Shared Borrowers, Shared Stress: The Credit-Line Channel of Contagion*

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We propose a novel channel of shock propagation in the banking system: when a distressed bank curtails credit, firms substitute by drawing more heavily on alternative credit lines, triggering liquidity outflows at other banks. Using detailed US supervisory data, we show that this channel is quantitatively significant and provides a more granular system-wide view of liquidity risk among banks. *(JEL D85, E44, G21, G28, L14)*

The financial crisis of 2007–09 prompted new approaches for diagnosing and monitoring systemic risk. Market-based measures such as CoVaR (Adrian and Brunnermeier, 2016), MES and SRISK (Acharya, Pedersen, Philippon, and Richardson, 2017; Brownlees and Engle, 2017), as well as statistical connectedness measures (Diebold and Yılmaz, 2014), have since become standard tools. Yet these approaches remain largely *diagnostic*: they become informative only once stress has already materialised, rely on market prices that may be unreliable during periods of stress, and offer limited insight into the structural channels through which distress propagates. Direct interbank exposures, in turn, are too small relative to bank balance sheets to generate meaningful spillovers in modern systems. These shortcomings motivate the search for measures that are structural, observable to supervisors at high frequency, and capable of delivering real-time guidance during institutional failure.

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This paper proposes a new approach to measuring the systemic consequences of bank distress, based on the structure of banks' revolving credit-line commitments to the real economy. Our key insight is that these commitments generate *structural indirect linkages* across banks: two banks are connected whenever they provide credit lines to (firms in) the same industry. If a bank cuts credit availability during stress or defaults outright, firms shift their drawdowns to their alternative credit lines, mechanically generating liquidity outflows from those banks.[1] This mechanism delivers a bank-by-bank *spillover matrix*, pinned down by the distribution of utilised and undrawn credit-lines across industries. We use it to derive a measure of *systemicness*, the stress a bank transmits to the system.[2] Using supervisory data rather than market prices, these measures give regulators real-time guidance at the critical margin: whether to bail out a troubled bank or bear the systemic consequences of its failure.

We find that the credit-line channel generates large, time-varying, and heterogeneous systemic spillovers across banks. While larger banks tend to be more *systemic* we show that most of the variation in systemicness cannot be attributed balance sheets aggregates. In baseline calculations, the additional drawdowns triggered by distress at a single large bank are sizable relative to other institutions' *Cash and Reserves*, pushing a non-trivial number of banks close to regulatory liquidity constraints. We validate the mechanism externally: exposure to negative shocks transmitted through the credit-line network predicts a decline in stock returns.

Beyond measuring systemic risk, our framework provides a structural bridge between the real economy and the banking system. Because the credit-line network is generated by sectoral borrowing patterns, it naturally captures how real-economy shocks propagate to banks and how bank distress feeds back into firms' access to liquidity.

Related Literature A useful way to organize the literature on systemic risk is through the concepts of *systemicness* and *vulnerability*, terms introduced by Greenwood et al. (2015). Many empirical and theoretical approaches can be interpreted as constructing—explicitly or implicitly—a spillover matrix S, whose rows capture how stress at one institution affects

[1]Evidence from the global financial crisis shows that firms drew heavily on pre-committed revolving credit lines following the failure of Lehman Brothers, generating substantial liquidity outflows for banks (Ivashina and Scharfstein, 2010). Our contribution is to measure the resulting bank-to-bank spillover structure systematically and in real time using supervisory data.

[2]Our use of the term *systemicness* follows Greenwood, Landier, and Thesmar (2015), who introduced this terminology.

others (systemicness) and whose columns capture how stress originating elsewhere affects a given institution (vulnerability). Figure 3 provides a schematic illustration of this matrix representation and the associated notions of systemicness and vulnerability.

Theoretical work in this literature varies primarily in the way network links are defined. One strand models *direct linkages* such as interbank lending or cross-holdings (Allen and Gale, 2000; Gai, Haldane, and Kapadia, 2011; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015; Elliott, Golub, and Jackson, 2014). A second strand emphasizes *indirect exposures* through overlapping portfolios or common external assets (Cabrales, Gottardi, and Vega-Redondo, 2017; Greenwood et al., 2015; Wagner, 2011; Duarte and Eisenbach, 2021). In both settings, the resulting spillover matrix captures how shocks propagate—through contractual links, risk-sharing arrangements, or fire-sale externalities.

Empirical approaches map naturally into the framework described above. Some papers measure systemicness and vulnerability (summaries of S) without recovering the full matrix S. For example, Acharya et al. (2017) and Brownlees and Engle (2017) propose measures of vulnerability based on capital shortfall under market stress, while Adrian and Brunnermeier (2016) develops a measure of systemicness based on conditional risk contributions. Greenwood et al. (2015) derive both concepts within a structural fire-sale framework, but focus on aggregate exposures rather than estimating a full matrix of pairwise spillovers.

In contrast, a smaller literature seeks to recover bilateral spillovers directly, i.e., to estimate the full matrix S. The "connectedness" framework of Diebold and Yılmaz (2014) provides statistical estimates of pairwise spillovers based on vector autoregressions. Using granular exposure data, Denbee, Julliard, Li, and Yuan (2021) assess the role of interbank network structure during the Global Financial Crisis, while Elsinger, Lehar, and Summer (2006) compare the quantitative importance of direct interbank exposures and overlapping portfolios for financial stability.

