1
Public, rated firm indicator	56,950	0.38	0.48	0	0	1
Borrowers with *Compustat* data:						
Total book assets ($mm)	31,473	12,290	71,575	158	1,229	16,624
Book leverage ratio	31,344	0.37	0.27	0.06	0.34	0.70
Earnings to assets ratio	29,767	0.07	0.25	0.00	0.07	0.16
S&P debt rating indicator	32,654	0.55	0.50	0	1	1

Table 1 (continued)

C. Loan Characteristics
(Based on 69,805 loan facilities)

	$N =$	Mean	SD	10^{th}	50^{th}	90^{th}
Syndicated loan terms:						
Facility amount ($mm)	69,805	278	658	17	100	600
Maturity (months)	63,998	49	54	12	54	83
Spread on drawn funds (bps)	60,490	224	150	49	210	400
Term loan indicator	69,805	0.31	0.46	0	0	1
Syndicate structure:						
# of lenders in the syndicate	69,805	7.20	7.34	2	5	16
# of lead arrangers in the syndicate	69,805	1.32	0.70	1	1	2
% retained by lead arranger(s)	16,529	31.71	21.59	9.2	25.71	60
Purpose of loan indicators:						
Working capital/corporate	69,805	0.62	0.49	0	1	1
Refinancing	69,805	0.21	0.41	0	0	1
Acquisitions	69,805	0.24	0.43	0	0	1
Backup lines	69,805	0.07	0.26	0	0	0
Loan performance:						
Loan default indicator	33,237	0.06	0.25	0	0	0

Table 2: Summary Statistics of Distance Measures

This table reports summary statistics of various distance measures. Distance between two lenders is measured by their Euclidean distance as they are positioned in the Euclidean space based on their specializations in the U.S. syndicated loan market. Rows (I)-(V) compute distance in terms of lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively, in all panels. Panel A summarizes distance between any two lenders that were among the top 100 lead arrangers of each year between 1988 and 2010. Panel B shows lender distance at the syndicated loan facility level, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous year. Panel C shows distance maintained by the lender, which is the average distance on the loan facility level for all the loans arranged by the lender during the year.

A. Distance between Two Lenders
(Based on 228,502 lender pair-years)

	$N=$	Mean	SD	10^{th}	50^{th}	90^{th}
(I) Distance in borrower 1-digit SIC	228,428	0.845	0.343	0.385	0.863	1.295
(II) Distance in borrower 2-digit SIC	228,428	0.897	0.311	0.455	0.943	1.285
(III) Distance in borrower 3-digit SIC	228,428	0.894	0.308	0.455	0.943	1.274
(IV) Distance in borrower state	228,396	0.903	0.322	0.444	0.953	1.337
(V) Distance in borrower 3-digit zip code	224,388	0.887	0.313	0.435	0.962	1.271

B. Lender Distance in Syndicated Loans
(Based on 69,805 loan facilities)

	$N=$	Mean	SD	10^{th}	50^{th}	90^{th}
(I) Distance in borrower 1-digit SIC	69,540	0.435	0.184	0.239	0.401	0.679
(II) Distance in borrower 2-digit SIC	69,540	0.447	0.186	0.249	0.409	0.698
(III) Distance in borrower 3-digit SIC	69,540	0.435	0.188	0.235	0.397	0.688
(IV) Distance in borrower state	69,540	0.469	0.188	0.266	0.435	0.717
(V) Distance in borrower 3-digit zip code	69,529	0.473	0.207	0.250	0.432	0.758

C. Distance Maintained by Lead Arrangers
(Based on 1,708 lead arranger-years)

	$N=$	Mean	SD	10^{th}	50^{th}	90^{th}
(I) Distance in borrower 1-digit SIC	1,705	0.635	0.219	0.390	0.598	0.946
(II) Distance in borrower 2-digit SIC	1,705	0.668	0.231	0.401	0.632	1.016
(III) Distance in borrower 3-digit SIC	1,705	0.663	0.236	0.392	0.621	1.020
(IV) Distance in borrower state	1,705	0.674	0.233	0.412	0.633	1.035
(V) Distance in borrower 3-digit zip code	1,702	0.703	0.248	0.410	0.671	1.065

