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An integrated macroprudential stress test of bank liquidity and solvency ☆

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ABSTRACT

We propose a new measure of systemic financial distress that incorporates idiosyncratic and systemic risks in the financial system network. Using this measure, we develop an integrated stress test of bank liquidity and solvency risks based on the dynamics of financial distress within the banking system network. We apply this stress test framework to the US banking system and identify systemic vulnerability of individual banks as well as the resilience of the system as a whole to an economic shock. The framework helps us identify and monitor systemic interdependencies between banks. The proposed stress testing framework is useful for practical macroprudential monitoring and is informative for policy making.

1. Introduction

The global financial crisis of 2007–2008 has revealed the need for a better macroprudential policy in order to enhance financial stability and to limit the propagation of systemic risk. The crisis has shown that impairment of financial stability can impose significant costs on the real economy in terms of economic growth and social welfare. It is widely accepted in the literature that systemic risk is the main threat to financial stability. Thus, to protect the real economy from a significant volatility in the financial system, it is necessary to detect and to gauge potential sources of systemic risk that emerges at the system level. Meanwhile, to protect the financial system from the growth variations of the real economy, it is necessary to assess the robustness of the response mechanism of the financial system to macroeconomic shocks. To this end, macroprudential stress tests have been considered as the main tool of macroprudential policy (Tarullo, 2016).

The current practice of macroprudential stress testing has improved in the aftermath of the financial crisis. However, the underlying techniques and models that have been developed prior to the crisis have remained broadly the same and there are still some limitations that need to be addressed (Borio et al., 2014). In particular, a recent report from the Basel Committee on Banking Supervision (BCBS) highlights two main limitations; namely, considering liquidity and solvency interactions and considering systemic risk (BCBS, 2015). The International Monetary Fund (IMF) makes a similar recommendation in its 2014 Review of the Financial Sector Assessment Program (FSAP). The review stresses the need to strengthen the systemic focus of the financial stability assessment and to deepen the analytical treatment of interconnectedness (IMF, 2014).

In this paper, we develop and illustrate with an empirical application, an integrated macroprudential stress test of bank liquidity and solvency risk. The proposed approach employs a network theory to introduce a new measure of systemic distress that incorporates microprudential as well as macroprudential risks in the banking system network. Our approach integrates liquidity risk and solvency risk and provides a convenient method to identify the point at which liquidity risk becomes solvency risk. In addition, the proposed stress testing framework is flexible as it allows the stress tester to further use different stress scenarios to assess the impact of liquidity shocks on solvency, and vice versa. The framework also provides a variety of output metrics that capture idiosyncratic as well as systemic economic

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risks at the individual bank level and the overall banking sector as a whole. Yet, the framework is tractable enough to be useful for practical macroprudential monitoring and informative for policy-making.

An important strength of our approach is that it explicitly links liquidity risk and solvency risk in order to incorporate their interactions in the stress testing framework. These interactions have often been neglected in existing stress-testing methodologies. We create this link by estimating both the probability of a bank becoming illiquid and the probability of a bank becoming insolvent based on the same factor; namely, the bank's distress level. We estimate these probabilities using a Merton-type model that is based on the seminal work of Black and Scholes (1973) and Merton (1974). In so doing, we assume that bank distress is a continuous state with varying levels that depend on both idiosyncratic and systemic risks of each bank, whereas illiquidity and insolvency occur at specific points of highly elevated distress. The higher the distress level of a bank the closer it gets to its illiquidity and insolvency points.

Another important strength of our approach is the way in which we incorporate interconnectedness between banks into the stress test design. Given that our purpose is to assess the vulnerability of banks, it is more appropriate to focus on a bank's systemic distress rather than its systemic importance. We approximate a bank's systemic distress using a novel measure named *DistressRank*. This measure fully incorporates the interbank network topology. It is based on the notion that the distress level of a bank is a function of its idiosyncratic risk as well as its systemic risk stemming from being connected to counterparties through interbank assets or liabilities. DistressRank also captures the dynamics on the network as it changes with the change in banks' distress levels.

We construct stress scenarios in two different ways, where the first is designed to assess the resilience of the banking system to macroeconomic shocks, and the second is designed to assess the possibility of amplifying endogenous shocks within the banking system and transmitting them to the macroeconomy. The empirical application of the stress test framework to the US banking system shows how it can be effectively used to identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. It also shows how the proposed approach can be effective for monitoring and assessing systemic interdependencies among banks. The proposed approach, thus, provides a tool for the banking system supervisors to analyse the current state of the system stability and to monitor the evolution of contagion and systemic risk within the system.

Our findings point out the importance of considering interconnectedness in designing macroprudential stress tests. At the system level, the systemic loss due to feedback loops is shown to be significant compared to the direct loss that results from the initial shock to the system. Ignoring these feedback effects may lead to a significant underestimation of systemic loss. At the bank level, the results confirm that interlinkages play a significant role in identifying individual banks' vulnerability. On this premise, we use DistressRank as a measure of a bank's systemic distress. The results show that a bank's DistressRank is associated with its systemic feedback loss.

Our findings also lend insights into the possibilities of distress propagation within the system. Applying the proposed framework to the US banking system enables us to identify banks that are most vulnerable to system-wide shocks. In addition, we identify the liquidity distress dependence and solvency default dependence between banks in the system. A striking finding is that banks that are not directly connected through interbank assets or liabilities are still subject to distress from each other through *common counterparties*.

The remainder of this paper is organised as follows. Section 2 provides an overview of macroprudential stress testing in the literature. Section 3 develops an initial model for illiquidity distress propagation. Section 4 extends the model to link illiquidity to insolvency. Section 5 introduces a framework for an integrated macroprudential stress test of liquidity and solvency risk. Section 6 provides an overview of the data used in this paper and presents various results with regard to the stress test. Section 7 concludes the paper.

2. Related literature

We develop our stress testing framework based on a balance sheet setting which is the natural approach to macroprudential stress testing. This approach has been shown to be generally informative and unbiased with the ability to predict banks' losses and equity returns due to change in macroeconomic factors (Philippon et al., 2017). It is specially useful in cases of limited or poor market data availability, as the main data required for the test is extracted from banks' balance sheets (Ong and Čihák, 2014). Early models under this approach provide a framework for an aggregate stress test of the financial system (e.g. Blaschke et al., 2001; Bunn et al., 2005), however, they are fundamentally financial simulations with no formal links to the macroeconomy (Buncic and Melecky, 2013). More recent models attempt to establish this link by using satellite models to link the macroeconomic variables to bank's asset quality (Čihák, 2007). A more sophisticated, yet tractable, accounting-based stress test is introduced by Drehmann et al. (2010), in which they model assets and liabilities simultaneously. This model integrates credit and interest rate risk in the banking book and provides a framework to assess the impact of different investment strategies on the bank's profitability. Also, Gourieroux et al. (2012) provide a stress testing framework based on balance sheets but with a focus on bank solvency risk. Another example is the model provided by Greenwood et al. (2015) in which fire sales due to deleveraging cause shocks across bank balance sheets leading to spillover among banks. Nevertheless, It is worth noting that the quality of any analysis that follows a balance sheet approach to stress testing depends on the granularity and availability of the data. Some models attempt to overcome this limitation and provide sophisticated techniques to perform stress testing in cases of limited data (e.g. Segoviano and Padilla, 2006; Ong et al., 2010).

In theory, liquidity and solvency risks interact and can cause each other through banks' interactions (Diamond and Rajan, 2005). However, empirical evidence on the nexus between liquidity and solvency risks is scarce. Some studies have attempted to establish the link between liquidity and solvency in order to incorporate it into macroprudential stress tests. In particular, Schmitz et al. (2017) suggest that bank funding costs are correlated with bank capital as a result of the interconnections between funding costs and market expectations about bank solvency. Other studies suggest a significant impact of solvency on bank funding costs (Hasan et al., 2016), which appears to be nonlinear with higher sensitivity of funding cost at lower levels of bank solvency (Aymanns et al., 2016). The relationship seems to be intuitive when we consider the interactions between liquidity and solvency. When a bank faces a liquidity shortage, it might be forced to sell its less liquid assets. If other banks with similar conditions adopt the same approach of selling less liquid assets, the initial liquidity shortages may lead to fire sales and consequently declines in asset prices, hence, causing solvency problems (Lee, 2013). Similarly, concerns about bank insolvency can cause liquidity shortages. Increased expectations about a bank insolvency (e.g. declines in credit rating) can increase deposit withdrawal and interbank funding costs as depositors and interbank counterparties, respectively, become less confident about the bank creditworthiness, hence causing a liquidity shortage for the bank (Pierret, 2015). Thus, propagation channels between liquidity and solvency are common and, for macroprudential purposes, they should be integrated within a unified stress testing framework. However, the focus of macroprudential stress testing frameworks has usually been on solvency risk, while liquidity risk is assessed using satellite models on a stand-alone basis.

Our proposed methodology is closely related to the Macrofinancial Risk Assessment Framework (MFRAF) that has been developed by the Bank of Canada and integrates solvency and liquidity risk (Gauthier et al., 2012b). In the framework, solvency risk is triggered by a macro shock, whereas liquidity risk arises as a result of solvency concerns or deterioration in liquidity position. We use a similar framework that considers potential market liquidity risk and interbank counterparty credit risk through a network model. Another macroprudential stress testing model that integrates solvency and liquidity risk has been developed by the Hong Kong Monetary Authority (Wong and Hui, 2009). Our methodology shares some characteristics with this model with regard to combining elements of balance sheet-based and market price-based approaches to stress testing. In this model, solvency risk of an individual bank depends on the market value of its total assets, calculated through a Merton-type model. In contrast, we estimate solvency and liquidity risks based on the volatility of liquid assets instead of total assets. In this model, liquidity risk is assessed by introducing an exogenous shock to asset prices which leads to increases in the bank's solvency risk and deposit outflow and reduction in its liquidity generation capability.