Table 1 summarizes the classification: aggregate-only versus full-network methods, and structural versus reduced-form approaches. Our paper fits into the "structural–full-network" category, but differs by introducing an indirect, non-price-based contagion mechanism arising from banks' overlapping credit line exposures.

Evidence for credit-line channel of contagion was provided by Ivashina and Scharfstein (2010) who document large drawdowns of pre-committed corporate credit lines following the collapse of Lehman Brothers and show that banks more exposed to Lehman through shared corporate borrowers experienced particularly strong liquidity outflows.

Table 1: Systemic risk measures: scope and approach

Paper	Scope	Method
Greenwood et al. (2015, JFE)	aggregates only	structural
Duarte and Eisenbach (2021, JF)	aggregates only	structural
Acharya et al. (2017, RFS)	aggregates only	structural
Brownlees and Engle (2017, RFS)	aggregates only	reduced-form
Adrian and Brunnermeier (2016, AER)	aggregates only	reduced-form
Diebold and Yılmaz (2014, JE)	full matrix	reduced-form
Elsinger et al. (2006, MS)	full matrix	structural
Denbee et al. (2021, JFE)	full matrix	structural
This paper	full matrix	structural

Notes: "Aggregates only" summarizes methods focusing on row or column aggregates of the spillover matrix S (systemicness or vulnerability). "Full matrix" refers to approaches that estimate bilateral coefficients s_{ij}. "Structural" methods derive S from explicit economic models; "reduced-form" methods rely on statistical or market-based dependence. The table highlights that relatively few approaches deliver a structural, bilateral spillover matrix that can be constructed without relying on market prices.

Our mechanism is related to a literature on asset-side bank runs, in which funding stress occurs through the higher-than-usual drawdown of committed credit lines rather than through depositor withdrawals. Bräuning and Ivashina (2024) and Huang (2025) develop dynamic models in which revolving credit lines and liquidity management interact to generate self-reinforcing funding stress at individual banks.

Finally, we provide an argument why *similar real exposure*—connected banks tend to have correlated portfolios of loans to firms—can in fact improve welfare because it prevents huge shocks from traveling across otherwise unconnected components in the financial system. This complements Elliott, Georg, and Hazell (2021) who show that banks want (and empirically have) similar real exposure even though that is a source of systemic risk.

1 Institutional Background: Credit Lines

Revolving credit lines are a central component of corporate finance and an important source of liquidity insurance for firms. Unlike term loans, credit lines allow firms to flexibly adjust borrowing by drawing down or repaying funds in response to short-term liquidity needs. As documented by Sufi (2009), credit lines account for a substantial share of firms' bank financing, while utilisation rates are typically well below one, leaving significant unused capacity during normal times.

This unused capacity plays a key role during periods of financial stress. When uncertainty rises or access to market-based finance deteriorates, firms tend to draw more heavily on their existing credit lines to secure precautionary liquidity. Empirically, utilisation rates increase sharply during stress episodes, reflecting firms' reliance on pre-committed bank credit as a buffer against funding shocks (Sufi, 2009; Kiernan, Yankov, and Zikes, 2022).

From the perspective of banks, these drawdowns represent liquidity outflows that are largely outside their immediate control. Importantly, many firms maintain credit lines with multiple banks. As a result, when one bank reduces lending or fails to honour its commitments, firms can reallocate their drawdowns toward remaining lenders with available headroom. This institutional feature implies that liquidity stress at one bank can generate additional, unexpected outflows at other banks through shared borrowers.

These contractual features of revolving credit lines—high flexibility, partial utilisation, and multi-bank relationships—provide the institutional foundation for the credit-line spillover mechanism formalised in the next section.

2 The Credit-Line Channel of Contagion

To fix ideas, consider a single sector s that maintains credit lines with several banks a, b, and c (this is illustrated in the left panel of Figure 1). Let ℓ_{is} denote the *utilized* (i.e. drawn) amount of sector s's credit line with bank $i \in \{a, b, c\}$. Suppose that bank a defaults or otherwise refuses to honour its commitment to sector s. The sector suddenly loses access to liquidity equal to the outstanding amount ℓ_{as}.[3]

Luckily, sector s typically has unused capacity on the credit lines it maintains with the surviving banks b and c; empirically, utilisation rates are well below one (see Figure 5). As a result, the sector can attempt to compensate the shortfall ℓ_{as} by drawing more heavily on these remaining credit lines. From the perspective of banks b and c, this shows up as an *unexpected liquidity outflow*—a drawdown that is not driven by their own fundamentals but by the failure of their competitor. This is the essence of the credit-line channel of contagion: *shared borrowers imply shared stress.*

[3] In the empirical implementation, ℓ_{is} is measured as sector-level utilized credit lines for bank i using the FRY–14Q data described in Section 3.