Table 3: Effect of Distance on Likelihood of Being Chosen As A Syndicate Member

This table reports coefficient estimates from regressions relating the likelihood of a potential lender (that was among the top 100 lead arrangers in the previous year) being chosen as a syndicate member by the lead arranger (that was also among the top 100 lead arrangers in the previous year) to the distance between the potential lender and the lead arranger. The dependent variable is an indicator variable for whether the potential lender is indeed a syndicate member (0 if no and 1 if yes) in Panel A and an ordinal variable for the role of the potential lender in the syndicate (0 if non-member, 1 if participant, 2 if co-agent, and 3 if co-lead) in Panel B. The independent variable of interest is the distance between the potential lender and the lead arranger in the previous year. Columns (I)-(V) use distance as an independent variable based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by year are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

A. Syndicate Member Indicator

Syndicate member indicator	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Distance from lead arranger	-0.064***	-0.068***	-0.067***	-0.063***	-0.046***
	(0.0029)	(0.0035)	(0.0035)	(0.0038)	(0.0024)
Previous relationships with lead	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.00004)	(0.00004)	(0.00004)	(0.0004)	(0.00004)
Previous relationships with borrower	0.087***	0.087***	0.087***	0.087***	0.087***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Market share, previous year	-0.053	-0.077**	-0.076**	-0.059*	-0.011
	(0.0321)	(0.0302)	(0.0303)	(0.0305)	(0.0376)
$N =$	10,734,322	10,734,322	10,734,322	10,734,384	10,725,803
Adjusted R^2	0.4096	0.4102	0.4101	0.4094	0.4072

B. Syndicate Role

Syndicate Role Depth	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Distance from lead arranger	-0.089***	-0.096***	-0.093***	-0.090***	-0.066***
	(0.0046)	(0.0053)	(0.0053)	(0.0056)	(0.0037)
Previous relationships with lead	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***
	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
Previous relationships with borrower	0.149***	0.148***	0.148***	0.148***	0.149***
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0076)
Market share, previous year	0.309***	0.273***	0.276***	0.293***	0.362***
	(0.0647)	(0.0633)	(0.0640)	(0.0640)	(0.0716)
$N =$	10,734,322	10,734,322	10,734,322	10,734,384	10,725,803
Adjusted R^2	0.4363	0.4367	0.4366	0.4363	0.4348

Table 4: Effect of Distance on Frequency and Depth of Relationships between Lenders

This table reports coefficient estimates from regressions relating the frequency and depth of relationships between two lenders (that were among the top 100 lead arrangers in the previous year) to the distance between them. The dependent variable is the frequency of being members in the same syndicate during one year in Panel A and the depth of all these relationships (computed as the sum of an ordinal variable indicating 0 if non-member, 1 if participant, 2 if co-agent, and 3 if co-lead over all syndicated loans originated during the year) in Panel B. The independent variable of interest is the distance between the two lead arrangers in the previous year. Columns (I)-(V) use distance as an independent variable based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. All regressions include year and lead arranger fixed effects. Robust standard errors allowing for clustering by year are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

A. Frequency of Relationships between Lenders

Frequency of relationships	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Distance from the other lead arranger	-0.667***	-1.025***	-1.105***	-0.836***	-0.796***
	(0.1178)	(0.1750)	(0.1864)	(0.1567)	(0.1564)
Frequency of relationships, previous year	0.902***	0.901***	0.900***	0.901***	0.902***
	(0.0684)	(0.0684)	(0.0684)	(0.0684)	(0.0684)
Market share, previous year	5.603***	4.723**	4.511**	5.104***	5.235***
	(1.8517)	(1.7811)	(1.7650)	(1.8232)	(1.8070)
$N =$	228,428	228,428	228,428	228,340	224,386
Adjusted R^2	0.8311	0.8312	0.8312	0.8311	0.8310

B. Depth of Relationships between Lenders

Depth of relationships	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Distance from lead arranger	-0.604**	-0.894**	-0.900**	-0.735**	-0.775***
	(0.2187)	(0.3474)	(0.3644)	(0.2910)	(0.2580)
Depth of relationships, previous year	1.572***	1.571***	1.571***	1,571***	1.571***
	(0.1162)	(0.1161)	(0.1161)	(0.1162)	(0.1161)
Market share, previous year	29.176***	28.449***	28.394***	28.770***	28.772***
	(6.4122)	(6.3151)	(6.3449)	(6.4105)	(6.4114)
$N =$	228,428	228,428	228,428	228,340	224,386
Adjusted R^2	0.7842	0.7843	0.7843	0.7842	0.7842