Our approach rests on the insight of the Merton-type models of default risk that are based on the seminal work of Black and Scholes (1973) and Merton (1974). In these models, equity of the firm can be viewed as a call option held by owners on its total assets, where the strike price is equal to the outstanding debt owed to creditors at maturity. In this context, a market-implied probability of default can be estimated as the probability that the market value of the firm's assets falls below the book value of its liabilities (Bohn and Crosbie, 2003). An example of applying this approach to systemic risk is the theoretical model of Tasca et al. (2014) who use the Merton framework to quantify joint default probability of individual banks in order to study the impact of leveraging and diversification on systemic risk. We use the same logic to estimate two types of probability for each individual bank; namely, the probability of illiquidity and the probability of insolvency. We deviate, however, from the standard approach in that we base the estimation of both probabilities on liquid assets only instead of total assets. Our rationale is that, in the short run, the variability in total assets is derived mainly from the variability of liquid assets. This twist enables us to link liquidity and solvency risks directly as both are estimated based on the same factor.

Our methodology is also related to the Contingent Claims Analysis (CCA) that relies on a Merton-type framework to construct a risk-adjusted balance sheet of individual banks (Gray and Malone, 2008; Gray and Jobst, 2010). The CCA model can be used for macroprudential stress testing by applying a macroeconomic shock to the risk-adjusted balance sheet of individual banks and then estimating the change in banks' market value of equity and probability of default. However, the CCA model limits its focus to solvency risk and lacks the systemic view as it does not provide a method to measure aggregated risk at the system level. Our methodology also shares some characteristics with the distress dependence model of Segoviano and Goodhart (2009) who investigate the effect of macroeconomic variables on bank losses where the joint probability distribution of banks is constructed with Copulas. They model the financial system as a portfolio of banks and use non-parametric statistical techniques to construct a multivariate density function for the financial system. Then, they estimate a joint probability of default and a banking stability index of the whole banking system.

We base our stress test on a network model that provides a convenient way to incorporate systemic risk and interconnectedness into the stress testing framework. Early studies of financial contagion suggest that financial networks can provide a better way to study the linkages among financial institutions (e.g. Allen and Gale, 2000; Freixas et al., 2000). More recent studies support the same notion and emphasise that financial networks can help provide better measurement of systemic risk and financial instabilities (e.g. Gai et al., 2011; Gai and Kapadia, 2010; Glasserman and Young, 2015; Elliott et al., 2014; Acemoglu et al., 2015; Glasserman and Young, 2016). In this spirit, we depict the relationships within the banking sector as a network in which banks represent the nodes and financial exposures represent the edges between these nodes. This approach to studying the financial markets, in general, enables us to better understand the interconnectedness and the propagation of distress. This is also the approach followed by some regulatory (e.g. Gauthier et al., 2012b; Wong and Hui, 2009; Sole and Espinosa-Vega, 2010) and academic (e.g. Gauthier et al., 2012a; Levy-Carciente et al., 2015) stress testing frameworks. Sole and Espinosa-Vega (2010) use a network setting to simulate the impact of credit and funding shocks on a set of connected banking systems. Levy-Carciente et al. (2015) use a bipartite bank-asset network to design a solvency stress test of the Venezuelan banking system. Gauthier et al. (2012a) use a network model to estimate a bank's macroprudential capital requirements as a function of its contribution to the system-wide risk.

3. Illiquidity distress

This section provides a simple model of liquidity risk where we use a balance sheet approach to derive a measure of systemic illiquidity distress of a bank in a financial system.

3.1. A system of networked balance sheets

We model an interbank market that consists of a number of banks $N \in \{1, \ldots, N\}$. The assets of each bank are divided into liquid assets and illiquid assets denoted as A_i^L and A_i^F, respectively. In addition, the liabilities of each bank consist of short-term obligations denoted as L_i^S, and long-term obligations denoted as L_i^F. The net worth of bank i is E_i and is equal to the difference between its total assets and its total liabilities. Thus, the balance sheet identity of bank i can be represented as

$$A_i^L + A_i^F = L_i^S + L_i^F + E_i \tag{1}$$

Furthermore, we differentiate between two sources of liquid assets; namely, interbank liquid assets and other liquid assets denoted as A_i^B and A_i^O respectively, where $A_i^L = A_i^B + A_i^O$. Similarly, the short-term obligations are divided into interbank short-term obligations, L_i^B, and other short-term obligations, L_i^O, where $L_i^S = L_i^B + L_i^O$. The interbank liquid assets and short-term obligations represent assets and liabilities originating from the interbank market (e.g. interbank repo or derivatives transactions), whereas other liquid assets and other short-term obligations are not related to the interbank market and might include cash or short-term securities.

The separation of interbank liquid assets and short-term obligations enables us to model the liquidity interlinkages across banks in the interbank market as a weighted directed graph whose vertices represent banks and edges represent interbank assets and liabilities. The assets, in monetary units, of bank i with bank j are denoted by A_{ij} where $i \neq j$, which represents the amount that bank i should receive from bank j as a result of some financial transaction (e.g a derivatives contract). Similarly, the interbank liabilities of bank i to bank j is denoted by L_{ij} where $i \neq j$, which represents the amount that bank i should pay to bank j. It then follows that, the interbank liquid assets of bank i are given by $A_i^B = \sum_{j=1}^N A_{ij}$, whereas the interbank liabilities of bank i are given by $L_i^B = \sum_{j=1}^N L_{ij}$.

3.2. Liquidity coverage matrix

Banks use their stock of liquid assets to cover their own liquidity requirements. Thus, we can define a *liquidity coverage ratio* for a bank i as

$$\ell_i = \frac{A_i^L}{L_i^S} \tag{2}$$

which measures the ability of bank i to meet its short-term obligations, whether within the interbank market or to outside counterparties. The higher the liquid assets as compared to short-term obligations, the higher the liquidity coverage ratio, and the more liquid the bank is.

Furthermore, in order to measure the ability of bank i to cover its obligation to another counterparty j within the interbank market, we introduce ℓ_{ij} as the bank i's *relative liquidity coverage ratio* to bank j, where

$$\ell_{ij} = \frac{[A_i^L - L_i^S] - A_{ij} + L_{ij}}{L_{ij}} \tag{3}$$

This ratio represents the ability of bank i to cover its interbank obligation to bank j using its net liquidity ($A_i^L - L_i^S$), after paying all other obligations and before exchanging any liquidity with bank j. This is why we adjust the net liquidity stock of bank i in the numerator by subtracting the liquidity exposure that is owed to bank i by bank j and adding back the liquidity exposure owed to bank j by bank i, to reflect a case before exchanging liquidity.

3.3. Illiquidity distress matrix

It is clear from Eqs. (2) and (3) that the better the liquidity position of a bank as measured by its liquidity coverage ratios the lower the threat of illiquidity distress that the bank is exposed to. It is also worth noting that ℓ_{ij} provides a proxy to the relative vulnerability of bank j to the liquidity distress that might arise at bank i. In other words, the lower this ratio is, the higher the probability that bank i will fail to honour its obligation to bank j, and the higher the vulnerability of bank j.

We use this notion to develop an illiquidity distress matrix defined as $\mathbf{D} = [d_{ij}]$, where an element d_{ij} represents the relative vulnerability of bank i to the illiquidity distress of bank j; in other words, the contribution of bank j to the vulnerability of bank i. We then define d_{ij} as

$$d_{ij} = \frac{a_{ij}}{\ell_{ji}} \tag{4}$$

where a_{ij} is the respective element from the adjacency matrix $\mathbf{A}$ of interbank network which is defined as $\mathbf{A} = [a_{ij}]$, where $a_{ij} = 1$ if banks i and j are connected and $a_{ij} = 0$ otherwise.

3.4. DistressRank: A measure of systemic distress

The network literature suggests that the centrality of a node in a given network is a function of its interconnection with its neighbours. One method to quantify this centrality is a measure called *eigenvector-centrality*, which is based on the notion that the centrality of a node is proportional to the sum of centralities of its neighbours (Newman, 2010). Applying this notion to our financial network results in

$$c_i = \frac{1}{\lambda} \sum_{j=1}^{N} a_{ij}\ c_j \tag{5}$$

where c_i is the eigenvector centrality of bank i and $\lambda \neq 0$ is a constant. Thus, the eigenvector centrality can provide a relative ranking of banks. One advantage of this method is that it bases the ranking on both local information related to direct neighbours and global information of the network given that the ranking of neighbours is based on the ranking of their neighbours, and so on Scott (2017).

However, eigenvector centrality is a purely topological measure that is solely based on the adjacency matrix $\mathbf{A}$. This limitation renders it subject to two main disadvantages when it comes to ranking banks in a financial network. First, it assumes equal contribution of all exposures in the network in determining the centrality of a given bank. This assumption is not valid as it ignores the state of the bank's counterparty, i.e. its distress level. A bank is more vulnerable to banks with high distress levels compared to other banks. Second, eigenvector centrality ignores the dynamics in the network as it is based on the mere existence of an exposure between two banks rather than the weight of this exposure. Hence, it is time-independent as it does not change in response to changes in the weights of exposure or the states of banks.

Therefore, we propose *DistressRank* as an improvement on the standard eigenvector centrality to overcome the disadvantages mentioned above. To this end, we estimate DistressRank based on the distress matrix $\mathbf{D}$, which was introduced in Eq. (4). Let ρ_i be the DistressRank of bank i, which can be defined as

$$\rho_i = \frac{1}{\lambda} \sum_{j=1}^{N} d_{ij}\ \rho_j \tag{6}$$

where $\lambda \neq 0$ is a constant. With some rearrangements, Eq. (6) can be rewritten in matrix notation as

$$D \cdot \rho \ = \ \lambda \cdot \rho \tag{7}$$

which is a standard eigenvector–eigenvalues problem where λ is an eigenvalue and ρ is its corresponding $1\ x\ N$ vector. Given that the matrix $\mathbf{D}$ is non-negative and according to the Perron–Frobenius theorem (Meyer, 2000), the above eigenvector–eigenvalues problem has a unique solution at $\lambda = \lambda_{max}$. In other words, only the largest eigenvalue λ_{max} results in the desired non-negative eigenvector ρ which represents the DistressRank vector of banks where the ith entry corresponds to the DistressRank of the ith bank. Eq. (7) can be solved iteratively using the power iteration method (Newman, 2010).

