Syndication, Interconnectedness, and Systemic Risk

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Abstract

Syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects. We develop a novel measure of bank interconnectedness using syndicated corporate loans. Interconnectedness is positively related to both bank size and diversification; diversification, however, matters more than size. We find that interconnectedness is positively correlated with various bank-level systemic risk measures including SRISK, CoVaR, and DIP, and such a positive correlation mainly arises from an elevated effect of interconnectedness on systemic risk during recessions. Using a market-level measure of systemic risk, CATFIN, we also find that interconnectedness increases aggregate systemic risk during recessions.

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"Examples of vulnerabilities include high levels of leverage, maturity transformation, interconnectedness, and complexity, all of which have the potential to magnify shocks to the financial system. Absent vulnerabilities, triggers [such as losses on mortgage holdings] would generally not lead to full-blown financial crises."

– Ben S. Bernanke, Monitoring the Financial System, 2013.

1 Introduction

The financial crisis of 2007-2009 demonstrated how large risk spillovers among financial institutions caused a global systemic crisis and worldwide economic downturn. The collapse of the interbank market at the beginning of the crisis suggested an important channel of contagion among financial institutions through contractual relationships (Gai and Kapadia, 2010; Gai et al., 2011). A second important channel is commonality of asset holdings. As banks have similar exposure to assets such as real estate loans, a decline in asset prices can affect the banking system because of direct exposure of banks to similar assets as well as fire sale externalities (F. Allen et al., 2012; May and Arinaminpathy, 2010). Common exposures of banks are of first order importance as indicated by Federal Reserve Chairman Bernanke in his speech at the Conference on Bank Structure and Competition in May 2010 in Chicago: [1]

"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] Common exposures have played an important role in various historical crises: The Savings & Loans crisis in the U.S. in the 1980s was caused by maturity mismatch of the asset and liability side of banks' balance sheets and a shock to (i.e., increase of) interest rates (Ho and Saunders, 1981). The Asian financial crisis in the 1990s was associated with exchange rate risks. The recent crises in Ireland and Spain were associated with a decline in real estate prices. The 2007-2009 financial crisis involved a decline in real estate prices as well as various forms of contagion magnifying the extent of the crisis (Hellwig, 2014, 1995).

In this paper, we study interconnectedness in the form of overlapping asset portfolios among financial institutions examining the organizational structure of loan syndicates. The syndicated loan market provides an ideal laboratory to study interconnectedness of banks. It is the most important funding source for non-financial firms (Sufi, 2007) and banks repeatedly participate in syndicated loans arranged by one another. We know borrower and lender identities and are thus able to track banks' investments in this market in order to quantify common risk exposures.

We develop a novel measure of interconnectedness for which the key component is the "distance" (similarity) between two banks' syndicated loan portfolios measured as the Euclidean distance between two banks based on their relative industry exposures. We document a high propensity of bank lenders to concentrate syndicate partners rather than to diversify them, as lead arrangers are more likely to collaborate with banks with similar corporate loan portfolios. Consequently, interconnectedness through common corporate loan exposures increases over time. We find that bank size and diversification are important drivers of interconnectedness. Importantly, our results suggest that diversification has a larger explanatory power, partly mitigating concerns that our results reflect size effects.

Diversification is an important (risk management) motive for banks to syndicate loans (Simons, 1993).[2] Recent theoretical work, however, has shown that full diversification is not optimal as it can increase systemic risk through various forms of financial contagion (F. Allen et al., 2012; Castiglionesi and Navarro, 2010; Ibragimov et al., 2011; Wagner, 2010).[3] One important channel that explains how shocks propagate through financial systems is information contagion. If one bank is in trouble, investors reassess the risk of other institutions that they believe have similar exposures. Short-term investors may decide not

[2] Substantial benefits for banks and borrowers are possible explanations for the rapid growth of the syndicated loan market since 1989. Appendix 1 shows the growth of this lending on an annual basis. Note that even in the 2007 – 2009 crisis years, its size was still extremely large.
[3] Beale et al. (2011) model a network of banks with overlapping asset portfolios. The authors find that banks should diversify (but in different asset classes) if systemic costs are large.

to roll over their investments if solvency risks are high but engage in precautionary liquidity hoarding (Acharya and Skeie, 2011).[4]

A second important concern is fire sale externalities (Shleifer and Vishny, 2011). In a systemic shock, selling-off assets can lead to mark-to-market losses for banks holding similar exposures (Cifuentes et al., 2005). Moreover, higher asset price volatility might lead to tighter margins forcing other banks to liquidate assets jointly causing a further drop in asset prices and an increase in liquidation costs. An important problem is that those banks that would be natural buyers of these securities usually engage in the same strategies and thus invest in similar assets. As they are overleveraged and most likely have to liquidate these assets themselves, they are not available as buyers. Those market participants that eventually buy the assets value them less further dislocating prices from fundamental values.[5]

In the next part of the paper, we test this empirically relating interconnectedness to various market based measures of systemic risk. Similar to approaches used in stress tests that have been conducted in the U.S. and Europe since 2008, the construction of these measures is to estimate losses in a stress scenario and determine a bank's equity shortfall after accounting for these losses. These measures capture asset price as well as funding liquidity risks associated with interconnectedness using market data (Acharya et al., 2014).

We employ three frequently used bank-level systemic risk measures: (1) SRISK (Acharya et al., 2010; Brownlees and Engle, 2011), CoVaR (Adrian and Brunnermeier, 2009), and (3) DIP (Huang et al., 2009).[6] All three concepts measure a co-movement of equity or credit default swap (CDS) prices without the notion of causality, i.e., a bank can contribute to systemic risk of the financial system because it initiates

[4] After the U.S. government did not bail out Lehman Brothers in September 2008, investors reassessed the possibility of future bank bailouts and were unwilling to lend (particularly on an unsecured basis) to banks causing a break-down of the interbank market. During the sovereign debt crisis, U.S. Money Market Mutual Funds withdrew their funding from several European banks completely in fall 2011 because of concerns about exposure of banks to risky sovereign debt and the solvency of these institutions (Acharya and Steffen, 2014).

[5] This is precisely what happened in the fall of 2008 following the bankruptcy of Lehman Brothers. Commercial banks, broker-dealers, hedge funds, etc., were heavily exposed to short-term funding collateralized with mortgage-backed securities, which used to be safe securities. After the Lehman Brother default, short-term funding market dried up causing investors specialized in these securities to sell the assets, which resulted in massive price declines and losses.

[6] Other market-based measures (e.g., based on stock return volatility) are developed in Diebold and Yilmaz (2014).

a contagious event or because of its exposure to a common factor. Moreover, all measures are constructed to estimate cross-sectional differences in systemic risk at a point in time.

We find a positive and significant correlation between our interconnectedness measure and various systemic risk measures including SRISK, CoVaR, and DIP. Controlling for bank size as well as various fixed effects, we show that, consistent with our introductory quote, interconnectedness amplifies systemic risk during recessions. Another way of interpreting this result is that interconnectedness of banks is a useful tool to forecast cross-sectional differences in banks' contribution to systemic risk if a severe crisis occurs. Various tests suggest that our results are consistent across different systemic risk measures and model specifications.

At the market aggregate level, interconnectedness also elevates the bank sector systemic risk measure, CATFIN, during recessions. It suggests that diversification benefits brought by the syndication process are accompanied with important negative externalities that will eventually lead to enhanced systemic risk during crises. In other words, interconnectedness magnifies the consequences of a systemic crisis.

While our paper is related to the literature on networks in interbank markets (Gai and Kapadia, 2010; Gai et al., 2011), there are important differences. Both of the aforementioned papers investigate contagion in a network of contractual claims, or domino contagion; they analyze, conditional on one bank failing, how shocks sequentially affect contractual partners. Usually, these papers model the default of one bank that initiates contagion and also incorporate a time lag until the shock reaches a bank further away in the network.

We are agnostic about contractual relationships between banks in our sample. Our modest goal is to construct a measure of common exposures of banks that can generate various forms of contagion as described above and that eventually even amplifies domino effects as we have seen in the recent financial crisis.[7] Importantly, we document that common exposures to large corporate loans increases systemic risk.

[7] AIG insured virtually all banks' exposures to mortgage backed securities. While banks' exposures were transformed into counterparty credit risk to AIG, AIG's risk was now driven by real estate prices increasing the correlation among

In contrast to examples of domino contagion, however, interconnectedness through common exposures does not reflect whether or not banks are sequentially affected. In fact, if shocks are large enough, banks with common exposures to these shocks might default simultaneously even before a domino effect sets in.[8]

The paper proceeds as follows. In Section 2, we describe the empirical methodology, in particular, derive our measures of distance and interconnectedness, and discuss various systemic risk measures as well as the related literature. Data are described in Section 3. Sections 4 and 5 discuss our empirical results on interconnectedness in loan syndications and the implications of such interconnectedness for systemic risk. Finally, we conclude in Section 6 with some policy implications.

2 Empirical Methodology

In this section, we first develop our interconnectedness measure and then briefly describe the different systemic risk measures used in the empirical tests. All variables are defined in Table 1.

2.1 Measuring Interconnectedness

In this subsection, we describe how we measure distance between two banks based on lending specializations. We then explain how we construct our interconnectedness measure.

2.1.1 Distance between Two Banks

The focus of our analysis is the U.S. syndicated loan market. We use four proxies for bank syndicated loan specializations related to borrower industry. Specifically, we use the borrower SIC industry division,[9] the 2-digit, 3-digit, and 4-digit borrower SIC industry to examine in which area(s) each bank has heavily

all banks insured by AIG. Subsequent fire sales and information contagion amplified the effects from domino contagion due to, e.g., liquidity hoarding, leading to AIG's bailout in September 2008.

[8] The empirical literature on contagion in finanical systems is surveyed in Upper (2011). This literature finds that even though the likelihood of domino contagion is low, the consequences can affect large parts of the banking system if this type of contagion occurs.

[9] The SIC industry division is defined with a range of 2-digit SIC industries (see Appendix 2 for detail) whereas 2-digit SIC indicates the major group and 3-digit SIC indicates the industry group.

invested.[10] We then compute the distance between two banks by quantifying the similarity of their loan portfolios. The detailed construction of our distance measure is as follows.

For each month during the January 1989 to July 2011 period, we compute each lead arranger's total loan facility amount originated during the prior 12 months using Dealscan's loan origination data.[11] There were approximately 100-180 active lead arrangers each month; as a result, we obtain a total of 37,311 unique lead arranger-months. We then compute portfolio weights for each lead arranger 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) j within 12 months prior to month t.[12] 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 the lender can be specialized in.

Next, we compute the distance between two banks as the Euclidean distance between them in this J-dimension space:

$$\text{Distance}_{m,n,t} = \sqrt{\sum_{j=1}^{J}\left(w_{m,j,t} - w_{n,j,t}\right)^2}, \qquad (1)$$

where $\text{Distance}_{m,n,t}$ is the distance between bank m and bank n in month t ($m \neq n$). Appendix 2 provides an example on how distance is computed between two banks as specified in (1). We show the computation of distance based on borrower SIC industry division among JPMorgan Chase, Bank of America, and Citigroup, the top three lead arrangers as of January 2007. According to their portfolios of syndicated loans originated during the previous twelve months (i.e., January-December 2006), Citigroup had a different loan portfolio from those held by either JPMorgan Chase or Bank of America, investing more heavily in the manufacturing, transportation, communications, electric, gas, sanitary, and services industries and less heavily in retail trade, finance, insurance and real estate. As a result, the distance computed between

[10] Borrower geographic location, e.g., the state where the borrower is located and the 3-digit borrower zip code, can also be used to examine lender specializations. Analyses based on borrower location provide similar results.
[11] Loan amount is split equally over all lead arrangers for loans with multiple leads.
[12] We consider the portfolio of syndicated loans originated during the previous 12 months the best representation of a bank's lending specializations. Results of our paper still hold if we extend this 12-month period to the mean/median loan maturity, which is 48 months.