Table 5: Close versus Distant Syndicates

This table reports the mean differences between close and distant syndicates on various borrower and loan characteristics, that is, the mean of close syndicates minus the mean of distant syndicates ($\mu_{Close} - \mu_{Distant}$). The sample of 69,805 syndicated loan facilities is split into two sub-samples based on the yearly median of the lender distance at the loan level. The sub-sample of close syndicates consists of syndicates in which lender distance is below the median of the originating year, whereas the sub-sample of distant syndicates consists of the remaining syndicates. Lender distance at the syndicated loan facility level is defined as the average distance between the lead arranger(s) and all the other syndicate members in the previous year. Columns (I)-(V) use distance based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. * indicates that the mean difference is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Borrowers characteristics:					
Private firm indicator	-0.057***	-0.048***	-0.052***	-0.079***	-0.061***
Rated firm indicator	0.069***	0.061***	0.062***	0.115***	0.079***
S&P investment-grade indicator	0.071***	0.057***	0.060***	0.077***	0.059***
Previous loan indicator	0.057***	0.062***	0.063***	0.073***	0.073***
Ln [sales at closing]	0.399***	0.341***	0.361***	0.538***	0.397***
Loan characteristics:					
Ln [facility amount]	0.272***	0.211***	0.220***	0.410***	0.259***
Maturity in months	-3.70***	-3.07***	-3.18***	-0.75***	-3.11***
Term loan indicator	-0.063***	-0.058***	-0.059***	-0.034***	-0.049***
% retained by lead arranger(s)	-0.868**	-0.626*	-0.708**	-1.722***	-0.433
Spread on drawn funds (bps)	-35.20***	-26.97***	-28.06***	-15.82***	-25.00***
Loan default indicator	-0.014***	-0.012***	-0.007**	-0.0002	-0.005**

Table 6: Effect of Distance on Loan Share

This table reports coefficient estimates from regressions relating the loan share taken by a lender in the syndicate to the distance between the lender and the lead arranger. The dependent variable is the share of the loan taken by the lender in percentage. The independent variable of interest is the distance between the lender and the lead arranger in the previous year. Columns (I)-(V) use distance as an independent variable based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by year are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

% taken by a syndicate member	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Distance from lead arranger	-1.748***	-1.985***	-2.079***	-2.284***	-1.800***
	(0.1646)	(0.1425)	(0.1373)	(0.1626)	(0.1380)
Previous relationships with lead	0.0001**	0.0001**	0.0001**	0.0001*	0.0001***
	(0.00005)	(0.00004)	(0.00004)	(0.00004)	(0.00003)
Previous relationships with borrower	0.177***	0.174***	0.173***	0.173***	0.174***
	(0.0156)	(0.0158)	(0.0160)	(0.0157)	(0.0156)
Market share, previous year	10.269***	9.921***	9.822***	9.677***	10.025***
	(0.5802)	(0.5932)	(0.6046)	(0.6178)	(0.6254)
$N =$	159,605	159,605	159,605	159,608	159,549
Adjusted R^2	0.8244	0.8248	0.8249	0.8255	0.8245

Table 7: Effect of Distance on Loan Pricing

This table reports coefficient estimates from regressions relating loan pricing to the lender distance at the syndicated loan facility level. The dependent variable is the interest spread over LIBOR on drawn funds measured in basis points in all panels. The independent variable of interest is the lender distance of the loan, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous year. Columns (I)-(V) use distance as an independent variable based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. All regressions include year, loan purpose, interest rate type, and borrower 2-digit SIC industry fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(I)	(II)	(III)	(IV)	(V)
	1-digit	2-digit	3-digit	State	3-digit
Spread on drawn funds (bps)	SIC	SIC	SIC		Zip
Lender distance	38.560***	29.016***	32.185***	-8.700	21.773***
	(5.2876)	(5.7544)	(6.2112)	(5.6138)	(5.7166)
Private borrower indicator	5.460	5.519	5.474	6.103*	5.499
	(3.6374)	(3.6572)	(3.6580)	(3.6385)	(3.6491)
Public, unrated borrower indicator	-22.197***	-22.257***	-22.251***	-21.975***	-22.306***
	(2.9414)	(2.9669)	(2.9651)	(2.9972)	(2.9867)
S&P investment-grade indicator	-58.800***	-58.911***	-58.939***	-58.777***	-58.986***
	(3.7791)	(3.7737)	(3.7704)	(3.7677)	(3.7699)
Ln [1 + # previous loans by borrower]	0.731	0.682	0.717	0.447	0.691
	(1.4006)	(1.3961)	(1.3957)	(1.3774)	(1.3927)
Ln [borrower's sales at closing]	-6.515***	-6.570***	-6.540***	-6.796***	-6.578***
	(1.2113)	(1.2103)	(1.2087)	(1.2094)	(1.2081)
Ln [loan facility amount]	-20.794***	-20.923***	-20.909***	-21.245***	-20.974***
	(1.1053)	(1.1084)	(1.1017)	(1.1218)	(1.1089)
Ln [loan maturity in days]	3.880*	4.046**	4.040**	4.194**	4.102**
	(2.0005)	(2.0030)	(2.0031)	(2.0042)	(1.9999)
Term loan indicator	71.144***	71.252***	71.203***	71.553***	71.362***
	(3.6660)	(3.6823)	(3.6893)	(3.6511)	(3.6781)
$N =$	36,402	36,402	36,402	36,402	36,401
Adjusted R^2	0.5014	0.5007	0.5009	0.4999	0.5004