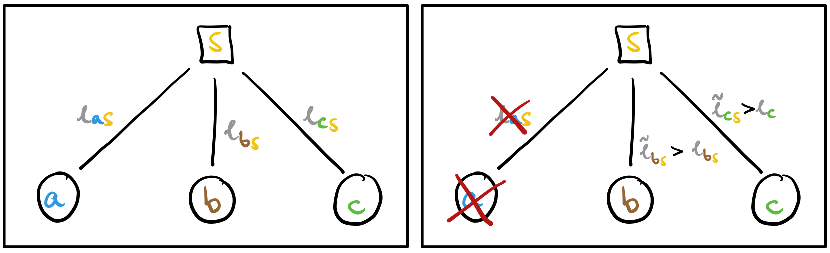

Figure 1: Sector s has credit lines at multiple banks. After bank a defaults Sector s compensates using the other credit lines.

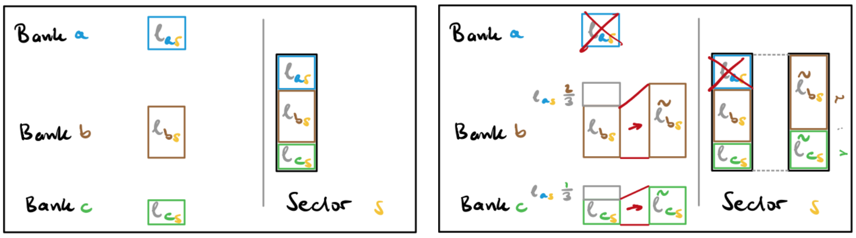

Figure 2: Illustration of the simple credit-line re-allocation rule

2.1 Allocation of the liquidity shortfall

We now formalise how the lost funding from bank a is reallocated across the remaining lenders to the sector. Let ℓ_{as} denote the outstanding (utilized) amount of sector s's credit line with bank a. When bank a is in trouble, we assume that it reduces its lending to sector s by an amount $\Delta\ell_{as} \geq 0$.[4] Sector s then turns to its surviving lenders to fill this gap.

In the baseline specification, the shortfall $\Delta\ell_{as}$ is split among the remaining (non-a) lenders of sector s in proportion to their baseline outstanding lending.[5] That is, the additional drawdown from bank b is given by

$$\tilde{\ell}_{bs} - \ell_{bs} = \frac{\ell_{bs}}{\sum_{d\neq a} \ell_{ds}} \Delta\ell_{as} = \frac{\Delta\ell_{as}}{\sum_{d\neq a} \ell_{ds}} \ell_{bs},$$

where ℓ_{bs} denotes the original outstanding amount and $\tilde{\ell}_{bs}$ the post-shock outstanding amount. This rule has the advantage of being simple, transparent, and directly implementable using sector-level utilized credit lines from the Y–14Q data.

[4]In the baseline application, we consider the extreme case of a full default, $\Delta\ell_{as} = \ell_{as}$, but smaller shocks can be analysed in exactly the same way.

[5]In Section 4 we compare two different allocation rules: (1) proportional to utilized credit (but no more than unutilized), and (2) proportional to unutilized credit.

2.2 From sector-level shocks to bank-to-bank spillovers

The additional drawdowns induced by a default at bank a accumulate across all sectors to create a system-wide pattern of liquidity outflows. For a given surviving bank b, the total additional outflow (across all sectors) is

$$\text{total outflow}_{a\to b} := \sum_{s'} \tilde{\ell}_{bs'} - \ell_{bs'},$$

where the sum runs over all sectors s' to which bank b is exposed. To obtain scale-free spillover measures, we normalise this total outflow. We define

$$\tilde{s}_{ab} = \frac{\text{total outflow}_{a\to b}}{\text{total utilized}_b} = \frac{\sum_{s'} \tilde{\ell}_{bs'} - \ell_{bs'}}{\sum_{s'} \ell_{bs'}}$$

where we normalize by the total utilized credit lines of bank b, and

$$s_{ab} = \frac{\text{total outflow}_{a\to b}}{\text{liquidity buffer}_b},$$

where we normalize by a measure of bank b's liquidity buffer. In the United States, the relevant measure is high quality liquid assets (HQLA). Banks are required to hold sufficient HQLA to buffer liquidity needs in a 30-day-period of stress. A useful proxy for HQLA are cash & reserves, which is easily accessible for big banks. Both spillover measures $\tilde{s}_{a,b}$ and $s_{a,b}$ can be computed from regulatory FR Y-14 and FR Y9C data described in Section 3.

While $\tilde{s}_{ab}$ measures the percentage increase in credit line lending by bank b (in response to sector drawdowns) that would be induced by a given reduction in credit line lending by bank a, $s_{a,b}$ measures the fraction of its liquidity buffer bank b needs to use to cover that additional lending. If $s_{a,b}$ is close to one, the default of bank a would eat up almost all of b's liquidity buffer through the credit line channel. This means there is no buffer left for other transmission mechanisms or shocks.

The credit-line spillover matrix Collecting these spillovers yields the *credit-line spillover matrix*

$$S = \big(s_{ab}\big)_{a,b}.$$

This matrix is the key object we use in the empirical analysis to quantify the systemic risk involved with individual banks: In particular, the rows of S capture how much stress a given bank can transmit to the rest of the system (*systemicness*), while the columns capture how much stress a bank would have to bear as a result of other banks facing distress (*vulnerability*); see Figure 3.