Citigroup and either JPMorgan Chase or Bank of America is greater than the distance between JPMorgan Chase and Bank of America whose portfolios were more similar to each other.[13]

2.1.2 Bank-level Interconnectedness

To measure the interconnectedness at the bank-level, we first take the weighted average of the distance between a given lead arranger and all the other lead arrangers in the syndicated loan market. As a smaller Euclidean distance means higher interconnectedness, we then linearly transform the weighted average of distance into an interconnectedness measure for the bank such that it is normalized to a scale of 0-100 with 0 being least interconnected and 100 being most interconnected.[14] That is, a higher value indicates a more interconnected bank. Specifically, the interconnectedness of bank i in month t, $\text{Interconnectedness}_{i,t}$, equals:

$$\text{Interconnectedness}_{\text{i,t}} = \left(1 - \frac{\sum_{i \neq k} x_{i,k,t} \cdot \text{Distance}_{i,k,t}}{\sqrt{2}}\right) \times 100, \qquad (2)$$

where $\text{Distance}_{i,k,t}$ is the distance between bank i and bank k in month t as defined in (1), and $x_{i,k,t}$ is the weight given to bank k in the computation of bank i's interconnectedness. We use two kinds of weighting schemes: First, we assign equal weights to all other lead arrangers (“equal-weighted interconnectedness”). The second weight is the number of collaborative relationships between bank i and bank k relative to the total number of relationships bank i had with all lead arrangers in the syndicated loan market during the prior twelve months (“relationship-weighted interconnectedness”).[15] These two alternative weighting schemes allow us to examine interconnectedness along different dimensions so that our results not only account for interconnectedness among all the lead arrangers via the "equal-weighted" measure but also show (incremental) effects from banking relationships via the "relationship-weighted" measure.

2.1.3 Market-aggregate Interconnectedness

[13] Appendix 3 summarizes the pairwise distance among the top ten lead arrangers as of January 2007. Note that the distance measure must lie within the range of 0 to $\sqrt{2}$ due to the definition of Euclidean distance.

[14] We can also interpret an interconnectedness value of 0 as being not interconnected at all (i.e., having a loan portfolio completely different from all the other banks' portfolios) and 10 as being totally interconnected (i.e., have a loan portfolio exactly same as all the other banks' portfolios).

[15] A collaborative relationship is identified if bank j is bank i's participant lender, co-lead, or lead arranger.

Next, we construct a monthly "Interconnectedness Index" aggregating bank-level interconnectedness to the market level. This market-aggregate interconnectedness measure is an equal-weighted average of interconnectedness of individual banks. That is, the market-aggregate Interconnectedness Index in month t, Interconnectedness Index_t, equals:

$$\text{Interconnectedness Index}_t = \sum_i \frac{1}{N_t} \cdot \text{Interconnectedness}_{i,t}, \quad (3)$$

where $\text{Interconnectedness}_{i,t}$ is the interconnectedness of bank i as defined in (2) and N_t is the number of lead arrangers as of month t.[16]

2.1.4 Diversification and Competitiveness

Diversification is an essential vehicle for banks to reduce risk. Thus, loan syndication can help a bank to diversify its asset portfolio. We construct the following diversification measure for banks to understand how loan portfolio diversification interacts with interconnectedness:

$$\text{Diversification}_{i,t} = \left[1 - \sum_{j=1}^{J} \left(w_{i,j,t}\right)^2\right] \times 100, \quad (4)$$

where $\text{Diversification}_{i.t}$ measures the diversification level of bank i in month t and, as in (1), $w_{i,j,t}$ is the weight lead arranger i invests in specialization j (i.e., industry) within 12 months prior to month t. The notion behind the measure is that as a bank becomes more diversified, $\sum_{j=1}^{J} \left(w_{i,j,t}\right)^2$ becomes smaller, so that the measure for diversification grows larger.

Another important measure is the competitiveness of the syndicated loan market, and we use a Herfindahl index to proxy for market competitiveness. This index is constructed as follows:

$$\text{Herfindahl}_t = \sum_i \left(y_{i,t}\right)^2 \times 100, \quad (5)$$

[16] An alternative weight can be the market share of each lead arranger in the syndicated loan market. The equal weight is chosen here so that the aggregate interconnectedness of the syndicated loan market is unlikely to be driven solely by large banks. More importantly, the aggregate systemic risk measure of the banking sector, CATFIN, is essentially an equal-weighted VaR measure. We chose equal weights to be consistent. Results based on this alternative weight are qualitatively similar and are available upon request.

where $y_{i,t}$ is the market share of bank i in the syndicated loan market based on the total loan amount the bank originated as a lead arranger during the twelve-month period prior to month t. A more competitive syndicated loan market corresponds to a smaller Herfindahl index.

2.2 Measuring Systemic Risk

To analyze the link between loan portfolio interconnectedness and systemic risk, we use four systemic risk measures proposed in the recent literature: (i) systemic capital shortfall (SRISK), (ii) contagion value-at-risk (CoVaR), (iii) distress insurance premium (DIP), and (iv) CATFIN. These measures are briefly described below.

2.2.1 SRISK

SRISK is a bank's U.S.-Dollar capital shortfall if a systemic crisis occurs, which is defined as a 40% decline in aggregate banking system equity over a 6-month period. This measure is developed in Acharya et al. (2010) and Brownlees and Engle (2011).[17] SRISK is defined as

$$\begin{aligned} \mathrm{SRISK} &= \mathrm{E}\big((\mathrm{k}(\mathrm{D}+\mathrm{MV})-\mathrm{MV})\big|\mathrm{Crisis}\big) \\ &= \mathrm{kD}-(1-\mathrm{k})(1-\mathrm{LRMES})\mathrm{MV}, \end{aligned} \tag{6}$$

where D is the book value of debt that is assumed to be unchanged over the crisis period, LRMES is the long-run marginal expected shortfall and describes the co-movement of a bank with the market index when the overall market return falls by 40% over the crisis period.[18] LRMES × MV is then the expected loss in market value of a bank over this 6-month window. k is the prudential capital ratio which is assumed to be 8% for U.S. banks and 5.5% for European banks to account for differences between US-GAAP and IFRS. SRISK thus combines both the firm's projected market value loss due to its sensitivity with market returns and its (quasi-market) leverage.[19] Naturally, SRISK is greater for larger banks. To make sure that our results

[17] The results of this methodology are available on the Volatility Laboratory website (V-Lab), where systemic risk rankings are updated weekly both globally and in the United States (see http://Vlab.stern.nyu.edu/). V-Lab provides data for about 100 U.S. and 1,200 global financial institutions.
[18] V-Lab uses the S&P 500 for U.S. banks and the MSCI ACWI World ETF Index for European banks.
[19] A quasi-market leverage includes book value of debt plus market value of equity minus book value of equity.

are not driven solely by bank size, we conduct various tests. For example, we perform analyses using only LRMES, which is more of a tail risk rather than a size measure.[20] Moreover, our alternative systemic risk proxies such as CoVaR do not incorporate leverage to the same extent as SRISK.

While SRISK provides an absolute shortfall measure, it can also be expressed to reflect a bank's contribution to the shortfall of the financial system as a whole (or aggregate SRISK). This measure is called SRISK% (or relative SRISK) and is constructed by dividing SRISK for one bank by the sum of SRISK across all banks at each point in time.

2.2.2 CoVaR

Our second market-based measure of systemic risk is CoVaR (Adrian and Brunnermeier, 2009). CoVaR is the VaR of the financial system conditional on one institution being in distress and ΔCoVaR is the marginal contribution of that firm to systemic risk. The VaR of each institution is measured using quantile regressions and the authors use a 1% and 5% quantile to measure CoVaR:

$$\mathrm{Prob}\left(\mathrm{L} \geq \mathrm{CoVaR}_{\mathrm{q}} \middle| \mathrm{L}^{\mathrm{i}} \geq \mathrm{VaR}_{\mathrm{q}}^{\mathrm{i}}\right) = \mathrm{q}, \tag{7}$$

where L is the loss of the financial system, L^i is the loss of institution i, and q is the VaR quantile (for example, 1%). CoVaR measures spillovers from one institution to the whole financial system. Importantly, CoVaR does not imply causality, i.e., it does not imply that a firm in distress causes the systemic stress of the system, but rather suggests that it could be both, a causal link and/or a common factor (in terms of asset or funding commonality) that drives a bank's systemic risk contribution.

CoVaR is not as sensitive to size or leverage as SRISK. Moreover, in contrast to SRISK, CoVaR includes only the correlation with market return volatility, but not a bank's return volatility. Suppose that two banks have the same market return correlation, but bank A has low volatility while bank B has high volatility. Both banks would have the same CoVaR even though bank A is essentially of low risk.

2.2.3 DIP

[20] In fact, our data suggest that the correlation of LRMES and bank asset size is about 0.27 compared to a correlation of about 0.8 between asset size and SRISK.

We use the "Distressed Insurance Premium (DIP)" as our third market-based measure of systemic risk (Huang et al., 2011, 2009).[21] The four main components of DIP are: (1) the risk-neutral probability of default (PD), which is calculated from CDS prices using (2) loss given default (LGD) estimates, which are allowed to vary over time, (3) asset correlations which are measured using equity return correlations, and (4) the total liabilities of all banks.

Huang et al. (2009) construct a hypothetical portfolio of the total liabilities of all banks and use monte-carlo simulations to estimate the risk neutral probability distribution of credit losses for that portfolio. DIP is then a hypothetical insurance premium to cover the losses if total losses (L) (aggregated over all banks) exceed a certain threshold of total banks' liabilities (L_{min}). DIP can then be expressed as follows:

$$\mathrm{DIP} = \mathrm{E}^{\mathrm{Q}}(\mathrm{L}\,|\mathrm{L} > \mathrm{L}_{\min}) \tag{8}$$

$$\frac{\partial \mathrm{DIP}}{\partial \mathrm{L}^{\mathrm{i}}} = \mathrm{E}^{\mathrm{Q}}\left(\mathrm{L}^{\mathrm{i}}\,|\mathrm{L} > \mathrm{L}_{\min}\right)$$

DIP describes a conditional expectation of portfolio losses under extreme conditions. It is thus similar to an expected shortfall concept, but it is not defined using a percentile distribution but rather using an absolute loss threshold (L_{min}). In that sense, it is also similar to SRISK.[22] L^i is then the loss of an individual institution and determines the marginal contribution of a bank to the systemic risk of the financial sector ($\frac{\partial \mathrm{DIP}}{\partial \mathrm{L}^{\mathrm{i}}}$). While we consistently refer to this measure as "DIP" throughout the paper, we operationalize it using the loss of each individual bank in the regressions (i.e., L^i).

2.2.4 CATFIN

While SRISK, CoVaR, and DIP measure the cross-sectional differences in banks' contribution to systemic risk (that is, micro- or bank-level measures of systemic risk), CATFIN is an aggregate VaR measure of

[21] DIP is applied to evaluate systemic risk in the European banking sector by Black et al. (2012).