DistressRank is more suitable as a measure of systemic distress of a bank in a financial network because it assigns a rank to each bank in the network based on the distress of its counterparties. Thus, it is more suited for use with dynamic networks where the states of banks and the weights of exposures change during a distress propagation process. Here, we use DistressRank as one of the main metrics in our macroprudential stress test that is introduced in Section 5.

4. Illiquidity and insolvency

Assessing at what point liquidity risk becomes solvency risk is, at best, difficult. In this section we attempt to disentangle these two risks, and show how to express solvency risk in terms of liquidity risk.

4.1. From illiquidity to insolvency

Typically, a bank i is considered *illiquid* when $A_i^L \leq L_i^S$, in other words, when the market value of its liquid assets is less than the face value of its short-term obligations. The same logic can be extended to insolvency. A bank is considered *insolvent* when the market value of its assets falls below the face value of its obligations, where $E_i \leq 0$. Fig. 1 illustrates the relation between illiquidity and insolvency. We would expect a bank to be liquid and solvent as shown by the white area in this figure. Nevertheless, a bank might become illiquid while still being solvent as shown by the grey area. However, if the bank's illiquidity problem is severe enough, it can lead to insolvency as shown by the black area in the same figure.

Another way to consider insolvency is by limiting the focus to liquid assets and short-term liabilities. Insolvency occurs when the decline in liquid assets is severe enough to exceed the value of equity. In other words, the bank becomes insolvent if the market value of its liquid assets deteriorates to the extent that the net change in its liquidity at a given time is larger than its equity. That said, we can introduce a new condition for insolvency in terms of liquid assets by which a bank is considered insolvent if

$$E_i + \Delta A_i^L \leq 0 \tag{8}$$

where ΔA_i^L is the net change in the bank's liquidity position assuming that short-term liabilities are valued at face value.

Thus, one might argue that, in the short-run, both illiquidity and insolvency can be measured in terms of the change in liquid assets, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. That said, the illiquidity point for a bank is defined to be the point at which $A_i^L = L_i^S$, as mentioned above. At this

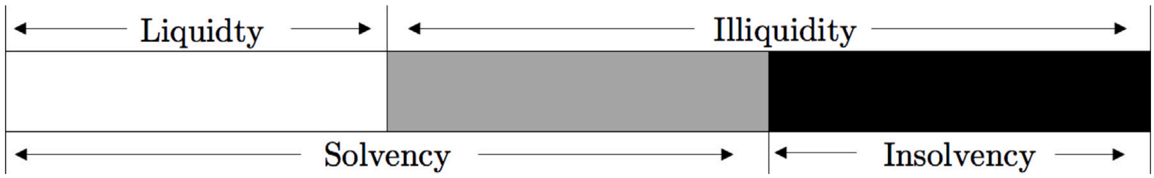


Fig. 1. From illiquidity to insolvency. The white area represents a healthy bank that is both liquid and solvent. The grey area represents a stage in which the bank has become illiquid, yet is still solvent. The black area represents the stage in which the bank has become both illiquid and insolvent.

point, we can estimate a bank's liquidity coverage ratio, denoted as ℓ_i^L, that corresponds to its illiquidity point as

$$\ell_i^L = \frac{A_i^L}{L_i^S} \tag{9}$$

Applying the same logic to insolvency, the insolvency point for a bank can be defined as the point at which $E_i = -\Delta A_i^L$, as shown by Eq. (8). At this point, we can also estimate a bank's liquidity coverage ratio, denoted as ℓ_i^S, that corresponds to its insolvency point as

$$\ell_i^S = \frac{A_i^L - E_i}{L_i^S} \tag{10}$$

where E_i represents the amount of liquid assets that, if depleted, the bank is considered to have reached the insolvency point.

4.2. From insolvency to illiquidity

One way to measure insolvency risk is to determine how far away a bank is from insolvency. This approach is called distance-to-default, which is developed based on the structural model of corporate debt introduced by Black and Scholes (1973). On this premise, we drive a measure of insolvency risk for individual banks in our system. We call this measure *distance-to-insolvency* (δ^S) which is completely analogous to and based on the distance-to-default measure in the Moody's KMV model (see Bohn and Crosbie, 2003). The main difference in our approach is that we estimate the distance-to-insolvency using liquid assets and short-term liabilities only, instead of total assets and total liabilities in the distance-to-default model, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. However, liquid assets of banks are not directly observed which make it difficult to assign a specific dynamic process to the bank liquid assets. Therefore, in the same vein of the structural model of Merton (1974), we assume that the liquid asset A^L of a given bank follows a geometric Brownian motion such that $dA_t^L = \mu_{A^L} A_t^L d_t + \sigma_{A^L} A_t^L dW_t,\ A_0^L > 0$, where μ_{A^L} is the mean rate of return on the liquid assets and σ_{A^L} is the liquid asset volatility. We further assume that there are no bankruptcy charges where the liquidation value equals the bank value, and that the debt and equity of the bank are frictionless tradeable assets. Further, unlike the Merton model, we consider only one part of the bank's debt represented in its outstanding short-term liabilities with a face value of L^S and maturity T. Thus, at maturity T, if the total value of liquid assets is less than the short-term liabilities, the bank is considered illiquid. To quantify the bank's insolvency, the problem then reduces to identifying how deep into illiquidity a bank can be before the condition in Eq. (8) is satisfied and the bank becomes insolvent.

Based on the above assumptions and knowing a bank's insolvency point as derived from Eq. (10) above, the distance-to-insolvency of bank i, denoted as δ_i^S, can be defined as

$$\delta_i^S = \frac{ln\left(\frac{A_i^L}{\ell_i^S\ L_i^S}\right) + \left(\mu_{A_i^L} - \frac{1}{2}\sigma^2_{A_i^L}\right)T}{\sigma_{A_i^L}\sqrt{T}} \tag{11}$$

where $\mu_{A_i^L}$ and $\sigma_{A_i^L}$ are the mean and volatility of return on liquid assets and T is the time to maturity. It is worth noting from Eq. (11) that distance-to-insolvency is simply the number of standard deviations that the bank is away from insolvency. Furthermore, following the assumption in Black and Scholes (1973) that the random component of a firm's asset returns is normally distributed, we can define the *probability of insolvency* of a specific bank as

$$\chi_i^S = N\left[-\delta_i^S\right] \tag{12}$$

where $N(x)$ is the cumulative distribution function (CDF) of the standard normal distribution $N(0,1)$. Notice also that χ^S is similar to the probability of default in standard credit risk models.

We now turn to estimating two measures of illiquidity risk; namely *distance-to-illiquidity* and *probability of illiquidity*. Needless to say, these two measures are analogous to those measures that we introduced above to measure insolvency risk. Thus, in order not to repeat ourselves, we just extend the same logic we used with insolvency. In so doing, we argue that illiquidity can be viewed as a special case of insolvency in the short-run, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. Thus, knowing the illiquidity point ℓ_i^L of a given bank i as derived from Eq. (9), we can estimate the distance-to-illiquidity of this bank, denoted as δ_i^L, as follows

$$\delta_i^L = \frac{ln\left(\frac{A_i^L}{\ell_i^L\ L_i^S}\right) + \left(\mu_{A_i^L} - \frac{1}{2}\sigma^2_{A_i^L}\right)T}{\sigma_{A_i^L}\sqrt{T}} \tag{13}$$

Similar to the distance to insolvency, we can interpret the distance to illiquidity as the number of standard deviations that the bank is away from illiquidity. Finally, let χ_i^L be the probability of illiquidity for bank i. It follows that:

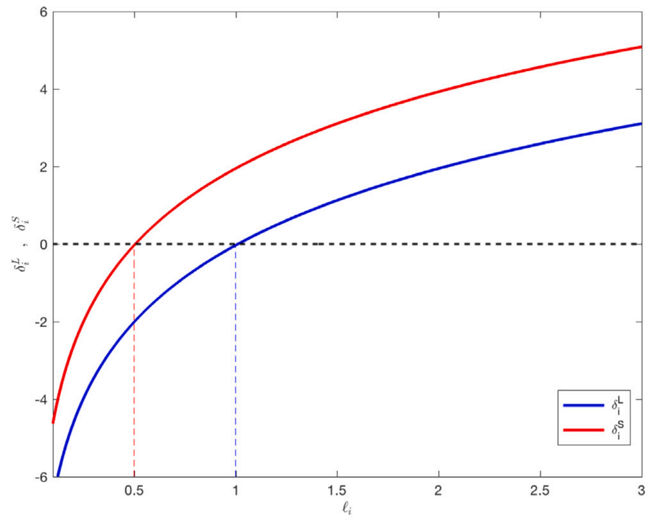
$$\chi_i^L = N\left[-\delta_i^L\right] \tag{14}$$

where $N(x)$ is the cumulative distribution function (CDF) of the standard normal distribution $N(0,1)$.