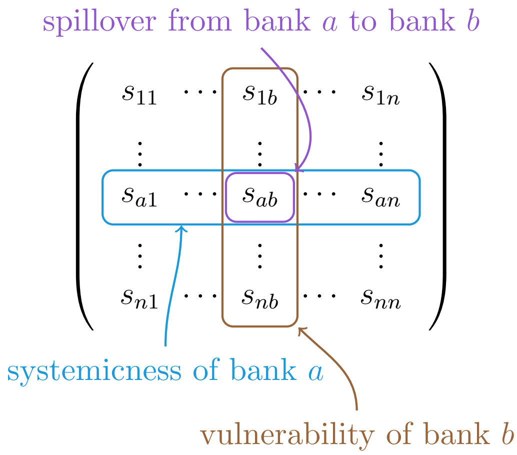

Figure 3: Structure of the credit-line spillover matrix. Each entry s_{ij} measures the liquidity spillover from bank i to bank j. Row summaries capture systemicness, while column summaries capture vulnerability.

2.3 Systemicness

The spillover matrix S summarises how credit-line shocks propagate through the banking system. We use it to measure how much liquidity stress a distressed institution can transmit to other banks.[6]

The *systemicness* of bank a depends on the row $(s_{ab})_b$: each entry s_{ab} is the spillover to another bank b. We define *systemicness* as the average spillover to other banks

$$\text{systemicness}_a := \frac{1}{N-1} \sum_{b \neq a} s_{ab},$$

where N is the number of banks.

Put differently, it measures how much of other banks' liquidity buffers would be depleted if bank a failed.

3 Data

This study uses confidential supervisory data from the Federal Reserve to construct a detailed, institution-level view of U.S. bank credit-line exposures and liquidity buffers. The FR Y–14 regulatory reports are submitted

[6]In the current iteration of the paper we do not report empirical results on banks' *vulnerability* (i.e. exposure to shocks originating elsewhere). Accordingly, we also omit a dedicated theoretical discussion of vulnerability and focus on systemicness.

Table 2: Summary statistics of the main variables from FR Y–14 and FR Y–9C.

Variable	Median	Q25	Q75
FR Y14 (loan-level data)			
committed credit lines	53.4	28.1	106.3
unutilized credit lines	29.6	14.4	72.6
utilized credit lines	24.3	12.1	36.9
FR Y9C (balance sheet data)			
cash and reserves	28.8	10.4	98.4
total assets	272.2	157.1	838.3

Notes: This table reports descriptive statistics for the FR Y–14 Corporate Loan Schedule and FR Y–9C Bank Balance Sheets. All quantities are expressed in billions of U.S. dollars. The unit of observation is bank-quarter. The sample period is 2015Q1–2024Q4. The sample is restricted to bank holding companies that are observed in at least 30 quarters (resulting in 23 BHCs)

by large U.S. bank holding companies stress-tested under CCAR/DFAST and provide loan-level data on corporate credit-line exposures. We combine these with the FR Y–9C Consolidated Financial Statements, which we use solely to measure liquidity buffers, specifically cash and reserves.

Credit-Lines from FR Y–14. The FR Y–14 *Corporate Loan Schedule* provides quarterly, loan-level data on commercial and industrial (C&I) credit exposures for large U.S. BHCs stress-tested under CCAR/DFAST. The Corporate Loan Schedule covers C&I facilities reported by these stress-test banks, including revolving credit lines, at the facility level. Each record includes committed amounts, outstanding balances, facility type (revolving credit line or term loan), and borrower NAICS industry codes. For data quality concerns we restrict the sample period to 2015–2024.

For each bank, sector, and quarter, we aggregate these data to construct matrices of drawn and undrawn revolving credit-line exposures. These credit-line exposures by sector form the key objects of interest.

Liquidity buffers from FR Y–9C. The FR Y–9C provides quarterly consolidated balance sheets and income statements for all U.S. BHCs. We use this dataset to measure liquidity buffers, focusing on *Cash and Due*

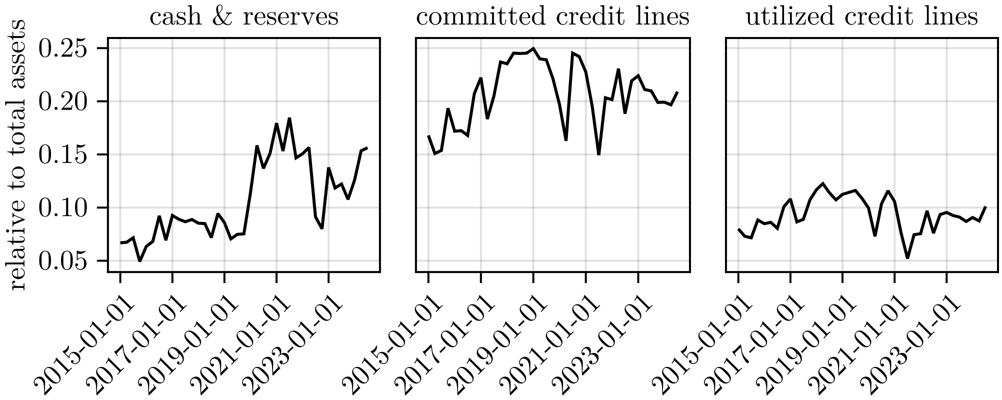

Figure 4: Aggregate balance-sheet and credit-line quantities relative to total assets.