[22] The major methodological difference between DIP, SRISK and CoVaR is that DIP is a risk-neutral measure, while SRISK and CoVaR are statistical measures using physical distributions. From an economic perspective, DIP is different compared to shortfall measures such as SRISK as the CDS spreads used to calculate default risk measure the potential losses to debt holders assuming all equity is wiped out. One can therefore also refer to DIP as a "bailout measure," which is quite often the focus in policy discussions.

systemic risk in the financial sector constructed as an unweighted average of three (parametric and non-parametric) VaR measures using the historical distribution of equity returns. Allen et al. (2012) show that micro-level measures are helpful in explaining the cross-sectional variations in systemic risk contributions, however, they do a poor job in forecasting macroeconomic developments. Thus, they develop CATFIN to forecast potential detrimental effects of financial risk taking by the overall financial sector on the macroeconomy. The intuition is that banks do not internalize the costs on the society when making risk-taking decisions, and CATFIN is supposed to capture these externalities.

Taken together, we employ four different proxies to capture risks to the stability of the financial system as a whole. Importantly, as explained above, SRISK, CoVaR, and DIP are estimates of the co-variation between individual banks and systemic risk. CATFIN, on the other hand, is an aggregate measure for the overall banking sector systemic risk.

3 Data and Summary Statistics

In this section, we discuss data sources we use for our study and provide summary statistics.

3.1 Data Sources

We use two primary sources to analyze the interconnectedness of banks in loan syndication and how such interconnectedness affects banks' systemic risk: (i) syndicated loan data and (ii) systemic risk data. Thomson Reuters LPC DealScan is the primary database on syndicated loans with comprehensive coverage, especially for the U.S. market. We use a sample of 91,715 syndicated loan facilities originated for U.S. firms between 1988 and July 2011 to construct our distance and interconnectedness measures. These loans present very similar characteristics as documented in the literature, e.g., Sufi (2007).

Interconnectedness is measured at the lead arranger (bank holding company) level. 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 fields: administrative agent, agent, arranger, bookrunner, coordinating arranger, lead arranger, lead bank, lead manager, mandated arranger, and mandated lead arranger.[23] Note that the "LeadArrangerCredit" and "LenderRole" fields generate similar identifications of lead arrangers.

We obtain the SRISK data from NYU V-Lab's Systemic Risk database and the CoVaR, DIP, and CATFIN data from the authors who proposed them as systemic risk measures. SRISK data covers 132 global financial institutions and 16,258 bank-months ranging from January 2000 to December 2011. We are able to match them with 5,939 lead arranger-months and 66 unique lead arrangers. The CoVaR data are quarterly covering 1,194 public U.S. financial institutions, of which 56 can be found in our interconnectedness data as lead arrangers in the syndicated loan market. The CoVaR data are available from the third quarter of 1986 to the fourth quarter of 2010, and the matched sample includes 1,844 unique lead arranger-quarters. The DIP data are weekly covering 57 unique European financial institutions from January 2002 to January 2013. We aggregate weekly data into monthly measures and obtain 5,235 bank-months with DIP measures. We are able to construct a matched sample of 22 unique lead arrangers and 1,414 lead arranger-months with our interconnectedness data.[24] The CATFIN data are monthly and available at the aggregate market level from January 1973 to December 2009. We match them with our monthly market-aggregate Interconnectedness Index and obtain a matched sample of 252 months.

3.2 Summary Statistics

Table 2 reports summary statistics for the distance, interconnectedness, and systemic risk measures we described in Section 2 as well as lead arranger (bank) and market characteristics. Distance is summarized of 5,223,284 lead arranger pair-months and interconnectedness of 37,311 lead arranger-months across four lender specialization categories, i.e., the borrower’s SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Interconnectedness can be equal- or relationship-weighted. While distance must lie within the range of 0 to $\sqrt{2}$ and interconnectedness must be within 0 to 100 by definition, the standard deviations of these measures imply that there is sufficient variation for empirical tests. Further, the

[23] See Standard & Poor's A Guide to the Loan Market (2011) for descriptions of lender roles.
[24] Appendix 4 lists lead arrangers for which the various systemic risk measures are available.

distributions of our distance as well as equal- and relationship-weighted interconnectedness measures across different specialization categories are similar to one another, which indicates that our measures capture both distance and interconnectedness in a similar fashion. Interestingly, the relationship-weighted interconnectedness tends to be greater than its equal-weighted counterpart and also has larger variation. We can interpret a bank's interconnectedness as how much overlap (similarity) its loan portfolio has with other banks' portfolios on average. For example, with a mean of 39 on relationship-weighted interconnectedness based on 2-digit, 3-digit, and 4-digit borrower SIC industry, we know that an average bank's loan portfolio is 39% overlapped with other banks' portfolios on average.

Summary statistics of SRISK, CoVaR, and DIP are reported at the lead arranger level. Of the 5,939 matched lead arranger-months, the average SRISK is $24.9 billion, SRISK% 2.5%, LRMES 3.8%, and quasi-market leverage ratio 17.8%. Of the 1,844 matched lead arranger-quarters, the 1% CoVaR is a decline of 2.3% or $15 billion of bank equity on average and the 5% CoVaR is a decline of 1.9% or $12.3 billion of bank equity on average.[25] Of the 1,414 matched lead arranger-months, the average DIP is 14.7 billion euros. All these measures show greater systemic risk for our sample of lead arrangers than an “average” financial institution in the SRISK, CoVaR, and DIP data sets.[26] The SRISK measures (SRISK, SRISK%, and LRMES) and CoVaR measures (1% and 5% CoVaR in percentage) have correlations ranging from 0.2 to 0.4 for the sample of lead arrangers for which the data is available. The correlation between DIP and SRISK is close to 0.8. The CATFIN measure suggests that there is a 28% probability of a macroeconomic downturn on average.

4 Interconnectedness of Banks in Loan Markets

[25] The CoVaR data are all expressed in the form of losses, i.e., negative numbers. In our empirical analyses, we multiply CoVaR with minus one so that a higher CoVaR implies higher systemic risk.

[26] For example, an average financial institution in the NYU V-Lab database has SRISK of $10.3 billion and SRISK% of 1.32%. An average public U.S. financial institution in the CoVaR data shows a decline of 1.15% or $0.785 billion at 1% CoVaR, and an average European financial institution in the DIP data shows a DIP of 10.9 billion euros.

In this section, we first show empirically how banks interact in the syndicated loan market. Then we explore the determinants of interconnectedness.

4.1 Collaboration in Loan Syndicates

A small distance between two banks as measured in equation (1) implies a similar asset allocation as to their corporate loan portfolios and thus more exposure to common shocks. To understand the role of syndication in producing commonality in corporate loan exposures, we examine the determinants of a bank's syndicated loan participation.

In order to make the data and computations manageable, we limit our interest to the top 100 lead arrangers in each month that hold an aggregated share of at least 99.5% of the total market. We estimate the following regression:

$$\text{Syndicate Member}_{m,n,k,t} = \alpha + \beta_1 \cdot \text{Distance}_{m,n,t} + \beta_2 \cdot \text{Lead Relationship}_{m,n,t}$$

$$+\beta_3 \cdot \text{Borrower Relationship}_{n,k} + \beta_4 \cdot \text{Market Share}_{n,t} + \text{Loan Facility}_k' + e_{m,n,k,t}, \tag{9}$$

where the dependent variable Syndicate $\text{Member}_{m,n,k,t}$ 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 month t and zero otherwise. $\text{Distance}_{m,n,t}$ measures the distance between lead arranger m and lender n based on their syndicated loan portfolios during the twelve months prior to month t. As a proxy for bank-to-bank relationships, Lead $\text{Relationship}_{m,n,t}$ is an indicator variable for whether lead arranger m had syndicated any loans with lender n prior to the current loan (no matter what roles the two lenders took). As a proxy for bank-to-firm relationships, Borrower $\text{Relationship}_{n,k}$ is an indicator variable for whether lender n arranged or participated in any syndicated loans that were made to the borrower prior to loan syndicate k. By including Lead $\text{Relationship}_{m,n,t}$ and Borrower $\text{Relationship}_{n,k}$ 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. Market $\text{Share}_{n,t}$ is the market share of lender n as a lead arranger during the twelve months prior to month t. We use Market $\text{Share}_{n,t}$ to proxy for lender n's reputation and market size or power. Loan Facility_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 lead arranger level. The resulting sample size is almost 11 million lender pairs.

The results are reported in Table 3. Four distance measures are shown in Columns (I) to (IV), based on borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, respectively. In all regressions, our distance measures show negative coefficients that are significant at the 1% level. That is, the greater the portfolio similarity between a lender and the lead arranger, the greater the likelihood that the lender is chosen as a syndicate member. We also find that a lender's prior relationships with either the lead arranger or the borrower have significantly positive influence on the likelihood of being chosen as a syndicate member. The effect is especially strong for prior lender-borrower relationships, which is consistent with the findings in Sufi (2007). Moreover, lender n's market share increases its likelihood of being included in the syndicate.

Overall, the results suggest that lead arrangers tend to work with banks that have more similar corporate loan portfolios increasing the degree of interconnectedness of banks over time.

4.2 Determinants of Interconnectedness: Diversification versus Size

To understand the determinants of interconnectedness, we examine the effect of three bank characteristics: (i) total assets, (ii) diversification, and (ii) number of specializations. While total assets is a standard proxy for bank size, the next two variables indicate the level of diversification and breadth of the bank's syndicated loan portfolio.

We first examine correlation between interconnectedness and each of the three variables and then estimate the following multiple regression model:

$$\begin{aligned}\text{Interconnectedness}_{i,t} &= \alpha + \beta_1 \cdot \text{Total Assets}_{i,t} + \beta_2 \cdot \text{Diversification}_{i,t} \\ &+\beta_3 \cdot \text{Number of Specializations}_{i,t} + \text{Lead Arranger}_i + e_{i,t}, \qquad (10)\end{aligned}$$

where the dependent variable $\text{Interconnectedness}_{,t}$ is the level of interconnectedness of bank i in month t. $\text{Total Assets}_{i,t}$ is bank i's lagged total assets at the beginning of month t;[27] $\text{Diversification}_{i,t}$ is the diversification measure computed as in equation (3); and $\text{Number of Specializations}_{i,t}$ is the number of specializations the bank is engaged in as a lead arranger.[28] Lead Arranger_i is a vector of lead arranger (bank) fixed effects. Standard errors are heteroscedasticity robust and clustered at the lead arranger level.

Table 4 reports the results for both equal- and relationship-weighted interconnectedness based on four types of specializations. First, we show in Panel A significantly positive Pearson correlation coefficients between interconnectedness and total assets, diversification, and number of specializations – all at the 1% level, indicating positive association of these variables with interconnectedness. Equivalent to R^2 in a univariate regression setting where independent variables are individually included, the square of the Pearson correlation coefficient helps us assess the explanatory power of these variables for interconnectedness. We find that total assets, with Pearson correlation ranging from 0.30 to 0.34, only explains between 9% and 12% of the variation in interconnectedness. In contrast, diversification, with Pearson correlation in the range of 0.70-0.98, explains more than 70% of the variation in equal-weighted interconnectedness and about 50% or more variation in relationship-weighted interconnectedness. In other words, banks with concentrated loan portfolios are less interconnected relative to those with diversified portfolios. Number of specializations has Pearson correlation in the range of 0.46-0.77 and hence explains approximately 20-60% of the variation in interconnectedness. Overall, diversification and number of specialization are relatively more important determinants of loan market interconnectedness than bank size.