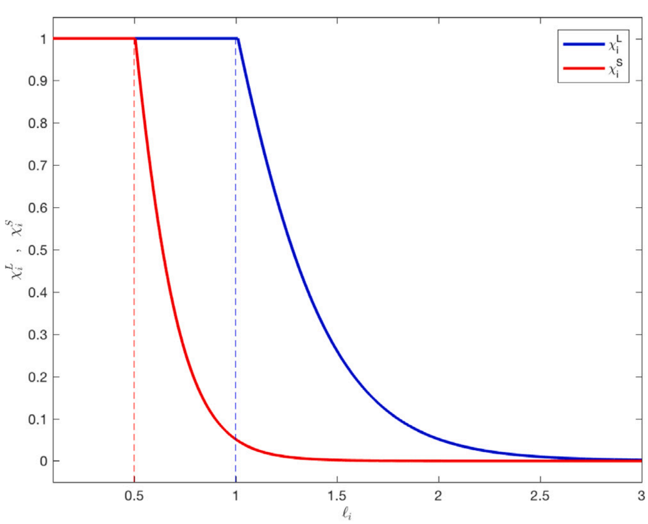
The relationship between the illiquidity and insolvency measures that we derive above can best be illustrated by Fig. 2. Let us assume a bank i that operates in a system with a system-wide illiquidity point (ℓ^L) and insolvency point (ℓ^S) of 100% and 50%, respectively. In panel (a), we estimate distance to insolvency (δ_i^S) and distance to illiquidity (δ_i^L), and in panel (b) we estimate the corresponding probabilities of insolvency (χ_i^S) and illiquidity (χ_i^L) over a range of liquidity coverage ratios (ℓ_i) from zero to 300%. The figure shows that as the liquidity coverage ratio decreases, both δ_i^L and δ_i^S decrease, while χ_i^L and χ_i^S increase in parallel. When ℓ_i reaches the illiquidity point of 100%, δ_i^L becomes zero, χ_i^L reaches 1, and the bank is considered to be illiquid. However, at the illiquidity point, the bank is still solvent as δ_i^S is still higher than zero and χ_i^S is still lower than 1. As the bank sinks more into illiquidity, its δ_i^S moves towards the insolvency point and its χ_i^S converges to 1. At the insolvency point of 50%, δ_i^S becomes zero, χ_i^S reaches 1, and the bank is considered to be insolvent.

5. A macroprudential stress testing framework

In this section we provide a framework for a macroprudential stress test based on the measures that we introduced in Sections 3 and 4. This framework is illustrated in Fig. 3. Also, in the subsections below, we outline this framework in terms of its inputs (distress scenario), process (distress propagation process), and outputs (DistressRank, Distress Dependence Matrix, Default Dependence Matrix, and Systemic Risk Matrix).



(a) Distance to Illiquidity & Distance to Insolvency



(b) Probability of Illiquidity & Probability of Insolvency

Fig. 2. The relationship between insolvency measures and illiquidity measures of a hypothetical bank i whose liquidity coverage ratio is denoted by ℓ_i. δ_i^L is the distance to illiquidity, and δ_i^S is the distance to insolvency. χ_i^L is the probability of illiquidity, and χ_i^S is the probability of insolvency. The system-wide illiquidity point (ℓ_i^L) and insolvency point (ℓ_i^S) are 100% and 50%, respectively.

5.1. Inputs: Distress scenario

The distress scenario in our framework refers to the set of shocks applied to individual banks, specific groups of banks, or all banks in the system with the aim to examine the systemic impact and vulnerability of individual banks and the stability of the system as a whole. The framework is flexible to include any plausible set of shock events. However, we limit the analysis to two types of shock, with each one designed to examine specific aspects of the stability of the system.

A- **The first scenario** involves applying a uniform shock to all banks in the system. The immediate effect of this shock is a proportional reduction in all banks' interbank assets leading to a reduction in liquidity positions. This scenario is also flexible to investigate the impact of a vector of heterogeneous shocks where each bank is affected differently.

B- **The second scenario** involves shocking banks sequentially. In each round a specific bank loses a given amount of its liquid assets and therefore becomes illiquid. The immediate effect of this shock is that the respective bank cross-defaults in all its interbank liabilities which leads to the write-off of the interbank assets of its counterparties. This scenario is flexible to include a group of banks instead of a single bank.

The feedback round effects and final results of each scenario are explained in more detail in Sections 5.2 and 5.4, respectively.

5.2. Distress propagation process

The distress scenario that is developed in our stress test is assumed to unroll in two rounds:

A- **During the first round**, the initial effects of shocks to banks' liquidity positions are estimated by applying the shock to the respective bank or banks. The total initial impact of the shock is equal to the sum of the liquidity loss of all banks affected by the initial shock.

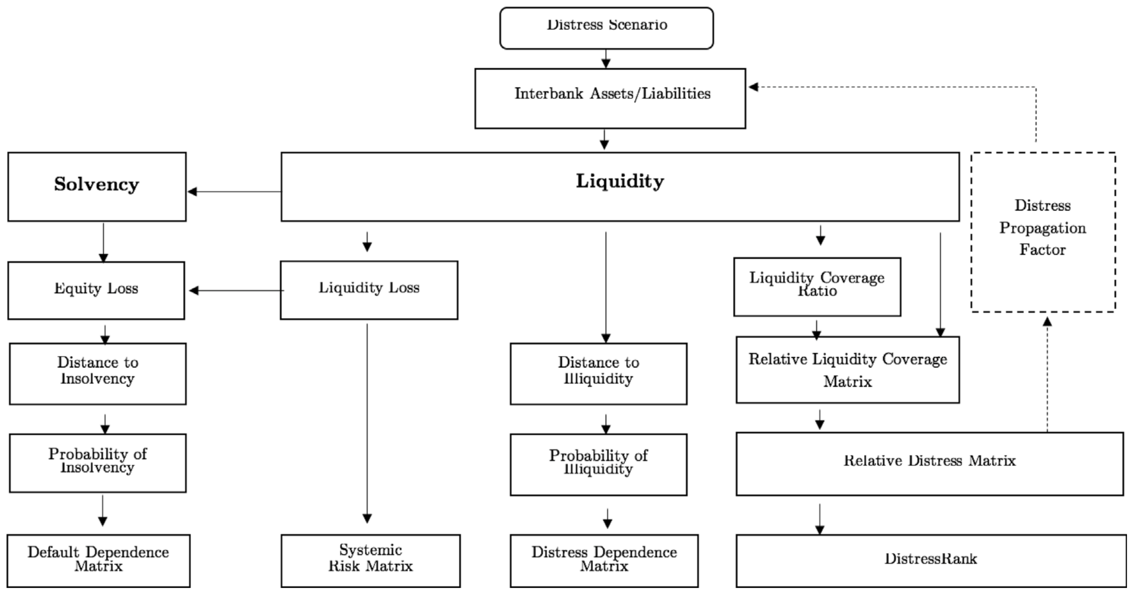


Fig. 3. A framework for an integrated macroprudential stress test of liquidity and solvency.

B- **During the feedback round,** the effects of the distress feedback loops within the system are estimated. The change in liquidity positions of individual banks leads to a change in their liquidity risk profiles. In other words, it leads to a change in each bank's liquidity coverage ratio as estimated by Eq. (2) and the relative liquidity coverage matrix as estimated by Eq. (3). As the liquidity risk of each bank changes, so does its ability to repay its obligations to its counterparties. This ability is translated into the relative distress matrix as estimated by Eq. (4). The market values of the interbank assets are re-estimated based on the expected value to be collected from counterparties. We estimate this expected value using a distress propagation factor that is directly derived from the relative distress matrix as follows

$$A_{ij}^{B}(t) = max\left[0\,,\quad A_{ij}^{B}(t-1)\left(\frac{d_{ij}(t-1)}{d_{ij}(t)}\right)\right] \tag{15}$$

where $A_{ij}^{B}(t)$ and $A_{ij}^{B}(t-1)$ are the interbank assets of bank i with bank j at time steps t and 0 of the distress propagation process, respectively; whereas $d_{ij}(t)$ and $d_{ij}(t-1)$ are the distress of bank i relative to bank j at time steps t and 0 of the distress propagation process, respectively. The idea is that, when the distress of bank j increases, bank i's exposure to bank j deteriorates proportionally, and if bank j becomes insolvent, bank i loses its assets with bank j. In fact, Eq. (15) assumes a zero recovery rate, an assumption that is widely followed in the financial contagion literature (see Gai and Kapadia, 2010; Markose et al., 2012). The mark-to-market process is represented by the dashed lines in Fig. 3. The change in the interbank assets matrix leads to repeating the same sequence of distress propagation in the system. This process continues until the initial shock to the system decays when no further significant changes in the system are expected.

After the second round of distress propagation concludes, the system arrives at a new steady state. We then estimate a few metrics to examine the stability of this system which we outline in Section 5.4.

5.3. Default propagation process

The stress test framework that we provide is capable of bridging the space between illiquidity and insolvency. This is possible due to the fact that we model the evolution of insolvency in terms of illiquidity as explained in detail in Section 4 and outlined by the far left column in Fig. 3. Under each distress scenario, as the liquidity risk of each bank evolves, so does its default risk. With every step in the unfolding of the distress scenario, the solvency status of each bank changes in parallel with the changes in its liquidity status. We monitor these changes be estimating for each bank the absolute change in equity, the distance to insolvency (see Eq. (11)) and the probability of default (see Eq. (12)).

5.4. Stress test output

The stress test framework presented here provides a variety of output metrics that aim to depict the individual banks and the system's stability. These metrics are presented in the bottom row in Fig. 3. We briefly explain these metrics below.

A- **DistressRank**
DistressRank provides a convenient way to depict the systemic vulnerability of each bank in the system. It is estimated based on the relative distress matrix and thus reflects the relative vulnerability of each bank to the distress of its counterparties. Banks with higher DistressRank measure are more vulnerable to system-wide shocks than otherwise comparable banks. The exact method of estimating DistressRank is explained in more detail in Section 3.4.

B- **Distress Dependence Matrix**
The distress dependence matrix provides a more detailed method to examine the systemic vulnerability of each bank in the system. In particular, for each pair of banks in the system, we estimate the pairwise conditional probability of illiquidity. The matrix is row-wise, meaning that it shows the probability of illiquidity of the bank specified in the row, given that the bank specified in the column has become illiquid. Thus, it provides an indicator of distress contagion possibilities within the system.