Table 8: Effect of Distance on Loan Default

This table reports coefficient estimates from regressions relating loan default to the lender distance at the syndicated loan facility level. The dependent variable is the loan default indicator (0 if no default and 1 if default). The independent variable of interest is the lender distance of the loan, which is the average distance between the lead arranger(s) and all the other syndicate members in the previous year. Columns (I)-(V) use distance as an independent variable based on lender specializations in 1-digit, 2-digit, and 3-digit borrower SIC industry, borrower state, and 3-digit borrower zip code, respectively. All regressions include year, loan purpose, interest rate type, and borrower 2-digit SIC industry fixed effects. Robust standard errors allowing for clustering by borrower 2-digit SIC industry are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Loan default indicator	(I) 1-digit SIC	(II) 2-digit SIC	(III) 3-digit SIC	(IV) State	(V) 3-digit Zip
Lender distance	0.008	0.001	0.003	-0.022	-0.005
	(0.0147)	(0.0143)	(0.0143)	(0.0160)	(0.0148)
Public, unrated borrower indicator	-0.014*	-0.014*	-0.014*	-0.013*	-0.014*
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)
S&P investment-grade indicator	-0.036***	-0.036***	-0.036***	-0.036***	-0.036***
	(0.0088)	(0.0088)	(0.0088)	(0.0088)	(0.0088)
Ln [1 + # previous loans by borrower]	0.009**	0.009**	0.009**	0.009**	0.009**
	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)
Ln [borrower's sales at closing]	0.0003	0.0003	0.0003	0.0001	0.0002
	(0.0020)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
Ln [loan facility amount]	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Ln [loan maturity in days]	0.023***	0.023***	0.023***	0.023***	0.023***
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Term loan indicator	0.028***	0.028***	0.028***	0.028***	0.028***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
$N =$	27,078	27,078	27,078	27,078	27,078
Adjusted R^2	0.0600	0.600	0.0600	0.0602	0.0600

Table 9: Effect of Distance on Systemic Risk

This table reports coefficient estimates from regressions relating a bank's contribution to the systemic risk of the financial system (*SRISK%*) to its interconnectedness in the syndicated loan market (*distance*). The dependent variable, *Ln [SRISK%]*, is the natural logarithm of *SRISK%*. The independent variable of interest is the distance maintained by a lead arranger, which is the average distance on the loan facility level for all the loans it arranged during the year. *Distance* used in this table is based on 1-digit borrower SIC industry. *European* is an indicator variable equal to 1 if the bank is headquartered in Europe. *Distance* × *European* is the interaction term of *Distance* and *European*. *Ln [leverage]* is the natural logarithm of the quasi-market leverage ratio calculated as (book assets - book value of equity + market value of equity) as a percentage of market value of equity. *Ln [market value]* is the natural logarithm of market value of equity. All regressions include year-quarter fixed effects. Robust standard errors are in parentheses. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
					Between		Between
Ln [SRISK%]	OLS	OLS	OLS	OLS	Effects	OLS	Effects
Distance	-2.778***	-2.924***	-3.439***	-3.549***	-3.836***	-1.996***	-2.279***
	(0.112)	(0.112)	(0.184)	(0.164)	(0.911)	(0.087)	(0.68)
European		0.407***	0.876***	0.485***	0.053		
		(0.038)	(0.092)	(0.082)	(0.696)		
Distance × European			0.685**	0.873***	0.646		
			(0.115)	(0.106)	(0.999)		
Ln [leverage]				0.972***	1.604***	1.171***	1.218***
				(0.039)	(0.365)	(0.03)	(0.23)
Ln [market value]						0.704***	0.662***
						(0.02)	(0.128)
$N =$	3,492	3,492	3,492	3,492	3,492	3,492	3,492
R^2 / Overall R^2	0.1594	0.1790	0.1845	0.3265	0.3021	0.4930	0.7325
Between R^2					0.5852		0.4775