In a next step, we include all variables jointly in multivariate regressions and report the results in Panel B of Table 4. In Regression (I), we include three additional indicator variables – whether the lead

[27] We collect lead arrangers' total assets from Bankscope and/or Compustat. While Bankscope provides annual data about financial institutions worldwide, Compustat has quarterly reports on U.S. public firms' financial/accounting information. In all regressions involving total assets, we use the lagged value that was reported for the year or quarter prior to but closest to month *t*.

[28] $\text{Number of Specialization}_{i,t}$ varies by the type of specializations. For example, it is the number of 2-digit borrower SIC industries to which the bank lends to as a lead arranger if the type of specializations on which the interconnectedness measure is based is the 2-digit borrower SIC industry.

arranger is a commercial bank (Bank), whether it is headquartered in Europe (Europe), and whether it is outside U.S. and Europe (Outside U.S. & Europe). We continue to find positive effects of total assets, diversification, and number of specializations on interconnectedness. While the coefficients on diversification and number of specializations are all significant at the 1% level, the coefficients on total assets are sometimes less or not significant. We also find that commercial banks have on average a slightly lower level of equal-weighted interconnectedness. The two location variables – Europe and Outside U.S. & Europe – control for the effect of accounting differences between US-GAAP and IFRS (for example, on reported total assets). An analysis of variance (ANOVA) suggests that lead arranger fixed effects explain about 60% or more of the variation in our interconnectedness measures; thus, including fixed effects eliminates a substantial part of the variation. However, even when we augment the regression with lead arranger fixed in Regression (II), the significant, positive effects of total assets, diversification, and number of specializations on the interconnectedness measures persist. Consistent with the correlation results, diversification and number of specializations have greater t-statistics than total assets in both regressions.

4.3 Time Trend in Interconnectedness

Figure 1 plots the monthly time series of the equal- and relationship-weighted market-aggregate Interconnectedness Indices based on 4-digit borrower SIC industry from January 1989 to July 2011.[29] We observe three time trends in the development of interconnectedness among banks that are lead arrangers in the U.S. syndicated loan market.

First, relationship-weighted interconnectedness has been consistently greater than its equal-weighted counterpart during our sample period (except that they got closer during a few months in 2001). This further indicates that banks tend to establish collaborative relationships with those that have similar asset allocation in their syndicated loan portfolios.

[29] Interconnectedness Indices based on borrower SIC industry division, 2-digit and 3-digit borrower SIC industry show similar trends.

Second, there was an overall increasing trend in market-aggregate interconnectedness from 1989 until 1995. This was mainly due to the sudden introduction of syndicated lending as a financing vehicle and the subsequent growth in the size and number of participants in the syndicated loan market. A possible explanation is the benefits to lenders from being able to syndicate large corporate loans. Syndicating, i.e., selling a large proportion of loans that banks originate themselves or participating in loans to borrowers banks usually do not have access to, helps them diversify their loan portfolios. Moreover, the development of the syndicated loan market accommodates the financing needs of large borrowers. Banks face regulatory restrictions such as single counterparty exposure limits as well as regulatory capital requirements that discourage retaining larger exposures to borrowers. The development of the syndicated loan market allows banks to continue lending to, and thus their relationship, with larger firms syndicating a greater fraction of the loan to other banks if exposure limits are binding. Similarly, they are able to reduce capital requirements as syndication removes part of the credit risk associated with the loan from the bank's balance sheet. In order to show that this increasing trend does not dominate our empirical results, we run all regressions excluding data prior to 1995 as a robustness test and find similar results.[30]

Another interesting trend is that interconnectedness dropped significantly during two crisis periods – first in 2001, then the period from mid-2008 to the end of 2009. It rose again, though, following the crises. The recent example is that since the beginning of 2010, interconnectedness has climbed back to the peak level we observed before the crisis, and the relationship-based interconnectedness has reached an even higher level.

5 Interconnectedness and Systemic Risk

In this section, we investigate whether interconnectedness increases a bank's contribution to systemic risk during recessions using cross-sectional as well as time-series tests.

5.1 Bank-level (Cross-sectional) Tests

[30] The results based on the post-1995 subsample are available upon request. The tests on SRISK and DIP are the same based on either the whole sample or the post-1995 subsample as SRISK and DIP data start from 2000.

Banks become interconnected as they invest in similar loan portfolios through loan syndication. In fact, this behavior reduces each bank's individual default risk via diversification of loan exposures and thus is beneficial from a microprudential perspective (Simons, 1993). However, interconnectedness creates systemic risk because not only are banks vulnerable to common shocks due to exposure to similar assets, but also because problems of some banks can spread throughout the syndicate network to other banks, for example, funding shocks or adverse asset price movements due to an increase in correlations among assets. Consequently, when a financial crisis occurs, interconnectedness will magnify the severity and consequences of the crisis (Bernanke, 2013). We thus examine whether more heavily interconnected banks in the syndicated loan market are greater contributors to systemic risk, particularly during recessions.

We match SRISK, CoVaR, and DIP as systemic risk measures with the time-series of our interconnectedness measure at the bank level. To more formally test their relationship, we first examine correlation between systemic risk and interconnectedness. Table 5 shows that Pearson correlation coefficients are significantly positive at the 1% level between all systemic risk measures (SRISK, 1% and 5% CoVaR, and DIP) and our equal- and relationship-weighted interconnectedness measures across all four types of specializations, indicating positive association between more interconnected banks and greater contribution to systemic risk.[31]

As a second step, we add control variables in a multiple regression setting. The general form of the regression we estimate is as follows:

$$\begin{aligned}\text{Systemic Risk}_{i,t} &= \alpha + \beta_1 \cdot \text{Interconnectedness}_{i,t} + \beta_2 \cdot \text{Recession}_t \\ &+ \beta_3 \cdot \left(\text{Interconnectedness}_{i,t} \times \text{Recession}_t\right) + \beta_4 \cdot \text{Total Assets}_{i,t} \\ &+ \beta_5 \cdot \text{Market Share}_{i,t} + \beta_6 \cdot \text{Systemic Risk}_{i,t-1} + \text{Lead Arranger}_i' + e_{i,t}.\end{aligned} \quad (11)$$

[31] Translating Pearson correlation coefficients into R^2 in a univariate regression setting where interconnectedness is the single independent variable, we find that such association is the strongest with 5% CoVaR (13-21%), followed by 1% CoVaR (10-17%), DIP (3-12%) and SRISK (3-4%).

The dependent variable Systemic $Risk_{i,t}$ is the systemic risk measure of bank i in month t, which can be either SRISK, CoVaR, or DIP. The key independent variable $Interconnectedness_{i,t}$ is the level of interconnectedness of bank i in month t. $Recession_t$ is an indicator variable equal to 1 if month t falls into recessions as measured by NBER recession dates.[32] We are interested in the role of interconnectedness during recessions. Thus, we include the interaction term ($Interconnectedness_{i,t} \times Recession_t$) in the regression. We control for bank size (Total $Assets_{i,t}$) and market power in loan syndication ($MarketShare_{i,t}$). A one-period lagged systemic risk measure (Systemic $Risk_{i,t-1}$) is included on the RHS of the regression due to its strong serial correlation. We further include lead arranger (bank) fixed effects. Standard errors are heteroscedasticity robust and clustered at the lead arranger level.

5.1.1 Interconnectedness and SRISK

Table 6 reports the multiple regression results for SRISK. Panel A includes the full sample whereas Panel B includes the subsample in which SRISK shows positive, that is, the financial institution does have a capital shortfall systemically. First, we see in both panels insignificant coefficients on both equal- and relationship-weighted interconnectedness measures across all four types of specializations. That is, during periods of economic expansions, interconnectedness neither elevates nor reduces SRISK. As discussed earlier, while there are substantial benefits from syndication, it simultaneously creates the potential for systemic risk. Our empirical findings, thus, suggest that in normal times the benefits of syndicated lending roughly offset the cost arising from systemic risk.

More importantly, we see that the coefficients on the interaction term between interconnectedness and NBER recessions are consistently positive and statistically significant for SRISK at the 1% level in Panel A and the 5% level in Panel B. These results show that interconnectedness contributes more positively to SRISK during recessions. Such a finding is consistent with an amplifying effect of interconnectedness on systemic risk during recessions suggested by Bernanke (2013). It is also important to note that the magnitude of the coefficients suggests that the “costs” arising from systemic risk during recessions more

[32] The NBER identifies three recession periods during our sample period: July 1990 – March 1991, March 2001 – November 2001, and December 2007 – June 2009.

than offset the “benefits” of syndication, and this effect is economically significant – an increases of one standard deviation in interconnectedness typically leads to an increase of $1.2-1.6 billion in SRISK, which is approximately a 5% increase from the mean SRISK.

The coefficients on a bank's total assets are significantly positive indicating that larger banks are more systemic.[33] The effect of market share as a lead arranger in the syndicated loan market is insignificant on SRISK in most cases. The one-month lagged SRISK has significantly positive coefficients consistently above 0.8 showing high persistence of SRISK over time.[34]

5.1.2 Interconnectedness and CoVaR

Table 7 reports results from regressing CoVaR on interconnectedness, recession, the interaction term of interconnectedness and recession, total assets, market share as a lead arranger, one-quarter lagged CoVaR, and lead arranger (bank) fixed effects. The regressions have the same specifications as in (11).

Results for 1% CoVaR in Panel A and 5% CoVaR in Panel B consistently show significantly positive coefficients on interconnectedness at the 5% level while the coefficients on the interaction term of interconnectedness and recession are not statistically significant. These findings show a magnifying effect of interconnectedness on CoVaR during all times, that is, both under normal economic conditions and during recessions. Although there is no incremental effect of interconnectedness during recessions, the total effect of interconnectedness on CoVaR is significantly positive – this can also be shown if we run the same regression with the subsample of recession times. The economic significance of the results can be shown by an increase of typically $0.6-0.9 billion in 1% CoVaR and $0.4-0.6 billion in 5% CoVaR associated with

[33] These results are consistent with our earlier results describing the drivers of interconnectedness in corporate loan markets. While bank size is an important factor, it is not a sufficient condition that eventually explains cross-sectional variation in interconnectedness and eventually systemic risk. Recent events provide a supporting narrative. For example, the default of the Portuguese lender Banco Espirito Santo (a relatively small bank with assets worth €81 billion) caused a global stock market decline in July 2014. Similarly, the Swiss regulator declared the Raiffeisenbank Schweiz Genossenschaft, a bank with assets of €28 billion, “systemically important” in August 2014 because its products cannot be easily replaced but are important for the Swiss economy. In other words, systemic importance of banks extends beyond size, and it is crucial to monitor other factors such as interconnectedness of banks.

[34] We also run tests using LRMES, which is a main componente of SRISK and more of a measure of tail risk, as the dependent variable and find that LRMES is magnified during recessions if banks are more interconnected.

an increase of one standard deviation in interconnectedness during recessions. Such increases are elevations of about 4-6% from the average CoVaR measures.

As mentioned in Section 2, CoVaR is defined such that it is not explicitly sensitive to size, and we see insignificant coefficients on a bank's total assets in the regression results for CoVaR when bank fixed effects are included. A bank's market share in the syndicated loan market seems to bear no effect on CoVaR, either. Strong persistence in CoVaR is indicated by the highly significant and positive coefficients (around 0.8) on the one-quarter lagged CoVaR.