C- **Default Dependence Matrix**
The default dependence matrix is another way to depict the dependency within the system in detail, while, at the same time linking illiquidity to insolvency. In particular, for each pair of banks in the system, we estimate the probability of insolvency of a given bank conditional on the other bank becoming illiquid. The matrix is also row-wise as it provides the probability of insolvency of the bank specified in the row, given that the bank specified in the column has become illiquid. Thus, it provides an indicator of default contagion possibilities within the system.

D- **Systemic Risk Matrix**
The previous metrics provide a convenient way to depict the systemic vulnerability and dependencies within the system. This is very important to assess the contagion possibilities in the system. The stress test also provides another way to do this through a systemic risk matrix which lends itself more to economic interpretation. In this matrix we quantify systemic vulnerability and impact in terms of expected economic loss. We explain the constituents of the systemic risk matrix in detail here as it was not introduced elsewhere.
Similar to previous matrices, each row represents the vulnerability of the bank in this row to the distress of other banks. Let V_{ij} be the expected loss of the bank in row i due to the distress of the bank in column j. Assuming that bank j has become illiquid, the loss that bank i encounters is equal to $[A_i^L(0) - A_i^L(T)]$ and in percentage terms it is $[(A_i^L(0) - A_i^L(T))/A_i^L(0)]$, where $A_i^L(0)$ and $A_i^L(T)$ are the total interbank liquid assets of bank i at times $t = 0$ and $t = T$, respectively. Then, the amount of expected liquidity loss can be estimated as

$$V_{ij} = (1 - R)\ \chi_j^L(0)\ \left[\frac{A_i^L(0) - A_i^L(T)}{A_i^L(0)}\right] \tag{16}$$

where R is the recovery rate and $\chi_j^L(0)$ is the probability of illiquidity of bank j at $t = 0$. We can then estimate the systemic expected liquidity loss of bank i as

$$V_i = \frac{A_i^L(0)}{\sum_i A_i^L(0)} \sum_j V_{ij} \tag{17}$$

This measure of systemic expected loss represents the systemic vulnerability of bank i measured as the probability-weighted expected liquidity loss of bank i due to the distress of other banks in the system. To enable comparability, this measure is weighted by the liquid assets of bank i to the total liquid assets in the system.
Similarly, let I_{ij} be the relative impact of bank i on bank j which represents the expected loss that the distress of bank i can induce to bank j. We can estimate this amount as

$$I_{ij} = (1 - R)\ \chi_i^L(0)\ \left[\frac{A_j^L(0) - A_j^L(T)}{A_j^L(0)}\right] \tag{18}$$

We can then estimate the systemic impact of bank i as the total expected liquidity loss caused to all other banks due to the distress of bank i, as follows

$$I_i = \sum_j \frac{A_j^L(0)}{\sum_i A_i^L(0)} I_{ij} \tag{19}$$

which represents the probability-weighted expected liquidity loss of other banks in the system due to the distress of bank i. Also, to enable comparability, this measure is weighted by the liquid assets of each bank j to the total liquid assets in the system. Finally, we provide a measure of the system-wide expected liquidity loss as

$$\Phi = \sum_i I_i \ = \sum_i V_i \tag{20}$$

where Φ is the probability-weighted systemic expected liquidity loss. This measure provides an indication of the system-wide stability. The higher the systemic expected loss, the lower the system stability.

Appendix provides a toy model to illustrate the dynamics of the stress test using simulated data of a simplified banking system.

6. Empirical application

In this section, we provide an overview of the data used and the main results of applying the stress test framework outlined in Section 5 to the US banking system.

6.1. Data and interbank network construction

The data used to implement the stress test is related to the largest 25 bank holding companies in the US based on interbank derivatives activities as of December 31, 2020.[1] For each holding company (bank henceforth), we obtain data about balance sheet holdings, liquidity coverage ratios, and derivatives exposures. The balance sheet data is collected from the Consolidated Financial Statements of banks (FR Y-9C reports) provided by the National Information Centre.[2] From these reports we extract information about total assets, total liabilities, derivatives assets and liabilities, and equity. We use the Quarterly Report on Bank Derivatives Activities from the Office of the Comptroller of the Currency to obtain data about the interbank exposures of each bank.[3] The data about liquidity coverage ratio is hand collected from the annual and quarterly reports of each bank. From these reports we collect the reported amounts of high quality liquid assets, net cash outflows expected over the next 30 days, and the liquidity coverage ratio of each bank.

We use the interbank derivatives exposures as they represent liquidity flows between banks and are included in calculating the liquidity coverage ratio that banks disclose in their reports (BCBS, 2013b). Any change in the amounts of derivatives assets or liabilities leads to changes in the estimated liquidity coverage ratio, and hence can be used as a way to monitor distress propagation within the interbank market. The network of derivatives assets and liabilities within the interbank market can be represented by the following matrix:

$$A^B = \begin{bmatrix} A_{11} & \dots & A_{1j} & \dots & A_{1N} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ A_{i1} & \dots & A_{ij} & \dots & A_{iN} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ A_{N1} & \dots & A_{Nj} & \dots & A_{NN} \end{bmatrix}$$

where A_{ij} represents the derivatives assets of bank i with bank j or the derivatives liabilities of bank j to bank i. The matrix size is $N \times N$ where N is the number of banks. The sum of a row represents the derivatives assets of the respective bank where $A_i^B = \sum_j A_{ij}$ and the sum of a column represents the derivatives liabilities of the respective bank where $L_j^B = \sum_i A_{ij}$. Unfortunately, the network of interbank exposures is not observable, as banks and supervisors do not provide granular data about bilateral exposures.

Since information on the bilateral interbank exposures is essential for our analysis, we estimate these data to fill in the interbank matrix. To this end, we use the Minimum Density (MD) method suggested by Anand et al. (2015). The idea behind MD is to distribute each bank's assets and liabilities among the lowest possible number of counterparties. The economic rationale for this is that the interbank network appears to be constructed based on relationships and, as a result, is sparse (Cocco et al., 2009) as banks aim to minimise the costs of establishing and maintaining linkages including the costs of information processing and risk management. This rationale is supported by studies of real-world financial networks of the US (Bech and Atalay, 2010) and Germany (Craig and von Peter, 2014).

[1] We use the term holding companies to refer to all types of holding companies under the direct supervision of the Federal Reserve Board including domestic bank holding companies (BHC), savings and loan holding companies (SLHC), U.S intermediate holding companies (IHC) and securities holding companies (SHC).

[2] available at https://www.ffiec.gov/nicpubweb/nicweb/nichome.aspx.

[3] available at https://www.occ.gov/topics/capital-markets/financial-markets/derivatives/derivatives-quarterly-report.html.

6.2. Results of the stress test

The proposed stress test offers a variety of metrics to assess the system resilience. We provide here an overview of the system before applying any stress scenarios. Then, we provide the results of applying the first and second stress scenarios to assess the system stability and systemic interdependencies, respectively.

6.2.1. System profile

As discussed in Section 3, DistressRank provides a relative rank of all banks within a system with regard to their vulnerability to the distress of other banks. In addition, DistressRank can be estimated before applying any stress scenarios which offers the advantage of depicting the stability of the system at any point of time. We use this indicator to provide an overview of the current state of the US banking system, as of 31 December 2020. Fig. 4 shows the interbank market network which comprises the 25 individual banks included in our stress test. On this network, the size of each bank is scaled proportionally to its DistressRank. As illustrated, Citi Group is the most vulnerable bank, followed by JPMorgan Chase and Goldman Sacks, while the two least vulnerable banks are Suntrust Banks and DB USA Corporation. The other banks have comparable ranks. Further illustration of DistressRank is provided in Fig. 5.

There is a striking observation that can be noticed from Fig. 4 about banks' DistressRank. The asset size of a bank does not entail its systemic vulnerability. For example, Bank of America is the second largest bank measured by total assets; however, its DistressRank is comparable to other smaller banks such as RBC USA Group and Capital One. Moreover, even a bank's interbank assets or liabilities alone do not completely determine its DistressRank. An example of this is Citi Group which has the second largest interbank assets but ranks third based on DistressRank. In fact, DistressRank is affected by the interconnectedness within the interbank market in addition to the size of both interbank assets and liabilities. This finding has some important implications for the methodology of identifying global systemically important banks (G-SIBs) (BCBS, 2013a). In particular, the methodology should consider systemic distress as well as systemic importance in measuring a bank's interconnectedness as one of the indicators used to identify G-SIBs.

6.2.2. System stability

We turn now to assess the stability of the banking system following our proposed stress testing framework. To this end, we implement the first stress scenario (as explained in Section 5) in which a uniform shock is applied to all banks in order to assess the resilience of the banking system to macroeconomic shocks. We use a vector of shocks that ranges from 1% to 25% decline in the interbank liquid assets, which are extreme enough, yet plausible. We can think of a shock as resembling a severe change in risk free rates or widening in credit spreads that affect all banks simultaneously. The initial shock leads to a proportional reduction in the interbank assets of all banks leading to reductions in their liquidity positions. Then, the distress propagation process unfolds. The stress testing exercise provides a variety of output metrics which are outlined below.

Fig. 6 shows the number of distressed banks that become illiquid or insolvent following each shock. As expected, both numbers increase with the increase in the shock applied to the system. It is worth noting that the increase in both numbers is not linear. This is due to the fact that whether a distressed bank becomes illiquid or insolvent depends not only on its liquidity position but also on the liquidity position of its counterparties and the severity of the shock. As illustrated, banks are resilient to small shocks up to 4%, while some banks reach the illiquidity point starting from shocks of as low as 5%. The insolvency point is reached much later as the first time a bank becomes insolvent occurs at a shock level of 19%.