Notes: Aggregate cash and reserves, committed credit lines, and utilized credit lines scaled by total bank assets, using FR Y–9C and FR Y–14 data.

from Depository Institutions (cash and reserves).

We merge FR Y–9C data with FR Y–14 using RSSD identifiers and restrict attention to bank holding companies that appear in both datasets. The resulting sample is a quarterly panel from 2015 to 2024, covering sectoral exposures across NAICS codes 11–92. Summary statistics on total assets, credit-line utilization, and liquidity buffers (cash and reserves) are reported in Table 2.

Figure 4 shows that credit-line commitments account for roughly 15–25% of total bank assets over the sample period, while utilized credit lines amount to about 5–10%. The corresponding utilization rate—utilized relative to committed credit lines—ranges between 35–50%, as shown in Figure 5. Cash and reserves, our measure of liquidity buffers, fluctuate between 5–20% of total assets (Figure 4). Throughout most of the sample, aggregate undrawn credit-line commitments exceed cash-and-reserves (Figure 5), implying that a sudden drawdown of credit can potentially generate liquidity pressures.

4 Results

This section reports measurements of bank-by-bank credit-line spillovers and systemicness described in Section 2. These measures are computed from supervisory data at a quarterly frequency. The resulting spillovers are economically meaningful and frequently large relative to cash and reserves.

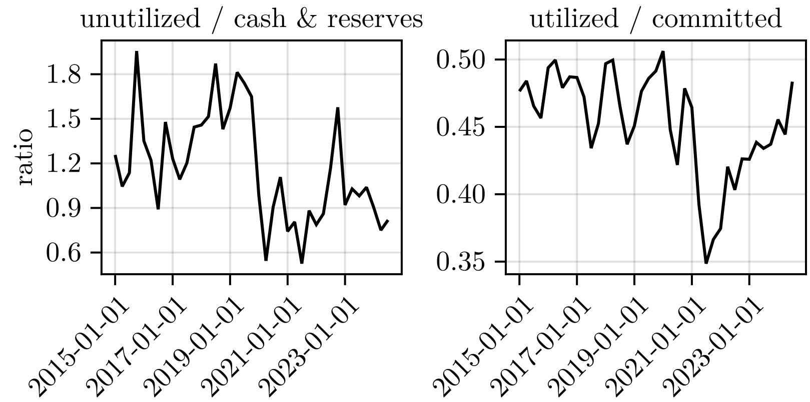

Figure 5: Aggregate credit-line ratios over time.

Notes: Aggregate utilization rate (utilized over committed credit lines) and aggregate undrawn credit lines relative to cash and reserves, computed quarterly from FR Y–14 and FR Y–9C data.

To illustrate how these objects vary over time, we present results for the same calendar quarter in three non-consecutive years.[7]

4.1 Credit-line spillovers

The credit-line spillover matrix $S = (s_{ab})$ represents, for each entry, the relative loss of bank b when bank a defaults on its commitments, and the resulting funding shortfall is reallocated according to the mechanism described in Section 2. Figure 6 presents the estimated spillover matrices for the same quarter in three illustrative, unspecified years. The figure illustrates variation in magnitude and concentration of spillovers across these years. Both normalizations—relative to utilized credit and relative to cash & reserves (C&R)—are shown to highlight different aspects of spillovers.

4.2 Systemicness across banks

We compare the cross-sectional distribution of systemicness for individual banks across the same three illustrative years shown in Figure 6. Systemicness quantifies the extent to which a bank's default causes losses at other banks, capturing both the breadth and intensity of spillovers.

Figure 7 displays systemicness across banks for the three years, under both normalizations. The figure highlights differences in dispersion, concentration, and ranking stability of systemicness across years.

[7]The specific calendar years are omitted for confidentiality reasons.

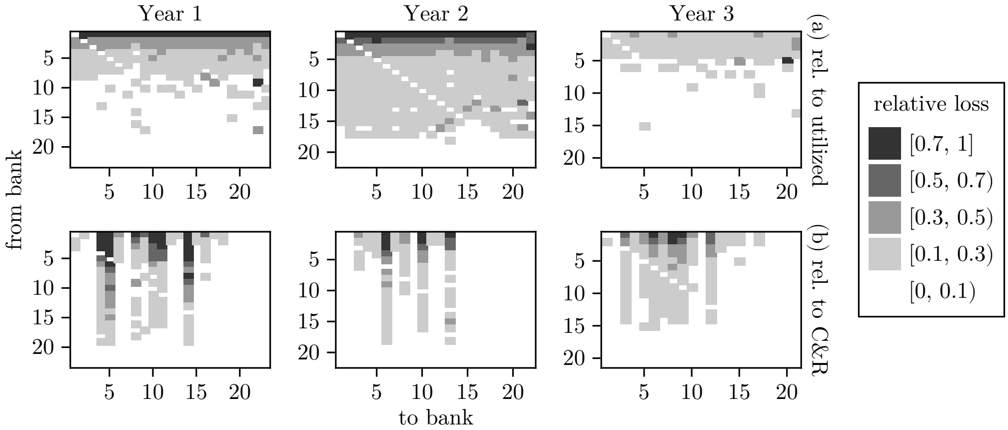

Figure 6: Credit-line spillover matrices for the same quarter in three illustrative years.