5.1.3 Interconnectedness and DIP

Similar to Tables 6-7, Table 8 reports coefficient estimates from regressing DIP in billions of euros on the same set of independent variables. Note that while the SRISK regressions cover 66 financial institutions in the U.S., Europe, and other areas globally, the CoVaR regressions include only 56 U.S. institutions, and the DIP regressions include 22 European banks.

Similar to the results for SRISK, we find that the coefficients on interconnectedness are not statistically significant. This again implies that in normal times, the benefits of syndicated lending cancel out the cost arising from systemic risk. We continue to observe positive coefficients on the interaction term of interconnectedness and recession, and they are significant at the 5-10% level. Thus, we interpret that higher interconnectedness leads to an elevated DIP during recessions. This is an economically significant effect as an increase of one standard deviation in interconnectedness is related to an increase of 1.5-2 billion euros in DIP, which represents a 10-14% increase from the average DIP. Table 8 also shows that a great amount of variation in DIP is absorbed by a bank's asset size and market share. DIP displays high persistence over time as SRISK and CoVaR.

5.2 Market-level (Time-series) Tests

SRISK, CoVaR, and DIP provide systemic risk measures for each bank individually and thus assess the cross-sectional differences in the contribution of banks to systemic risk. We can also ask whether more interconnectedness in the overall banking sector increases systemic risk of the banking sector over time. To assess this, we use an aggregate systemic risk measure, called CATFIN, which has been shown to forecast recessions that arise from the excessive risk-taking of the U.S. banking sector using different VaR measures (L. Allen et al., 2012). We estimate the following time-series regression:

$$\begin{aligned}\mathrm{CATFIN}_t = \alpha + \beta_1 \cdot \text{Interconnectedness Index}_t + \beta_2 \cdot \text{Recession}_t \\ +\beta_3 \cdot (\text{Interconnectedness Index}_t \times \text{Recession}_t) + \beta_4 \cdot \text{Market Size}_t \\ +\beta_5 \cdot \text{Herfindahl}_t + \beta_6 \cdot \mathrm{CATFIN}_{t-1} + e_t, \qquad (12)\end{aligned}$$

where the dependent variable CATFIN_t is the monthly time series of CATFIN. The key independent variables include (i) Interconnectedness Index_t, the monthly market-aggregate Interconnectedness Index, and (ii) (Interconnectedness $\text{Index}_t \times \text{Recession}_t$), the interaction term of Interconnectedness Index and recession. We include two other variables to control for market characteristics: Market Size_t is the size of the U.S. syndicated loan market measured by the total amount of newly originated loans during the previous twelve months, and Herfindahl_t is the Herfindahl index of the market. Standard errors are heteroscedasticity robust.

As reported in Table 9, our time-series tests show an elevated impact of interconnectedness on systemic risk during recessions consistent with the cross-sectional results obtained earlier. First, market-aggregate interconnectedness has neither significantly positive nor negative effect on CATFIN under normal economic conditions in most regressions. Next, we find positive coefficients on the interaction of Interconnectedness Index and recession, significant at the 5-10% level in five out of eight regressions. Standard deviation of the market-aggregate Interconnectedness Index varies from close to 30 to a little over 40. As a result, an increase of one standard deviation in Interconnectedness Index leads to an increase of 6-18% in CATFIN, the probability of a macroeconomic downturn, during recessions. Note that the average CATFIN over our sample period is at 28%. Thus, our results indicate in general that interconnectedness imposes both statistically and economically significant systemic costs during recessions. Aggregate systemic risk measured by CATFIN is also highly persistent over time as the systemic risk measures show at the bank level.

6 Conclusion

Syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects. While banks diversify syndicating loans to other banks, they reduce the diversity of the financial system because banks become more similar to one another. Using a novel measure of loan market interconnectedness and different market based measures of systemic risk, we find that interconnectedness of banks can explain the downside exposure of these banks to systemic shocks during recessions.

Our results have several important implications for banks and regulators. First, market based measures are informative during bad times because they pick up fundamental risks of banks precisely in a moment when banks are worried about their counterparties' exposure to various types of risks.

Second, we provide an important link from market-based measures to balance sheet risks, common exposures to large syndicated loans. This is important for regulators. Increases in market based systemic risk measures can alert them of higher risks in the financial system. Knowing that common exposures to large corporate loans are an important contributor to systemic risk helps regulators to monitor (the build-up of) risks in the system. We provide a first step in quantifying these exposures. Regulators with more detailed data can extend our analyses investigating and monitoring specific industry overlap, common exposures to leveraged loans or, for example, exchange rate risks that might be hidden in these loans. The Thai financial crisis of 1997-1998 illustrates this. International banks made loans in U.S. dollar to Thai banks and these, in turn, lent to Thai firms in U.S. dollar to eliminate the exchange rate risks. After the devaluation of the Baht against the dollar, firms could not repay their U.S. dollar denominated debt and the Thai banks started to default on foreign lenders. Before the crisis, the exposure to Thai banks was identified as credit risk and the, at hindsight more important, (correlated) exposure to the Baht remained hidden.

Third, an institution-oriented approach to assessing and limiting systemic risk exposure is insufficient as the narrative of the recent financial crises suggests. Banks do not internalize the risks they create for the financial system as a whole. Consequently, they invest too much and incur too much leverage. The Bank of International Settlement (BIS) published an updated methodology to identify "Global

Systemically Important Financial Institutions" (G-SIFIs) in July 2013 (BIS, 2013). The indicators to identify G-SIFIs comprise five factors: (1) bank size, (2) interconnectedness, (3) substitutability of services, (4) complexity, and (5) cross-border activity, each with an equal weight. While these factors include interconnectedness, its level is determined based on contractual relationships between financial institutions. We propose asset commonality through large corporate loans as an additional indicator that helps to identify G-SIFIS and to calibrate appropriate capital surcharges for these institutions.

Fourth, the Financial Stability Oversight Council (FSOC), which was created in the U.S. following the Dodd-Frank Wall Street Reform after the 2008-2009 financial crisis, has the mandate to monitor and address the overall risks to financial stability. It has the authority to make recommendations as to stricter regulatory standards for the largest and most interconnected institutions to their primary regulators. We propose a new method based on interconnectedness through large corporate loans as part of FSOC's systemic risk oversight and monitoring system.

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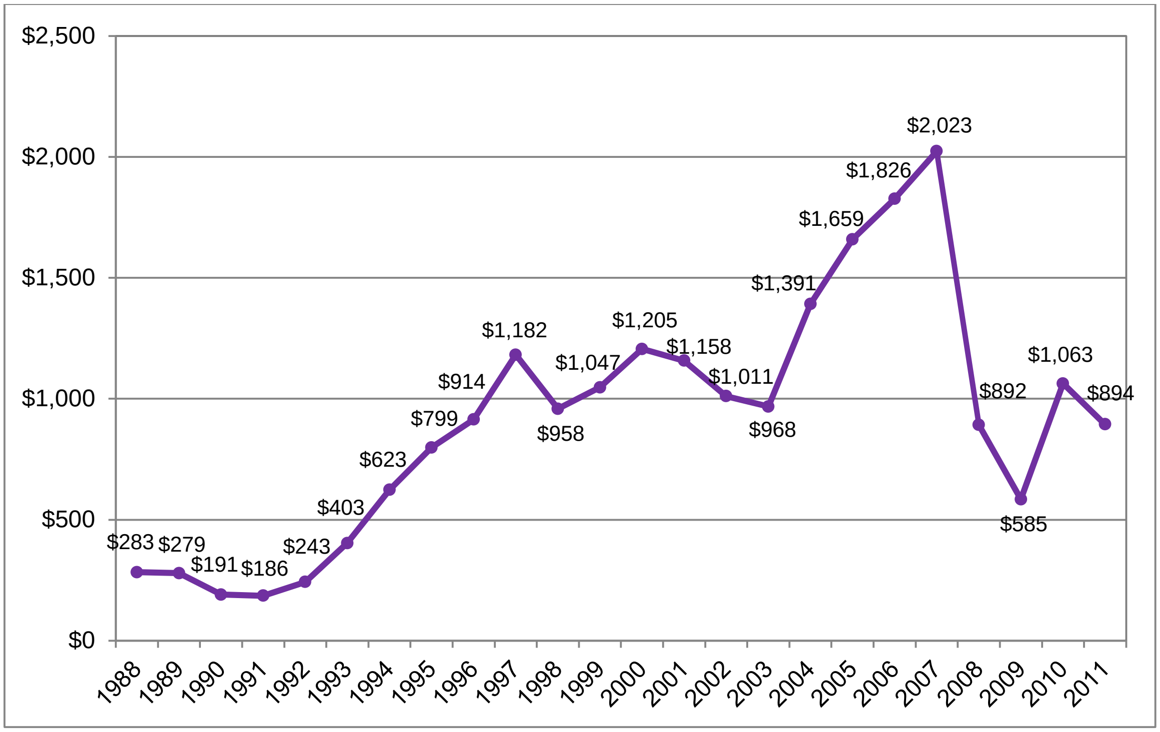
Appendix 1. The U.S. Syndicated Loan Market, 1988-2011

This appendix shows the size of the U.S. syndicated loan market by year from 1988 to 2011. Market size is measured by the total newly originated syndicated loan amount during the year in billions of U.S. dollars. Note that data for the year of 2011 are only available through July of that year.



Appendix 2. Examples of Computing Distance between Lead Arrangers

This appendix shows how distance is computed by examples. Distance between two lead arrangers 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 borrower SIC industry division. We show below the computation of such distance among JPMorgan Chase (JPM), Bank of America (BAC), and Citigroup (C), which were the top three lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

SIC Industry Division (2-digit SIC Industries)	JPM (1st)	BAC (2nd)	C (3rd)	$(JPM-BAC)^2$	$(JPM-C)^2$	$(BAC-C)^2$
Agriculture, Forestry & Fishing (01-09)	0.0288%	0.1695%	0.0000%	0.00000198	0.00000008	0.00000287
Mining (10-14)	5.0995%	3.7503%	4.7749%	0.00018203	0.00001054	0.00010498
Construction (15-17)	2.3374%	6.3482%	0.3057%	0.00160872	0.00041276	0.00365120
Manufacturing (20-39)	28.6855%	23.3487%	35.3001%	0.00284810	0.00437536	0.01428362
Transportation, Communications, Electric, Gas & Sanitary Services (40-49)	12.2990%	12.0246%	20.1229%	0.00000753	0.00612126	0.00655812
Wholesale Trade (50-51)	2.4575%	3.8202%	0.9026%	0.00018570	0.00024177	0.00085124
Retail Trade (52-59)	6.8148%	7.3637%	2.8273%	0.00003013	0.00159001	0.00205790
Finance, Insurance & Real Estate (60-67)	29.1845%	30.7133%	18.4803%	0.00023371	0.01145801	0.01496453
Services (70-89)	13.0931%	12.4389%	17.1766%	0.00004280	0.00166749	0.00224458
Public Administration (91-97)	0.0000%	0.0226%	0.1096%	0.00000005	0.00000120	0.00000076
Total	100%	100%	100%	0.00514075	0.02587847	0.04471981
			Distance:	0.07169901	0.16086787	0.21147059

Appendix 3: Distance among Top Ten Lead Arrangers

This appendix shows distance between any two top ten lead arrangers as of January 2007 based on their portfolios of syndicated loans originated during the previous twelve months. Distance between two lead arrangers 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 borrower SIC industry division. The top ten lead arrangers as of January 2007 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). Note that distance is the key component for computing interconnectedness – the smaller the distance between two lead arrangers, the more interconnected they are.