Fig. 7 provides a decomposition of systemic loss into first-round loss due to the initial shock and feedback loss occurring during second and upper rounds. Systemic loss is estimated at the system level as the total reduction in the value of banks' liquid assets. A striking observation that is shown in this figure is that the feedback loss can be as large as the initial loss due to the systemic shock. It can also exceed the initial loss at a high level of shocks. This observation highlights the need to consider the feedback loss due to interconnectedness between banks while designing macroprudential stress tests.

Another way to highlight the role of interconnectedness is to consider the relationship between DistressRank and systemic feedback loss at the bank level. We use DistressRank as a measure of systemic distress that captures interconnectedness, while a bank's systemic feedback loss is estimated as its share in the total feedback loss at the system level due to a specific shock. We limit the analysis here to a shock size of 10%. The result of this exercise is shown in Fig. 8. As illustrated, there seems to be a positive relationship between the DistressRank of a bank and its systemic feedback loss. To investigate this further, we run a simple regression of systemic feedback loss on DistressRank. The results show a positive slope which is significant at a 95% level with adjusted R^2 of 67%. This result confirms the importance of considering interconnectedness in designing macroprudential stress tests.

Finally, we illustrate the resilience of the system to shocks by tracing the change in the probability of illiquidity and the probability of insolvency of each bank following a specific shock. Figs. 9 and 10 show, for each bank, the change in probability of illiquidity and the change in probability of insolvency, respectively. Again, we limit the analysis to a shock size of 10% of interbank assets. As can be seen clearly from these figures, both probabilities show remarkable increase with almost all banks having higher probabilities of illiquidity and insolvency following the shock. While some banks become illiquid following the shock, some of them see their probability of insolvency nearly doubled.

6.2.3. Systemic interdependencies

So far, our analysis of stability has focused on the resilience of the system to a system-wide shock that represents a macroeconomic shock. We extend the analysis here to examine the interdependencies within the system. To this end, we implement the second stress scenario which involves shocking banks sequentially (see Section 5 for more details). The results of this exercise are shown below.

A- Systemic Distress Dependence

The distress dependence matrix provides insight into the interlinkages between banks and how vulnerable they are to the distress of each other. In particular, the output shown by this matrix can be viewed as the conditional change in the probability of illiquidity of the bank in the row relative to the bank in the column. In Fig. 11, we present the distress dependence matrix estimated for the group of 25 US banks included in the stress test. In this matrix, each cell represents the percentage change in the probability of illiquidity of the bank in the row given that the bank in the column has become illiquid. The diagonal of this matrix represents the implied percentage change in the probability of illiquidity of a given bank when this bank itself becomes illiquid. For better illustration, we provide the matrix as a heatmap. As can be seen from the matrix, distress dependence is higher among banks that are located at the upper left quadrant of the matrix. Put differently, large changes in the probability of illiquidity are associated with banks that have large interbank exposures with each other. For example, JP Morgan is more vulnerable to the distress of Citi Group, Goldman Sachs, and Bank of America compared to other banks in the sample. Another interesting observation is that the four most vulnerable banks; namely, JP Morgan, Citi Group, Goldman Sachs, and Morgan Stanley, derive their vulnerability from each other. This is explained by the fact that the exposure of these banks to each other represents a large portion of their overall interbank assets. Any distress that arises with one of them will definitely lead to a serious liquidity problem with the others. It is also worth noting that banks in the lower right quadrant seem to be

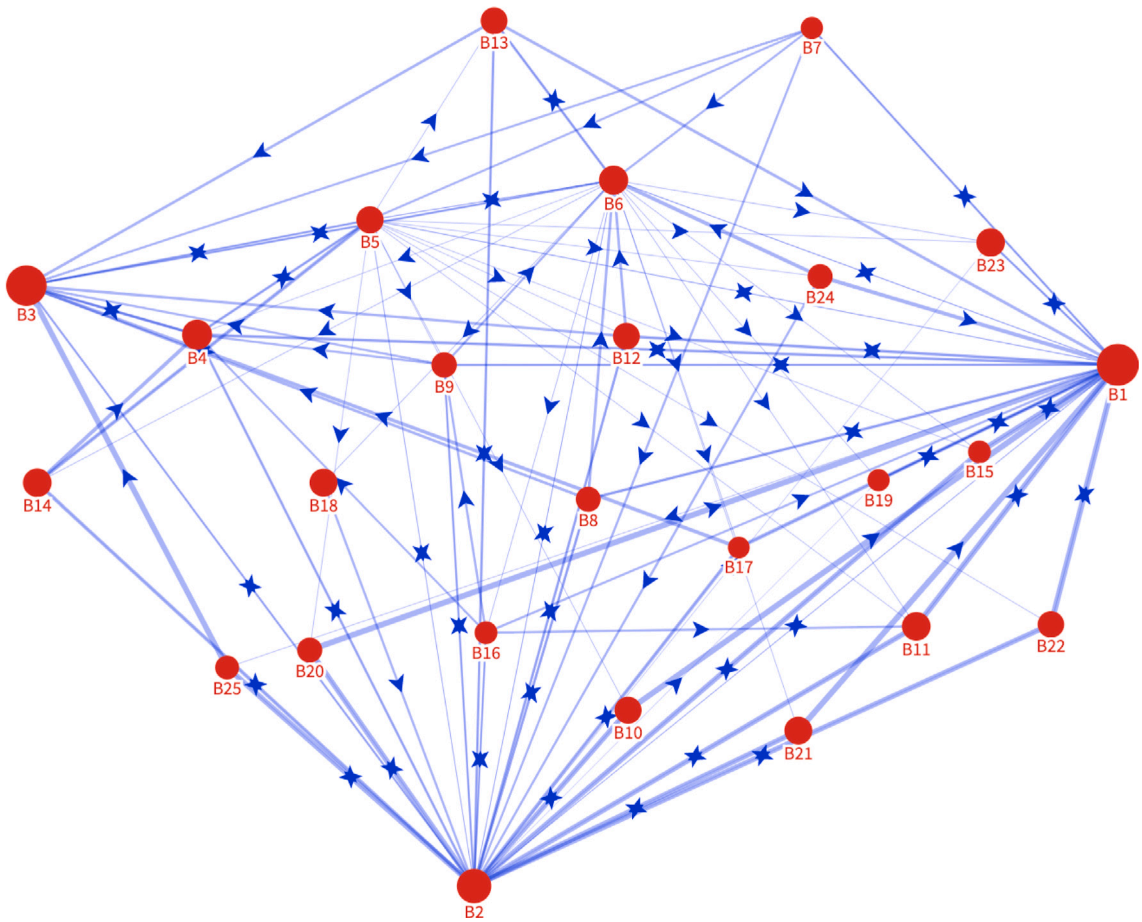


Fig. 4. The distress network and DistressRank of individual banks in the system. Nodes represent banks and links represent interbank exposures. The size and colour of each node are scaled proportionally to the value of its DistressRank. The width and colour of each link are scaled proportionally to the value of relative distress induced by the bank at the start of the link to the bank at the end of the link. Number of banks is 25. Banks' names are coded from B1 to B25 where B1: JPMorgan Chase & CO.; B2: Citigroup Inc.; B3: Goldman Sachs Group, Inc.; B4: Morgan Stanley; B5: Bank of America Corporation; B6: Wells Fargo & Company; B7: Mizuho Americas LLC; B8: SMBC Americas Holdings, Inc.; B9: HSBC North America Holdings Inc.; B10: State Street Corporation; B11: Bank of New York Mellon Corporation; B12: US Bancorp; B13: RBC US Group Holdings LLC; B14: Barclays US LLC; B15: PNC Financial Services Group, Inc.; B16: TD Group US Holdings LLC; B17: Northern Trust Corporation; B18: Truist Financial Corporation; B19: Credit Suisse Holdings (USA), Inc.; B20: Capital One Financial Corporation; B21: MUFG Americas Holdings Corporation; B22: Citizens Financial Group, Inc.; B23: BOK Financial Corporation; B24: Fifth Third Bancorp; and B25: Ameriprise Financial, inc.

resilient to the distress of each other mainly due to the fact that they have limited exposures to each other.

B- Systemic Default Dependence

The stress test output includes another interesting matrix called the default dependence matrix. This matrix examines the possibility that illiquidity distress evolves to become insolvency default. It is also similar to the distress dependence matrix in that it provides insight into the possibility of contagion within the system. The default dependence matrix is illustrated in Fig. 12 where each row represents the percentage change in the probability of insolvency of the bank in the row when the bank in the column becomes illiquid. Again, each cell can be viewed as the conditional change in the probability of insolvency of the bank in the row relative to the bank in the column. The diagonal of this matrix represents the implied percentage change in the probability of insolvency of a given bank when this bank itself becomes illiquid. For better illustration, the matrix is shown as a heatmap.

The same observations on the distress dependence matrix also apply here. The default dependence seems to be higher among banks in the upper left quadrant and lower among banks in the lower right quadrant. Again, this is due to concentration of exposure between big banks and each other or big banks and other smaller banks, while exposures between smaller banks and each other are limited. For example, Bank of America appears to be the most vulnerable bank to shocks from its counterparties and particularly from JP Morgan and Citi Group. If JP Morgan becomes illiquid, the probability of insolvency of Bank of America increases by 185%. Any distress at JP Morgan will definitely lead to a serious liquidity problem with its counterparties.

C- Systemic Risk Matrix

The systemic risk matrix provides an estimation of systemic expected loss of each bank due to other banks' distress. It provides another way to study the interdependence among banks by quantifying the systemic expected economic loss due to systemic distress between pairs of banks. Each cell in the matrix represents the expected loss of the bank in the row given that the bank in the column has become illiquid. The diagonal of this matrix represents the implied systemic loss of a given bank when this bank itself becomes illiquid. The matrix is shown in Fig. 13 as a heatmap. In this matrix, SysImpact stands for systemic impact of the bank in the column and is estimated as in Eq. (19) while SysVul stands for systemic vulnerability of the bank in the row and is estimated as in Eq. (17). The cell in the intersection of SysImpact and SysVul represents the systemic loss which is estimated as in Eq. (20). As explained earlier, to enable comparability, SysVul and SysImpact are estimated as a percent of the total liquid assets in the system.