Notes: Banks are ordered by total utilized credit lines. Each cell reports the relative loss of receiving bank b (horizontal axis) when sending bank a (vertical axis) defaults and its funding shortfall is reallocated according to Section 2. Losses are binned and shown under two normalisations: relative to utilised credit lines (top row) and relative to cash & reserves (bottom row).

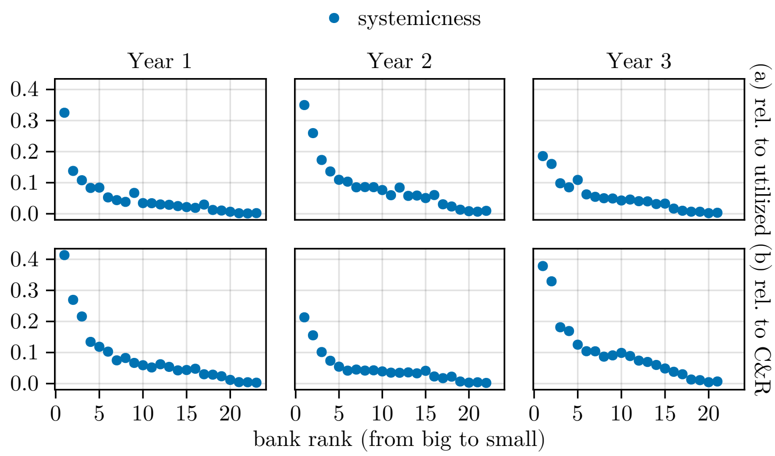

Figure 7: Systemicness across banks for the same calendar quarter in three illustrative years.

Notes: Banks on the horizontal axis are ordered by total utilized credit lines. The figure reports bank-level systemicness under two normalisations: relative to utilised credit lines and relative to cash & reserves.

Table 3: Balance-sheet aggregates explain less than half of the variation in systemicness

	Systemicness
Committed credit lines	-0.004^{**}
	(0.001)
Utilized credit lines	0.02741^{***}
	(0.00343)
Total assets	0.0895
	(0.0515)
N	883
R^2	0.467

Notes: The dependent variable is log(systemicness) at the bank–quarter level. Balance-sheet variables are measured in billions of U.S. dollars. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.

4.3 Systemicness is not explained by balance-sheet aggregates

Building on the cross-sectional and time-series evidence, we examine to what extent variation in systemicness can be accounted for by simple bank-level balance-sheet aggregates. As shown in Table 3, we regress log systemicness on committed credit lines, utilized credit lines, and total assets, all measured in billions of U.S. dollars. This specification asks whether banks that are larger or extend more credit are mechanically more systemic, abstracting from the detailed network structure embedded in the spillover matrix. Overall, the regression explains less than half of the variation in systemicness ($R^2 \approx 0.47$), indicating that a substantial share of both cross-sectional and time-series variation reflects effects that go beyond bank-level balance-sheet size.

4.4 Systemicness over time

To assess the time-series variation of systemic risk implied by the credit-line mechanism, we aggregate bank-level systemicness to the quarterly level. Figure 8 plots the cross-sectional mean of systemicness over time. Aggregate systemicness is relatively stable from 2015 to 2019 before it starts to spike in 2020Q1, coming down only in 2021Q3. This spike corresponds to

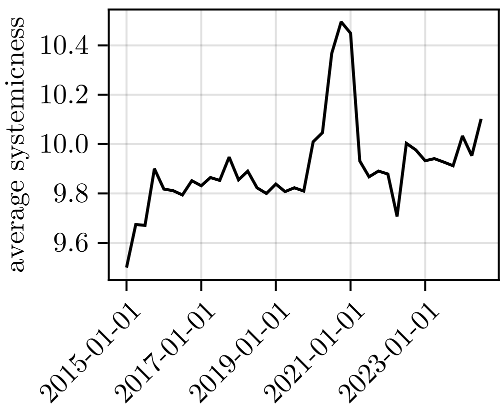

Figure 8: Evolution of aggregate systemicness over time.

an episode in which the (hypothetical) reallocation of credit-line funding losses would have more severe consequences for the banking system. Quantitatively, peak systemicness is 7% higher compared to the quiet period before.

5 Testing the mechanism: Spillovers and contemporaneous returns

This section tests the central prediction of the credit-line channel: banks that are more exposed to liquidity shocks experience larger *contemporaneous* declines in equity values. Because firms adjust their credit-line usage immediately following a contraction in lending by one bank, the mechanism implies that liquidity spillovers should be reflected in stock prices.

When a bank experiences a negative liquidity shock and restricts access to its credit lines, affected firms substitute toward their remaining lenders. Banks connected through common borrowers therefore face unexpected increases in drawdowns and liquidity outflows. The credit-line channel predicts that these spillovers generate immediate funding pressure, which should alter prices of exposed banks.