	JPM	BAC	C	WB	CSGN	DB	RBS	GS	BARC	UBSN
JPM	-									
BAC	0.0717	-								
C	0.1609	0.2115	-							
WB	0.2296	0.2102	0.2358	-						
CSGN	0.3351	0.3539	0.2805	0.3200	-					
DB	0.1739	0.1884	0.1352	0.1748	0.2834	-				
RBS	0.3021	0.3398	0.1875	0.2907	0.2983	0.2020	-			
GS	0.2515	0.2786	0.1347	0.1859	0.2587	0.1618	0.1808	-		
BARC	0.4385	0.4464	0.3492	0.2830	0.4334	0.3584	0.3752	0.2364	-	
UBSN	0.4058	0.4196	0.3909	0.4069	0.1685	0.4063	0.4284	0.3722	0.5222	-

Appendix 4. Lead Arrangers with Systemic Risk Measures

This appendix lists lead arrangers in the U.S. syndicated loan market for which various systemic risk measures are available. There are 66 lead arrangers with SRISK measures (Panel A), 56 with CoVar measures (Panel B), and 22 with DIP measures (Panel C).

A. Lead Arrangers with SRISK Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	AIG	AIG	34	Keycorp	KEY
2	Allied Irish Banks	ALBK	35	Lehman Brothers	LEH
3	American Express	AXP	36	Lloyds Banking Group	LLOY
4	Banco Bilbao Vizcaya Argentari	BBVA	37	Marshall & Ilsley	MI
5	Bank of America	BAC	38	Mediobanca	MB
6	Bank of China	F3988	39	Merrill Lynch	MER
7	Bank of Ireland	BKIR	40	Metlife	MET
8	Bank of Montreal	BMO	41	Mizuho Financial Group	F8411
9	Bank of New York Mellon	BK	42	Morgan Stanley	MS
10	Bank of Tokyo-Mitsubishi UFJ	F8306	43	National Bank of Canada	NA
11	Barclays	BARC	44	National City Corporation	NCC
12	BB&T Corporation	BBT	45	Natixis	KN
13	Bear Stearns	BSC	46	Nomura	F8604
14	BNP Paribas	BNP	47	Nordea Bank	NDA
15	Capital One Financial	COF	48	Northern Trust	NTRS
16	CIT Group	CIT	49	PNC Financial Services	PNC
17	Citigroup	C	50	Prudential	PRU
18	Comerica	CMA	51	Regions Financial Corp	RF
19	Commerzbank	CBK	52	Royal Bank of Canada	RY
20	Compass Bank	CBSS	53	Royal Bank of Scotland	RBS
21	Credit Agricole SA	ACA	54	Skandinaviska Enskilda Banken	SEBA
22	Credit Suisse	CSGN	55	Societe Generale	GLE
23	Crédit Lyonnais	FLY	56	Sovereign Bank	SOV
24	Danske Bank	DANSKE	57	State Street	STT
25	Deutsche Bank	DBK	58	Suntrust Banks	STI
26	Fifth Third Bancorp	FITB	59	Toronto-Dominion Bank	TD
27	Goldman Sachs	GS	60	UBS	UBSN
28	HSBC	HSBA	61	UniCredit SpA	UCG
29	Huntington Bancshares	HBAN	62	US Bancorp	USB
30	ICBC Asia	F601988	63	Wachovia Bank	WB
31	ING Group	INGA	64	Washington Mutual	WM
32	Intesa Sanpaolo SpA	ISP	65	Wells Fargo	WFC
33	JPMorgan Chase	JPM	66	Zions Bancorporation	ZION

B. Lead Arrangers with CoVaR Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	AIG	AIG	29	Huntington Bancshares	HBAN
2	American Express	AXP	30	Jefferies Finance LLC	JEF
3	Ares Capital Corp	ARCC	31	JPMorgan Chase	JPM
4	Associated Bancorp	ASBC	32	Keycorp	KEY
5	Bank of America	BAC	33	Marshall & Ilsley	MI
6	Bank of Hawaii	BOH	34	Mercantile Bank	MBWM
7	Bank of New York Mellon	BK	35	Metlife	MET
8	BankAtlantic	BBX	36	MetroWest Bank	MWBX
9	Banner Bank	BANR	37	Morgan Stanley	MS
10	BB&T Corporation	BBT	38	Northern Trust	NTRS
11	California Federal Bank	CAL.1	39	Paine Webber	PWJ.
12	Capital One Financial	COF	40	PNC Financial Services	PNC
13	Charter One Bank	CF.6	41	PrivateBancorp Inc	PVTB
14	Chemical Banking Corp	CHFC	42	Prudential	PRU
15	CIT Group	CIT	43	Raymond James Financial	RJF
16	Citigroup	C	44	Regions Financial Corp	RF
17	City National Bank	CYN	45	Signature Bank	SBNY
18	Comerica	CMA	46	State Street	STT
19	Cullen/Frost Bankers	CFR	47	Suntrust Banks	STI
20	Eaton Vance	EV	48	TrustCo Bank Corp	TRST
21	Federal Home Loan Mortgage Corp	3FMCC	49	UMB Financial Corp	UMBF
22	Fifth Third Bancorp	FITB	50	US Bancorp	USB
23	FINOVA Capital Corp	3FNVG	51	Valley National Bank	VLY
24	First Commonwealth Bank	FCF	52	Webster Bank	WBS
25	First Horizon National Corp	FHN	53	Wells Fargo	WFC
26	First Midwest Bancorp	FMBI	54	Whitney National Bank	WTNY
27	Goldman Sachs	GS	55	Wilmington Trust Corp	WL
28	Guaranty Bank	GBNK	56	Zions Bancorporation	ZION

C. Lead Arrangers with DIP Measures

	Financial Institution	Ticker		Financial Institution	Ticker
1	Allied Irish Banks	ALBK	12	ING Group	INGA
2	Banco Bilbao Vizcaya Argentari	BBVA	13	Intesa Sanpaolo SpA	ISP
3	Bank of Ireland	BKIR	14	Lloyds Banking Group	LLOY
4	Barclays	BARC	15	Mediobanca	MB
5	BNP Paribas	BNP	16	Natixis	KN
6	Commerzbank	CBK	17	Nordea Bank	NDA
7	Credit Agricole SA	ACA	18	Royal Bank of Scotland	RBS
8	Credit Suisse	CSGN	19	Skandinaviska Enskilda Banken	SEBA
9	Danske Bank	DANSKE	20	Societe Generale	GLE
10	Deutsche Bank	DBK	21	UBS	UBSN
11	HSBC	HSBA	22	UniCredit SpA	UCG

Figure 1. Time Series of Interconnectedness

This figure shows the time series of the monthly market-aggregate Interconnectedness Index from January 1989 to July 2011. Interconnectedness of a lead arranger is computed based on its distance from all the other lead arrangers in specializations in the U.S. syndicated loan market. Lender specialization in this figure is based on 4-digit borrower SIC industry. The market-aggregate Interconnectedness Index is an equal-weighted average of interconnectedness of all the lead arrangers. Two series of market-aggregate interconnectedness are shown below, and they employ equal and relationship weights at the lead arranger level, respectively.

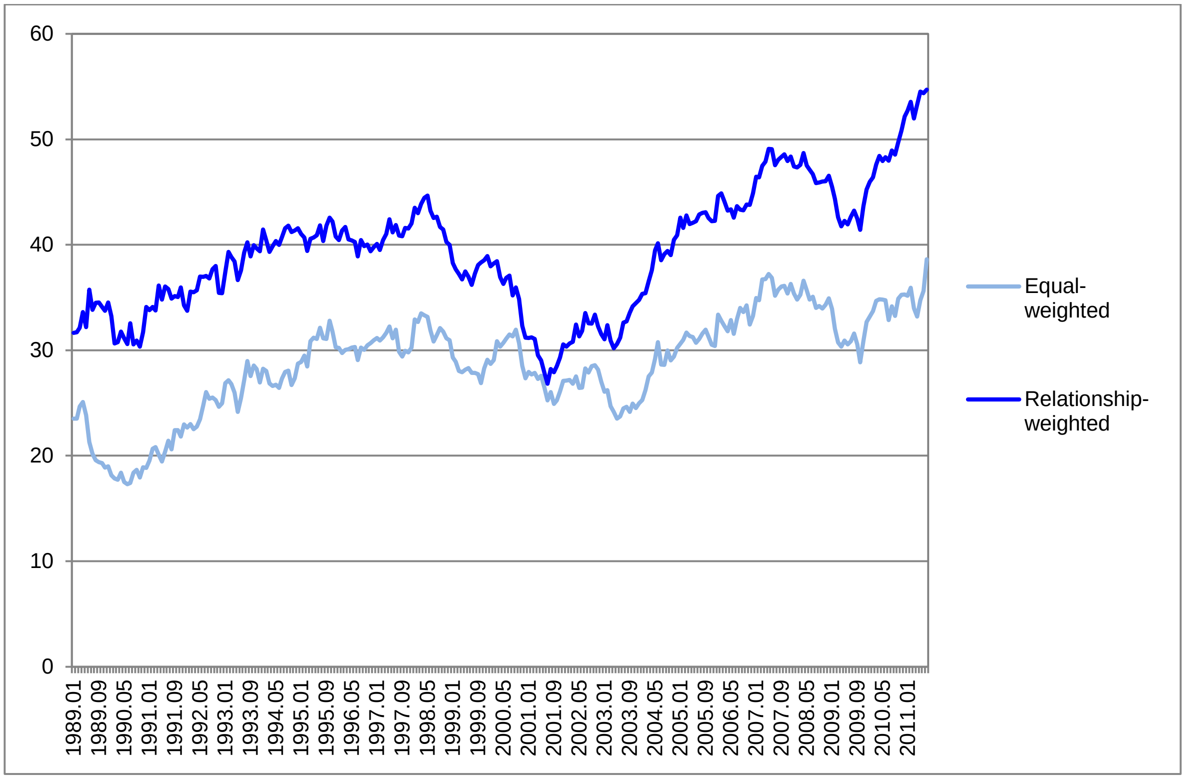


Table 1. Variable Definitions

This appendix lists the variables used in the empirical analysis and their definitions.