The systemic risk matrix confirms the same results obtained by analysing distress and default dependence matrices. As would be expected, systemic loss is more concentrated in the upper left quadrant and limited among banks in the lower right quadrant. Counterparties of large banks are more vulnerable to systemic risk compared to

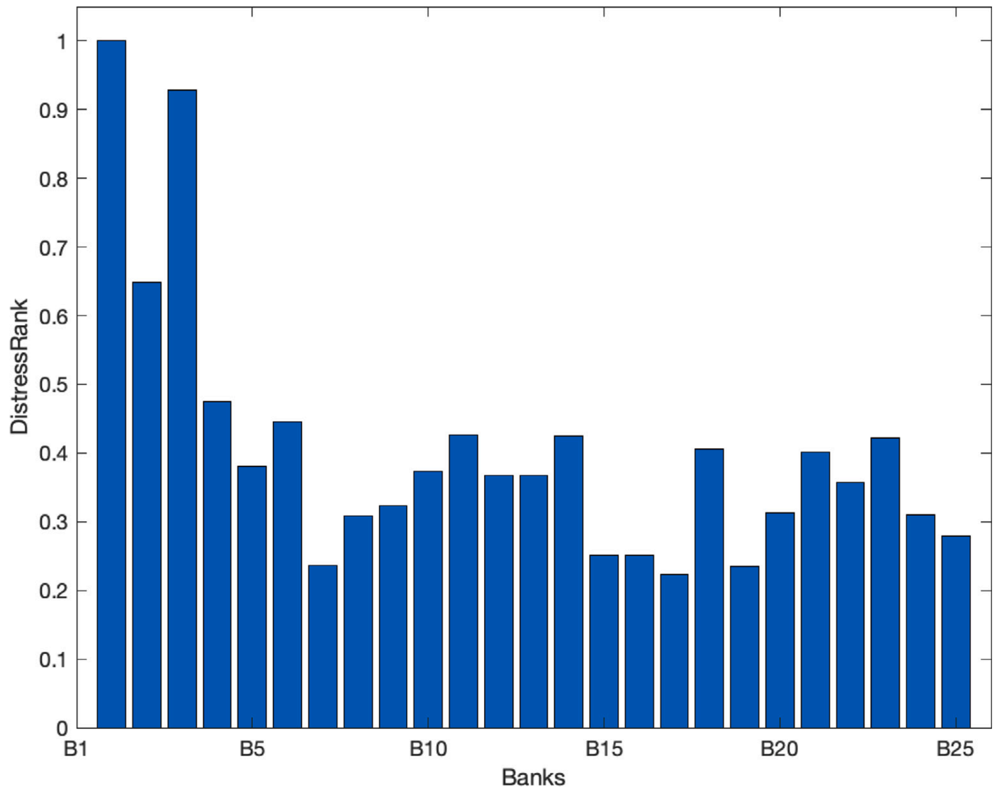


Fig. 5. The DistressRank of individual banks in the system. Number of banks is 25. Bank names are as in Fig. 4.

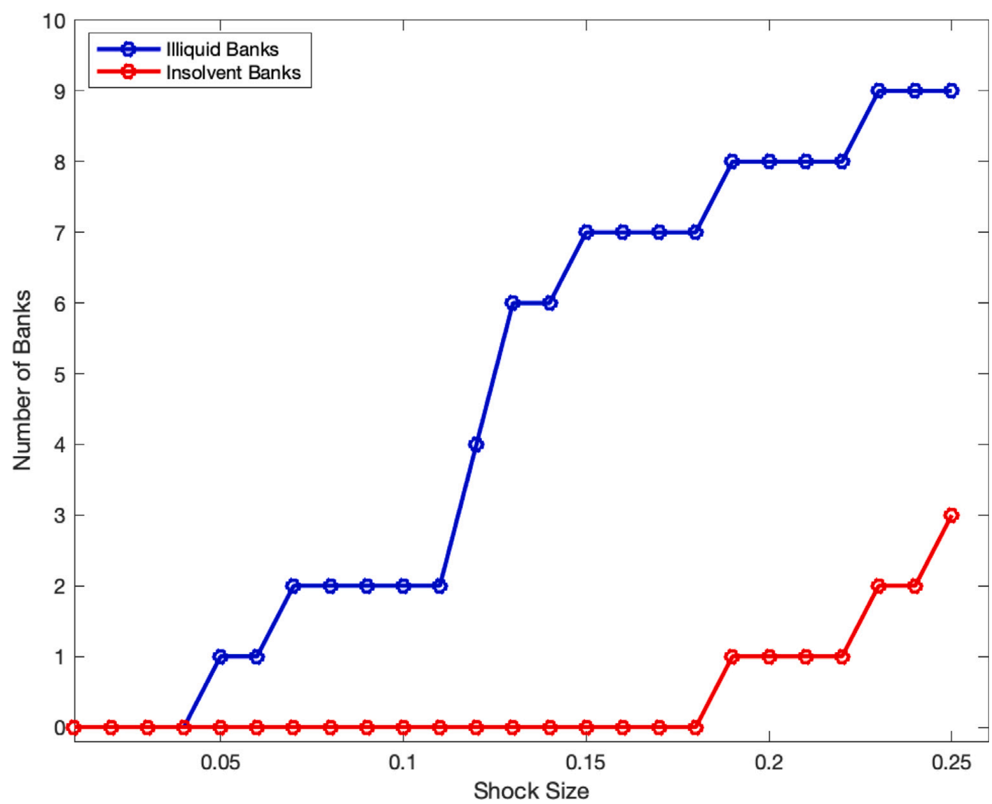


Fig. 6. Number of Illiquid and Insolvent Banks due to a specific shock to the interbank assets. Shock size ranges from 1% to 25% of interbank assets.

others. If JP Morgan becomes illiquid, it induces a 1.54% system-wide expected loss which represents its systemic impact on the system. Goldman Sachs has a systemic vulnerability of 1.21% which represents its probability-weighted expected loss from its counterparties. The expected systemic loss is 6.58% which represents a system-wide stability measure. The higher this indicator is the more fragile the system is,

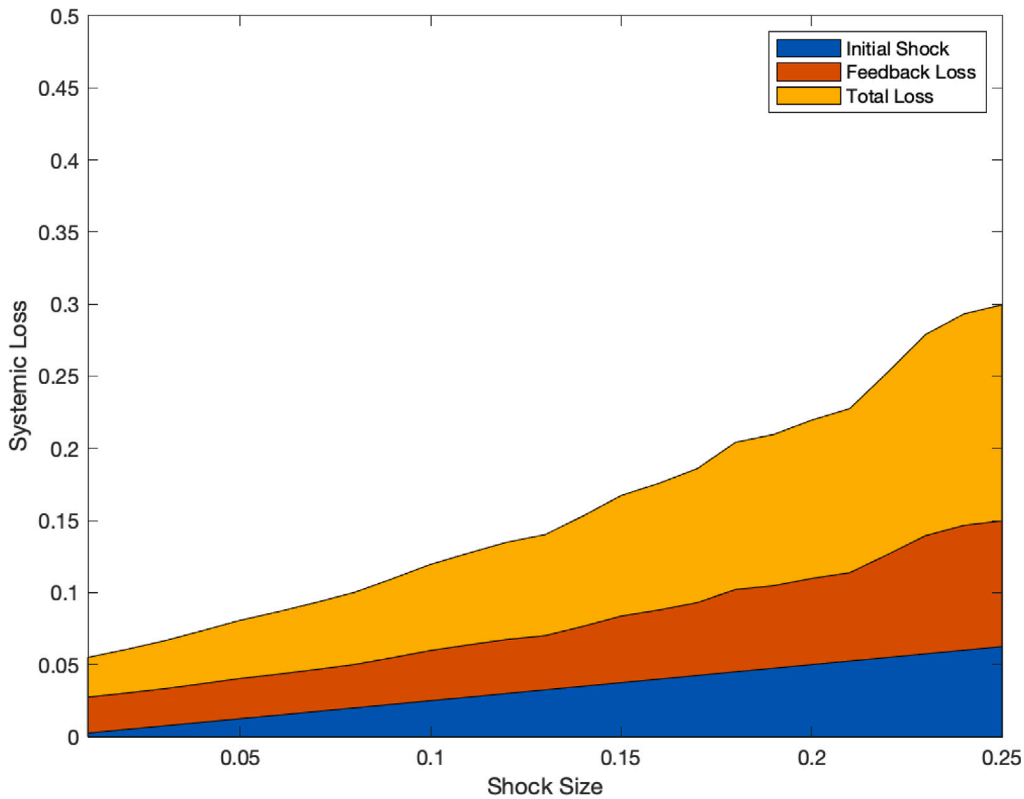


Fig. 7. Decomposition of systemic loss into first-round loss due to the initial shock and feedback loss occurring during second and upper rounds. Shock size ranges from 1% to 25% of interbank assets. Systemic loss is estimated at the system level as the total reduction in the value of banks' assets.