We summarize a bank's vulnerability to network spillovers using an exposure index that combines bank-level shocks with the directed spillover matrix. Specifically, exposure is defined as

$$\text{Exposure}_{i,t} = \frac{\sum_{j \neq i} S_{ji,t} \left[-\min(\varepsilon_{j,t}, 0) \right]}{\sum_{j \neq i} S_{ji,t}},$$

where $S_{ji,t}$ denotes the liquidity spillover coefficient from bank j to bank

Table 4: Exposure to Connected Banks and Contemporaneous Returns

	(1)	(2)	(3)	(4)
Exposure	-1.161^{***}	-1.536^{***}	-1.162^{***}	-1.537^{***}
	(0.093)	(0.096)	(0.092)	(0.096)
Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Observations	2,178	2,178	2,178	2,178
R^2	0.067	0.333	0.061	0.329

Notes: The dependent variable is the monthly bank equity return. Exposure is constructed as a weighted average of negative residualized shocks at other banks, using the spillover matrix as weights. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.

i, and $\varepsilon_{j,t}$ is the regression residual from a factor model described in Appendix A. Exposure aims to capture the intensity with which bank i is affected by adverse shocks originating at other banks through the credit-line network.

We let $r_{i,t}$ denote the return of bank i in quarter t. Our baseline regression focuses on the contemporaneous response,

$$r_{i,t} = \alpha_i + \tau_t + \beta_0 \, \text{Exposure}_{i,t} + u_{i,t},$$

where α_i and τ_t denote bank and quarter fixed effects. Identification comes from cross-sectional variation in exposures within a given quarter.

Table 4 reports estimates of β_0 under alternative fixed-effects specifications. Across all specifications, the coefficient on exposure is negative and statistically significant, highlighting that banks more exposed to negative liquidity shocks experience larger contemporaneous declines in their equity values. This finding provides direct empirical validation of the credit-line spillover mechanism.

Dynamic adjustment To further characterize how the initial valuation effect evolves over time, we estimate local projections of cumulative returns at longer horizons. Let $R_{i,t\to t+h}$ denote the cumulative return of bank i from quarter t to quarter $t+h$, with $R_{i,t\to t} = r_{i,t}$. We estimate

$$R_{i,t\to t+h} = \alpha_i + \tau_t + \beta_h \, \text{Exposure}_{i,t} + u_{i,t+h}, \qquad h \in \{0, 3, 6, 9\}.$$

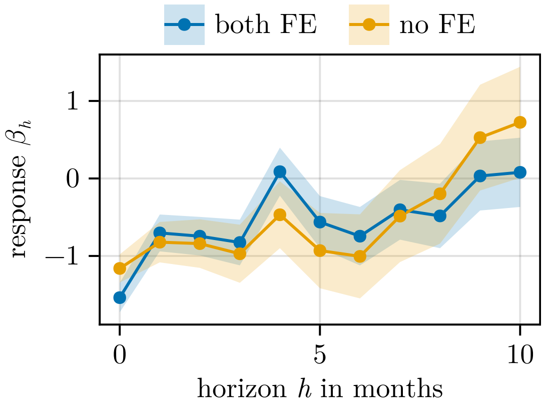

Figure 9: Dynamic response of bank stock returns to exposure to network spillovers

Notes: The figure plots local projection estimates of β_h from equation (5), where exposure is measured at time t and the dependent variable is the cumulative return $R_{i,t\to t+h}$. Shaded bands denote 95% confidence intervals.

Figure 9 plots the impulse response function implied by the sequence of coefficients $\{\beta_h\}$. While the impact response is strongly negative, the effect attenuates and eventually reverses at longer horizons, consistent with reallocation and business-stealing forces that operate beyond the immediate liquidity shock.

Taken together, these results show that the credit-line network generates economically meaningful liquidity spillovers that are priced in equity markets. The dynamic patterns provide additional evidence on how these initial shocks propagate and unwind over time, but the contemporaneous response constitutes the core empirical validation of the mechanism.

6 Conclusion

We develop a tractable framework to quantify how strongly banks transmit and receive liquidity shocks originating elsewhere in the banking system. The proposed mechanism is simple: when a distressed bank curtails credit, firms draw more heavily on alternative credit lines, triggering liquidity outflows at other banks.

Using granular US supervisory data, we highlight the quantitative relevance of this mechanism and document substantial dispersion across banks' systemic footprints. Overall, our findings underscore credit lines as an important channel of shock propagation and a measurable source of interconnectedness. Our work complements existing measures of systemic risk by providing a more granular view of liquidity risk across banks.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015): "Systemic Risk and Stability in Financial Networks," *American Economic Review*, 105, 564–608. 3

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2017): "Measuring systemic risk," *Review of Financial Studies*, 30, 2–47. 1, 3, 4

Adrian, T. and M. K. Brunnermeier (2016): "CoVaR," *American Economic Review*, 106, 1705. 1, 3, 4

Allen, F. and D. Gale (2000): "Financial Contagion," *Journal of Political Economy*, 108, 1–33. 3

Bräuning, F. and V. Ivashina (2024): "Bank runs and interest rates: A revolving lines perspective," Working paper. 4

Brownlees, C. and R. F. Engle (2017): "SRISK: A conditional capital shortfall measure of systemic risk," *Review of Financial Studies*, 30, 48–79. 1, 3, 4

Cabrales, A., P. Gottardi, and F. Vega-Redondo (2017): "Risk Sharing and Contagion in Networks," *Review of Financial Studies*, 30, 3086–3127. 3

Denbee, E., C. Julliard, Y. Li, and K. Yuan (2021): "Network risk and key players: A structural analysis of interbank liquidity," *Journal of Financial Economics*, 141, 831–859. 3, 4