Variable	Definition
Bank	An indicator variable for whether the lead arranger is a traditional commercial bank
Borrower Relationship	An indicator variable for whether a potential lender has previous relationships with the borrower
CATFIN	Aggregate systemic risk of the financial sector
CoVaR	1% or 5% contagion value-at-risk of a U.S. bank measured in billions of U.S. dollars or percentage
DIP	Distressed insurance premium of a European bank in billions of euros
Distance	Distance between two banks based on their syndicated loan portfolios as lead arrangers during the previous twelve months
Diversification	Diversification of a bank based on its syndicate loan portfolio
Europe	An indicator variable for whether the lead arranger is headquartered in Europe
Herfindahl	The Herfindahl index of the U.S. syndicated loan market
Interconnectedness	Interconnectedness of a bank
Interconnectedness Index	Market-aggregate interconnectedness
Lead Arranger	Lead arranger (bank) fixed effect
Lead Relationship	An indicator variable for whether a potential lender has previous relationships with the lead arranger
LRMES	Long-run marginal expected shortfall of a bank in percentage
Leverage	Quasi-market leverage of a bank in percentage
Loan Facility	Loan facility fixed effect
Market Share	Market share of a bank in the U.S. syndicated loan market based on the total loan amount the bank originated as a lead arranger
Market Size	The size of the U.S. syndicated loan market measured by the total amount of loans in billions of U.S. dollars
Number of Specializations	Number of specializations a bank is engaged in as a lead arranger
Outside U.S. & Europe	An indicator variable for whether the lead arranger is headquartered outside the U.S. and Europe
Recession	An indicator variable for whether a month falls into recessions as identified by the NBER
SRISK	Systemic capital shortfall of a bank measured in billions of U.S. dollars
SRISK%	Relative capital shortfall of a bank as a percentage of total systemic risk of the market
Systemic Risk	Any systemic risk measure
Syndicate Member	An indicator variable for whether a potential lender is chosen by the lead arranger to be a loan syndicate member
Total Assets	Book value of a bank's total assets in billions of U.S. dollars

Table 2. Summary Statistics

This table reports summary statistics of various distance, interconnectedness, and systemic risk measures as well as lead arranger (bank) and market characteristics. Distance between two lead arrangers 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. Interconnectedness of a lead arrangers can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations. Lender specializations include borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Systemic risk of a lead arranger is measured by SRISK, CoVaR, and DIP. Aggregate systemic risk of the banking sector is measured by CATFIN. We show below summary statistics of the distance measures of 5,223,284 lead arranger pair-months, the interconnectedness measures of 37,311 lead arranger-months, the SRISK measures of 5,939 lead arranger-months, the CoVaR measures of 1,844 lead arranger-quarters, the DIP measure of 1,414 lead arranger-months, and the CATFIN measure of 252 months. Lead arranger (bank) characteristics are reported of 37,311 lead arranger-months, and market characteristics are reported of 271 months.

	N =	Mean	SD	10^{th}	50^{th}	90^{th}
Distance Measures:						
Distance in Borrower SIC Division	5,216,624	0.912	0.385	0.378	0.975	1.414
Distance in 2-digit Borrower SIC	5,216,624	1.007	0.317	0.531	1.050	1.414
Distance in 3-digit Borrower SIC	5,216,624	1.009	0.310	0.540	1.049	1.414
Distance in 4-digit Borrower SIC	5,216,624	1.009	0.309	0.539	1.049	1.414
Interconnectedness Measures:						
Equal-weighted Interconnectedness:						
Based on Borrower SIC Division	37,311	35.7	12.5	17.5	37.6	51.6
Based on 2-digit Borrower SIC	37,311	28.9	14.1	12.4	27.8	48.8
Based on 3-digit Borrower SIC	37,311	28.7	14.8	11.8	28.0	49.4
Based on 4-digit Borrower SIC	37,311	28.7	15.0	11.7	28.0	49.5
Relationship-weighted Interconnectedness:						
Based on Borrower SIC Division	37,311	42.5	27.7	0	48.0	74.4
Based on 2-digit Borrower SIC	37,311	39.0	26.8	0	41.5	72.6
Based on 3-digit Borrower SIC	37,311	39.0	27.0	0	40.9	73.2
Based on 4-digit Borrower SIC	37,311	39.0	27.1	0	40.9	73.4
Systemic Risk Measures:						
SRISK:						
Systemic Capital Shortfall (SRISK) ($bn)	5,939	24.88	47.24	-7.79	6.07	88.30
Relative Capital Shortfall (SRISK%) (%)	5,939	2.52	4.12	0	0.58	7.27
Long-run Marginal Expected Shortfall (LRMES) (%)	5,939	3.80	2.46	1.81	3.31	6.20
Quasi-market Leverage (%)	5,939	17.80	29.88	5.07	10.91	32.42
CoVaR:						
1% CoVaR ($bn)	1,844	-15.0	30.8	-46.7	-2.22	-0.21
1% CoVaR (%)	1,844	-2.29	1.38	-3.89	-2.02	-0.94
5% CoVaR ($bn)	1,844	-12.3	21.6	-43.5	-2.12	-0.15
5% CoVaR (%)	1,844	-1.95	1.07	-3.13	-1.79	-0.83
DIP:						
DIP (€bn)	1,414	14.70	18.61	0.60	6.41	42.15
CATFIN:						
CATFIN (%)	252	28.25	12.93	14.72	25.46	44.70
Lead Arranger Characteristics:						
Total Assets ($bn)	20,045	285.67	457.50	7.17	98.06	782.90
Market Value of Equity ($bn)	19,865	21.46	34.24	0.79	8.59	57.97
Market Share as Lead Arranger (%)	37,311	0.73	2.78	0.00	0.03	1.16
# of Loans Arranged during 12 Months	37,311	35	112	1	4	83
$ of Loans Arranged during 12 Months ($bn)	37,311	6.67	30.9	0.02	0.23	10.4
Market Characteristics:						
Market Size ($bn)	271	918	504	238	959	1,650
Herfindahl	271	11.38	2.63	8.49	10.82	15.26

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 twelve months) being chosen as a syndicate member by the lead arranger 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. The independent variable of interest is the distance between the potential lender and the lead arranger based on their portfolios of syndicated loans originated during the previous twelve months. Columns (I)-(IV) use distance as an independent variable based on lender specializations in borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry, respectively. Control variables include an indicator variable for whether the potential lender has previous relationship with the lead arranger, an indicator variable for whether the potential lender has previous relationship with the borrower, and the market share of the potential lender as a lead arranger in the U.S. syndicated loan market during the previous twelve months. All regressions include loan facility fixed effects. Robust standard errors allowing for clustering by lead arranger 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.

Syndicate Member Indicator	(I) SIC Division	(II) 2-digit SIC	(III) 3-digit SIC	(IV) 4-digit SIC
Distance from Lead Arranger	-0.036***	-0.042***	-0.040***	-0.040***
	(0.0037)	(0.0032)	(0.0030)	(0.0030)
Previous Relationship with Lead	0.022***	0.020***	0.020***	0.020***
	(0.0022)	(0.0020)	(0.0020)	(0.0020)
Previous Relationship with Borrower	0.534***	0.533***	0.533***	0.533***
	(0.0104)	(0.0105)	(0.0104)	(0.0104)
Market Share as a Lead	0.004***	0.004***	0.004***	0.004***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Loan Facility Fixed Effects	Yes	Yes	Yes	Yes
N =	10,916,818	10,916,818	10,916,818	10,916,818
Adjusted R^2	0.3226	0.3229	0.3228	0.3228

Table 4. Determinants of Interconnectedness

This table examines a number of bank characteristics as potential determinants of interconnectedness. Interconnectedness of a lead arranger can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Bank characteristics include total assets (in billions of U.S. dollars), diversification, and the number of specializations the bank is engaged in. Panel A shows Pearson correlation coefficients between interconnectedness and bank characteristics, and Panel B reports results from multivariate regressions with and without lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger 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. Pearson Correlation

		Equal-weighted				Relationship-weighted			
Pearson Correlation	*N* =	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Total Assets	20,045	0.3068***	0.3325***	0.3377***	0.3358***	0.3004***	0.3247***	0.3307***	0.3294***
Diversification	36,090	0.8307***	0.9739***	0.9796***	0.9804***	0.7032***	0.7828***	0.8046***	0.8058***
# of Specializations	36,090	0.7699***	0.7398***	0.6042***	0.5485***	0.6651***	0.6087***	0.5074***	0.4611***

B. Multivariate Regressions

	Equal-weighted				Relationship-weighted			
Bank-level Interconnectedness	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Regression (I):								
Total Assets	0.001***	0.001***	0.001***	0.002***	0.001	0.001*	0.001**	0.001**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Diversification	0.266***	0.332***	0.352***	0.358***	0.441***	0.504***	0.537***	0.544***
	(0.0104)	(0.0040)	(0.0037)	(0.0036)	(0.0247)	(0.0153)	(0.0128)	(0.0123)
# of Specializations	0.751***	0.111***	0.039***	0.026***	1.957***	0.228***	0.076***	0.050***
	(0.0984)	(0.0127)	(0.0084)	(0.0067)	(0.2479)	(0.0389)	(0.0203)	(0.0157)
Bank Indicator	-1.080*	-0.957***	-0.916***	-0.830***	0.445	0.343	0.365	0.517
	(0.6146)	(0.2808)	(0.2610)	(0.2666)	(1.8161)	(1.4929)	(1.4909)	(1.5071)
Europe Indicator	0.082	0.863***	0.629**	0.582**	4.906***	5.687***	4.706***	4.552***
	(0.5901)	(0.2649)	(0.2495)	(0.2613)	(1.1415)	(0.9654)	(0.8976)	(0.9091)
Outside U.S. & Europe Indicator	0.203	1.114***	0.986***	0.957***	3.623**	4.975***	4.403***	4.276***
	(0.6175)	(0.2737)	(0.2731)	(0.2828)	(1.5182)	(1.3438)	(1.3393)	(1.3484)
N =	19,569	19,569	19,569	19,569	19,569	19,569	19,569	19,569
R^2	0.7519	0.9585	0.9657	0.9660	0.6075	0.7440	0.7759	0.7763
Regression (II):								
Total Assets	0.001***	0.002***	0.002***	0.002***	0.001**	0.001*	0.001***	0.002***
	(0.0006)	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0005)	(0.0004)	(0.0004)
Diversification	0.273***	0.347***	0.366***	0.370***	0.361***	0.442***	0.475***	0.482***
	(0.0130)	(0.0041)	(0.0044)	(0.0047)	(0.0268)	(0.0199)	(0.0198)	(0.0202)
# of Specializations	0.622***	0.164***	0.063***	0.043***	2.039***	0.387***	0.138***	0.092***
	(0.1388)	(0.0126)	(0.0104)	(0.0098)	(0.2543)	(0.0343)	(0.0235)	(0.0210)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	19,569	19,569	19,569	19,569	19,569	19,569	19,569	19,569
Adjusted R^2	0.8268	0.9726	0.9771	0.9773	0.7370	0.8299	0.8515	0.8520

Table 5. Correlation between Systemic Risk and Interconnectedness

This table reports Pearson correlation coefficient estimates between a financial institution's systemic risk and its interconnectedness in the U.S. syndicated loan market. Systemic risk is measured by systemic capital shortfall (SRISK) in billions of U.S. dollars, the opposite of 1% and 5% CoVaR in billions of U.S. dollars, and the monthly distress insurance premium (DIP) in billions of euros. Interconnectedness of a lead arranger can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. * indicates that the estimated coefficient is significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

		Equal-weighted				Relationship-weighted			
Pearson Correlation	N =	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
SRISK	5,939	0.2103***	0.2037***	0.2067***	0.2037***	0.1696***	0.1650***	0.1657***	0.1621***
-1% CoVaR	1,844	0.3781***	0.4081***	0.4067***	0.4053***	0.3250***	0.3616***	0.3701***	0.3705***
-5% CoVaR	1,844	0.4183***	0.4546***	0.4543***	0.4522***	0.3643***	0.4084***	0.4187***	0.4187***
DIP	1,414	0.2781***	0.3208***	0.3403***	0.3408***	0.1623***	0.2296***	0.2536***	0.2562***

Table 6. Interconnectedness and SRISK

This table reports coefficient estimates from regressions relating a financial institution's SRISK to its interconnectedness in the U.S. syndicated loan market. The dependent variable is systemic capital shortfall (SRISK) in billions of U.S. dollars. The independent variable of interest is the interconnectedness of a lead arranger, which can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Interconnectedness × Recession is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, and one-month lagged SRISK. Panel A reports result of the full sample whereas Panel B reports results of the subsample where SRISK shows positive, that is, the financial institution does have a capital shortfall systemically. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger 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. Full Sample

	Equal-weighted				Relationship-weighted			
SRISK	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness	0.014	0.012	0.016	0.018	-0.001	0.002	0.004	0.005
	(0.0151)	(0.0146)	(0.0157)	(0.0158)	(0.0059)	(0.0066)	(0.0070)	(0.0072)
Recession	-1.919*	-1.453	-1.581	-1.534	-1.382	-1.023	-1.165	-1.148
	(1.1370)	(0.9574)	(0.9864)	(0.9681)	(0.9466)	(0.8607)	(0.8935)	(0.8843)
Interconnectedness × Recession	0.085***	0.082***	0.085***	0.084***	0.052***	0.048***	0.050***	0.050***
	(0.0295)	(0.0266)	(0.0272)	(0.0267)	(0.0168)	(0.0158)	(0.0163)	(0.0161)
Total Assets	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Market Share	0.014	0.017	0.015	0.014	0.014	0.015	0.015	0.014
	(0.1482)	(0.1490)	(0.1491)	(0.1491)	(0.1447)	(0.1464)	(0.1465)	(0.1464)
Lagged SRISK	0.888***	0.887***	0.887***	0.887***	0.888***	0.888***	0.887***	0.887***
	(0.0133)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0134)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	5,674	5,674	5,674	5,674	5,674	5,674	5,674	5,674
Adjusted R^2	0.9790	0.9790	0.9790	0.9790	0.9790	0.9790	0.9790	0.9790

B. Subsample: SRISK > 0

	Equal-weighted				Relationship-weighted			
SRISK	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness	0.026	0.028	0.036	0.037	0.002	0.008	0.015	0.016
	(0.0257)	(0.0233)	(0.0237)	(0.0238)	(0.0120)	(0.0130)	(0.0134)	(0.0138)
Recession	-1.442	-0.598	-0.751	-0.684	-0.459	-0.141	-0.352	-0.334
	(1.5006)	(1.0926)	(1.1553)	(1.1301)	(1.0778)	(0.9707)	(1.0515)	(1.0394)
Interconnectedness × Recession	0.083**	0.071**	0.074**	0.072**	0.042**	0.039**	0.043**	0.042**
	(0.0391)	(0.0322)	(0.0337)	(0.0330)	(0.0207)	(0.0195)	(0.0209)	(0.0207)
Total Assets	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Market Share	0.228*	0.229*	0.224*	0.222	0.219	0.223	0.223	0.221
	(0.1335)	(0.1336)	(0.1337)	(0.1339)	(0.1367)	(0.1362)	(0.1351)	(0.1350)
Lagged SRISK	0.846***	0.846***	0.845***	0.846***	0.847***	0.847***	0.847***	0.847***
	(0.0138)	(0.0137)	(0.0138)	(0.0138)	(0.0137)	(0.0136)	(0.0137)	(0.0137)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	3,829	3,829	3,829	3,829	3,829	3,829	3,829	3,829
Adjusted R^2	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785	0.9785

Table 7: Interconnectedness and CoVaR

This table reports coefficient estimates from regressions relating a U.S. financial institution's CoVaR to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the opposite of 1% CoVaR in billions of U.S. dollars in Panel A and the opposite of 5% CoVaR in billions of U.S. dollars in Panel B. The independent variable of interest is the interconnectedness of a lead arranger, which can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Interconnectedness × Recession is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, and one-quarter lagged CoVaR. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger 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. 1% CoVaR

	Equal-weighted				Relationship-weighted			
– 1% CoVaR	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness	0.067**	0.087**	0.086**	0.085**	0.027**	0.040**	0.045**	0.045**
	(0.0278)	(0.0371)	(0.0371)	(0.0372)	(0.0131)	(0.0196)	(0.0218)	(0.0217)
Recession	0.272	0.607	0.519	0.584	0.289	0.435	0.435	0.426
	(1.3089)	(0.9511)	(0.9379)	(0.9222)	(0.5054)	(0.4922)	(0.5073)	(0.5030)
Interconnectedness × Recession	-0.017	-0.029	-0.026	-0.028	-0.014	-0.017	-0.017	-0.016
	(0.0420)	(0.0369)	(0.0366)	(0.0362)	(0.0164)	(0.0166)	(0.0171)	(0.0170)
Total Assets	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Market Share	0.343	0.336	0.335	0.335	0.346	0.344	0.343	0.343
	(0.3513)	(0.3498)	(0.3497)	(0.3492)	(0.3474)	(0.3481)	(0.3483)	(0.3480)
Lagged CoVaR	0.796***	0.794***	0.794***	0.794***	0.796***	0.794***	0.794***	0.794***
	(0.0331)	(0.0329)	(0.0330)	(0.0331)	(0.0329)	(0.0328)	(0.0329)	(0.0330)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,727	1,727	1,727	1,727	1,727	1,727	1,727	1,727
Adjusted R^2	0.8770	0.8772	0.8772	0.8772	0.8769	0.8770	0.8771	0.8771

B. 5% CoVaR

	Equal-weighted				Relationship-weighted			
– 5% CoVaR	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness	0.052**	0.067**	0.065**	0.064**	0.019**	0.029**	0.033**	0.032**
	(0.0206)	(0.0265)	(0.0262)	(0.0260)	(0.0088)	(0.0135)	(0.0149)	(0.0148)
Recession	0.436	0.660	0.612	0.667	0.373	0.483	0.497	0.493
	(1.4035)	(0.9818)	(0.9516)	(0.9434)	(0.4820)	(0.4688)	(0.4836)	(0.4791)
Interconnectedness × Recession	-0.017	-0.026	-0.024	-0.025	-0.012	-0.015	-0.015	-0.014
	(0.0472)	(0.0409)	(0.0403)	(0.0398)	(0.0181)	(0.0183)	(0.0189)	(0.0188)
Total Assets	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Market Share	0.061	0.055	0.054	0.054	0.064	0.062	0.061	0.061
	(0.1919)	(0.1901)	(0.1900)	(0.1896)	(0.1890)	(0.1888)	(0.1889)	(0.1887)
Lagged CoVaR	0.825***	0.823***	0.823***	0.823***	0.824***	0.823***	0.822***	0.822***
	(0.0399)	(0.0399)	(0.0401)	(0.0400)	(0.0394)	(0.0396)	(0.0398)	(0.0398)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,727	1,727	1,727	1,727	1,727	1,727	1,727	1,727
Adjusted R^2	0.8856	0.8858	0.8858	0.8858	0.8855	0.8856	0.8857	0.8857

Table 8: Interconnectedness and DIP

This table reports coefficient estimates from regressions relating a European financial institution's DIP to its interconnectedness in the U.S. syndicated loan market. The dependent variable is the monthly distress insurance premium (DIP) in billions of euros. The independent variable of interest is the interconnectedness of a lead arranger, which can be equal- or relationship-weighted and is computed based on its distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Interconnectedness × Recession is the interaction term of Interconnectedness and Recession. Control variables include the financial institution's total assets, market share as a lead arranger in the U.S. syndicated loan market during the previous twelve months, and one-month lagged DIP. All regressions include lead arranger fixed effects. Robust standard errors allowing for clustering by lead arranger 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.

	Equal-weighted				Relationship-weighted			
DIP	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness	0.007 (0.0131)	0.019 (0.0138)	0.020 (0.0153)	0.020 (0.0165)	-0.001 (0.0093)	0.010 (0.0108)	0.011 (0.0117)	0.012 (0.0128)
Recession	-3.341* (1.7060)	-1.814* (0.9407)	-1.842* (0.8954)	-1.699* (0.8708)	-1.916 (1.3573)	-1.691 (1.1033)	-1.953* (1.1157)	-1.867 (1.0994)
Interconnectedness × Recession	0.115** (0.0500)	0.091** (0.0353)	0.089** (0.0335)	0.085** (0.0329)	0.059* (0.0288)	0.059** (0.0254)	0.064** (0.0259)	0.062** (0.0256)
Total Assets	0.004*** (0.0006)	0.004*** (0.0006)	0.004*** (0.0006)	0.004*** (0.0005)	0.004*** (0.0006)	0.004*** (0.0006)	0.004*** (0.0006)	0.004*** (0.0006)
Market Share	1.387* (0.7944)	1.441* (0.7877)	1.395* (0.7870)	1.387* (0.7836)	1.346* (0.7761)	1.441* (0.7767)	1.409* (0.7924)	1.405* (0.7898)
Lagged DIP	0.781*** (0.0307)	0.779*** (0.0304)	0.779*** (0.0304)	0.779*** (0.0303)	0.781*** (0.0300)	0.780*** (0.0299)	0.779*** (0.0303)	0.779*** (0.0303)
Lead Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N =	1,392	1,392	1,392	1,392	1,392	1,392	1,392	1,392
Adjusted R^2	0.8638	0.8639	0.8639	0.8638	0.8637	0.8639	0.8639	0.8639

Table 9: Interconnectedness and CATFIN

This table reports coefficient estimates from regressions relating the aggregate systemic risk, CATFIN, to the aggregate interconnectedness in the U.S. syndicated loan market. The dependent variable is the monthly CATFIN in percentage. The independent variable of interest is the market-aggregate Interconnectedness Index, an equal-weighted average of interconnectedness of all the lead arrangers. Interconnectedness of a lead arranger can be equal- or relationship-weighted and is computed based on distance from all the other lead arrangers in specializations with regard to borrower SIC industry division, 2-digit, 3-digit, and 4-digit borrower SIC industry. Recession is an indicator variable equal to 1 if a month falls into the recession periods identified by NBER. Interconnectedness Index × Recession is the interaction term of Interconnectedness Index and Recession. Control variables include the size (measured by the total amount of newly originated loans in billions of U.S. dollars) and the Herfindahl index of the U.S. syndicated loan market and one-month lagged CATFIN. 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.

	Equal-weighted				Relationship-weighted			
CATFIN	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC	SIC Division	2-digit SIC	3-digit SIC	4-digit SIC
Interconnectedness Index	-0.419** (0.1897)	-0.328* (0.1796)	-0.278 (0.1744)	-0.284 (0.1757)	-0.065 (0.1591)	-0.140 (0.1778)	-0.140 (0.1812)	-0.132 (0.1818)
Recession	-23.132 (19.9899)	-11.274 (10.2329)	-11.143 (9.4148)	-10.735 (9.2833)	-15.213* (9.0832)	-16.426* (9.2893)	-15.587* (9.2279)	-15.460* (9.2708)
Interconnectedness Index × Recession	0.776 (0.5778)	0.551 (0.3611)	0.554* (0.3334)	0.539 (0.3284)	0.488** (0.2276)	0.560** (0.2479)	0.539** (0.2444)	0.536** (0.2445)
Market Size	-0.001 (0.0016)	-0.001 (0.0018)	-0.001 (0.0019)	-0.001 (0.0019)	-0.003 (0.0017)	-0.002 (0.0020)	-0.002 (0.0021)	-0.002 (0.0021)
Herfindahl Index	-0.299 (0.2514)	-0.253 (0.2440)	-0.236 (0.2442)	-0.238 (0.2441)	-0.129 (0.3087)	-0.213 (0.2962)	-0.222 (0.3031)	-0.208 (0.3006)
Lagged CATFIN	0.677*** (0.0693)	0.677*** (0.0683)	0.674*** (0.0686)	0.676*** (0.0686)	0.654*** (0.0707)	0.653*** (0.0702)	0.654*** (0.0702)	0.654*** (0.0701)
N =	251	251	251	251	251	251	251	251
R^2	0.6426	0.6428	0.6433	0.6431	0.6445	0.6457	0.6456	0.6456