Diebold, F. X. and K. Yilmaz (2014): "On the network topology of variance decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, 182, 119–134. 1, 3, 4

Duarte, F. and T. M. Eisenbach (2021): "Fire-sale spillovers and systemic risk," *Journal of Finance*, 76, 1251–1294. 3, 4

Ehresmann, P., J. M. Morelli, and J. J. Wang (2025): "Modeling Bank Stock Returns: A Factor-Based Approach," Feds notes. 18

Elliott, M., C.-P. Georg, and J. Hazell (2021): "Systemic risk shifting in financial networks," *Journal of Economic Theory*, 191, 105157. 4

Elliott, M., B. Golub, and M. O. Jackson (2014): "Financial networks and contagion," *American Economic Review*, 104, 3115–53. 3

Elsinger, H., A. Lehar, and M. Summer (2006): "Risk assessment for banking systems," *Management science*, 52, 1301–1314. 3, 4

Gai, P., A. Haldane, and S. Kapadia (2011): "Complexity, concentration and contagion," *Journal of Monetary Economics*, 58, 453–470. 3

Greenwood, R., A. Landier, and D. Thesmar (2015): "Vulnerable banks," *Journal of Financial Economics*, 115, 471–485. 2, 3, 4

Huang, Z. (2025): "Asset-side bank runs and liquidity rationing: A vicious cycle," *Management Science*, 71, 3537–3557. 4

Ivashina, V. and D. Scharfstein (2010): "Bank lending during the Financial Crisis of 2008," *Journal of Financial Economics*, 97, 319–338. 2, 3

Kiernan, K. F., V. Yankov, and F. Zikes (2022): "Liquidity provision and co-insurance in bank syndicates," Working paper. 5

Sufi, A. (2009): "Bank lines of credit in corporate finance: An empirical analysis," *Review of Financial Studies*, 22, 1057–1088. 4, 5

Wagner, W. (2011): "Systemic liquidation risk and the diversity–diversification trade-off," *Journal of Finance*, 66, 1141–1175. 3

A Specifying the factor model from Test 1

In this Appendix we spell out the factor model from Test 1 in Section 5.

The factor model in Ehresmann, Morelli, and Wang (2025) includes five systematic components:

- **Market excess return ($\mathbf{MKT}_t$):** the excess return on the aggregate equity market, capturing broad macroeconomic and financial-market risk.
- **Size factor ($\mathbf{SMB}_t$):** the return difference between small- and large-cap firms, capturing size-related risk and funding frictions.

- **Value factor ($\mathbf{HML}_t$):** the return difference between high and low book-to-market firms, capturing valuation and distress-related risk.

The remaining two factors capture bond-market risks and are proxied using publicly available data:

- **Default factor ($\mathbf{DEF}_t$):** proxied by BAA10Y, the Moody's seasoned Baa corporate bond yield relative to the 10-year Treasury yield. This measure captures time variation in credit risk conditions embedded in corporate bond yields.

- **Term factor ($\mathbf{TERM}_t$):** proxied by T10Y3M, defined as the difference between the 10-year Treasury yield and the 3-month Treasury bill yield. This measure captures interest-rate risk and the slope of the yield curve.

A.1 Factor Model

At the bank–month level, we estimate

$$r_{i,t}^{e} = \alpha + \boldsymbol{\beta}'\mathbf{F}_t + \varepsilon_{i,t},$$

where $r_{i,t}^{e}$ denotes the monthly excess return of bank i, $\mathbf{F}_t$ is the vector of the five factors, and $\varepsilon_{i,t}$ is the regression residual. We interpret $\varepsilon_{i,t}$ as a bank-specific shock orthogonal to systematic equity, credit, and interest-rate risks. As in the main text, we use the negative part of these residuals, $-\min(\varepsilon_{i,t}, 0)$, to construct downside shocks.

B Robustness for Test 1

We construct a variation of the exposure measure (using the non-normalized spillover coefficients as weights)

$$\text{Exposure}_{i,t}^{\text{sum}} = \sum_{j \neq i} S_{ji,t} \cdot \big(-\min(\varepsilon_{j,t}, 0)\big),$$

where $S_{ji,t}$ denotes the liquidity spillover coefficient from bank j to bank i, consistent with the notation in Section 5.

Table 5: Sum Exposure to Connected Banks and Contemporaneous Returns

	(1)	(2)	(3)	(4)
Sum Exposure	-0.158^{***}	-0.132^{***}	-0.203^{***}	-0.175^{***}
	(0.021)	(0.019)	(0.024)	(0.022)
Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes

Notes: The dependent variable is the monthly bank equity return. Sum exposure aggregates downside shocks at connected counterparties using liquidity spillover weights. Robust standard errors in parentheses. *** denotes significance at the 1% level.

Table 6: Sum Exposure to Connected Banks and Future Returns

	(1)	(2)	(3)	(4)
Sum Exposure	0.024	0.081^{***}	0.033	0.109^{***}
	(0.021)	(0.019)	(0.024)	(0.022)
Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes

Notes: The dependent variable is the monthly bank equity return at t+1. Sum exposure is measured at time t. Robust standard errors in parentheses. *** denotes significance at the 1% level.