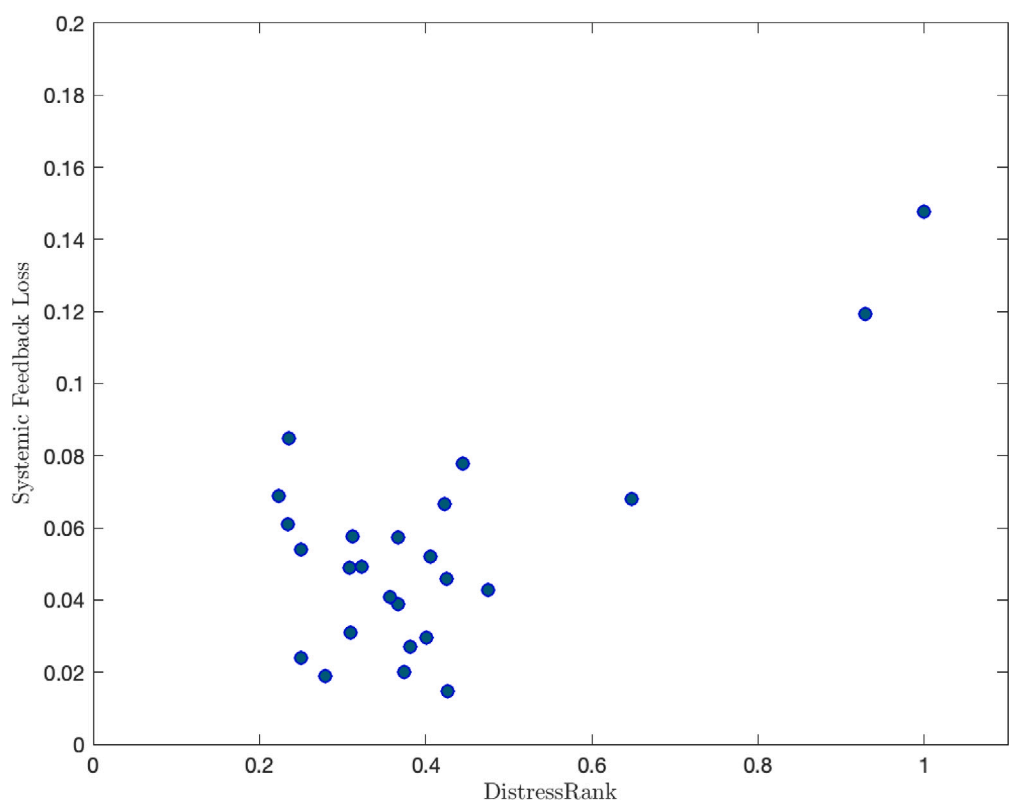


Fig. 8. DistressRank and systemic feedback loss. A bank's systemic feedback loss is estimated as its share in the total feedback loss at the system level due to a specific shock. Shock size is 10% of interbank assets. Each circle in the figure represents a bank.

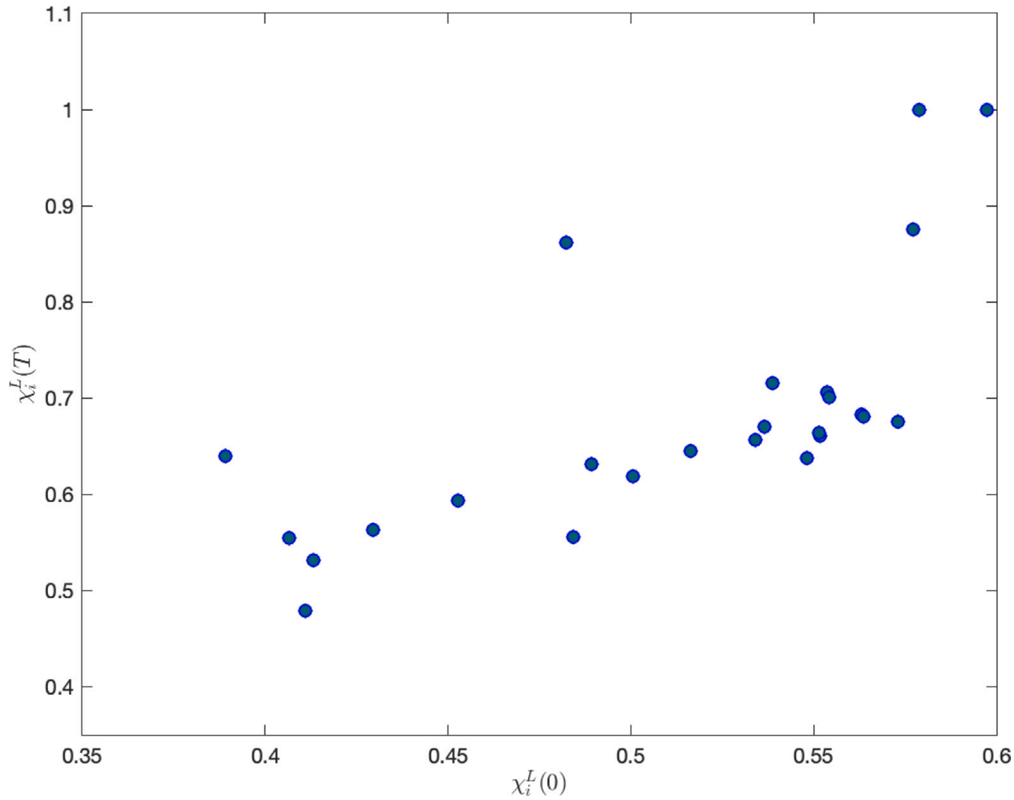


Fig. 9. Change in probability of illiquidity for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^L(0)$ and $\chi_i^L(T)$ are the probability of illiquidity of bank i before and after applying the shock to the system, respectively. Each circle in the figure represents a bank.

Fig. 10. Change in probability of insolvency for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^S(0)$ and $\chi_i^S(T)$ are the probability of insolvency of bank i before and after applying the shock to the system, respectively. Each circle in the figure represents a bank.

Bank	JPM	CITI	GS	MS	BOA	WF	MIZ	SMBC	HSBC	SS	BNM	USB	RBC	BAR	PNC	TD	NTR	TRST	CRS	CAP	MUFG	CIT	BOK	FITH	AMPR	
JPMORGAN CHASE & CO	250	149	137	120	152	120	140	171	94	56	65	92	97	91	77	98	38	61	56	73	42	58	50	24	62	JPM
CITIGROUP	81	181	172	124	150	87	56	140	75	127	55	43	143	35	74	110	39	107	94	76	58	27	19	12	84	CITI
GOLDMAN SACHS GROUP	51	113	320	130	77	46	83	89	138	127	95	80	26	116	25	10	22	37	13	93	60	55	31	96	45	GS
MORGAN STANLEY	94	144	163	154	76	59	104	37	137	148	43	51	66	80	87	96	24	85	96	95	59	10	50	7	85	MS
BANK OF AMER CORP	47	63	103	60	87	140	83	64	83	16	69	35	78	45	25	81	13	86	69	56	44	67	42	48	96	BOA
WELLS FARGO & CO	101	66	91	121	86	234	123	140	59	173	57	114	59	105	62	38	42	44	15	89	8	74	67	86	59	WF
MIZUHO AMERS LLC	75	81	52	112	140	123	135	98	90	105	67	75	64	102	90	86	83	82	19	81	26	43	55	87	56	MIZ
SMBC AMERICAS	157	147	138	100	29	65	87	71	62	66	95	92	22	22	63	58	88	63	68	23	49	15	51	20	73	SMBC
HSBC N AMER HOLDS	102	107	45	19	91	152	173	69	207	129	25	42	23	18	45	95	86	83	47	18	59	29	13	44	33	HSBC
STATE STREET CORP	155	50	38	119	134	126	102	87	136	226	90	117	70	13	47	107	49	75	51	33	71	10	83	12	56	SS
BANK OF NY MELLON COR	40	111	29	102	119	93	102	40	55	80	38	78	77	24	81	61	55	41	50	36	19	32	32	26	50	BNM
U.S. BANCORP	10	53	106	90	77	51	94	124	9	91	46	94	11	39	64	28	9	32	33	48	56	11	27	30	18	USB
RBC USA HOLDCO CORP	49	78	87	109	44	97	90	65	46	75	58	13	99	45	6	72	63	11	43	37	40	36	17	17	29	RBC
BARCLAYS US LLC	66	64	32	84	92	14	54	113	66	96	82	50	64	103	64	60	56	26	29	16	10	27	27	11	46	BAR
PNC FNCL SVC GROUP	61	50	79	84	48	48	77	72	70	19	58	30	67	80	93	24	58	17	17	2	40	33	19	12	19	PNC
TD GRP US HOLDS LLC	68	77	40	74	106	64	100	105	85	96	11	27	21	31	40	18	21	6	17	21	18	13	29	19	37	TD
NORTHERN TR CORP	66	40	119	42	99	111	115	61	115	118	72	21	43	22	25	27	74	33	33	42	35	36	31	37	24	NTR
TRUIST FINANCIAL CORP	37	87	41	88	40	71	82	27	55	52	45	63	73	36	7	24	27	59	16	34	28	15	10	22	38	TRST
CREDIT SUISSE HOLD USA	21	51	65	45	106	100	34	8	99	123	11	52	31	23	27	21	45	10	6	14	33	7	32	8	32	CRS
CAPITAL ONE FC	26	106	74	67	114	88	57	88	12	22	2	59	47	65	56	45	49	6	15	44	13	24	14	11	33	CAP
MUFG AMERS HOLDS CORP	34	49	74	52	30	63	69	34	73	33	35	32	22	19	11	20	39	37	27	6	21	38	24	22	13	MUFG
CITIZENS FNCL GRP	58	70	81	124	73	93	49	51	117	91	39	68	56	9	20	21	24	21	36	19	35	33	15	40	6	CIT
BOK FINANCIAL CORP	88	108	48	65	52	30	11	123	42	30	51	50	58	63	25	29	33	25	12	22	20	34	64	38	18	BOK
FIFTH THIRD BANCORP	68	45	110	66	28	38	51	63	62	86	50	52	19	49	45	22	18	7	32	13	27	11	6	71	19	FITH
AMERIPRISE FINANCIAL	69	38	25	91	102	22	85	88	91	10	28	33	18	15	18	46	17	26	9	39	36	30	9	12	80	AMPR

Fig. 11. Distress dependence matrix. Each cell in the matrix represents the percentage change in the probability of illiquidity of the bank in the row when the bank in the column becomes illiquid. The diagonal represents the implied percentage change in the probability of illiquidity of a given bank when it becomes illiquid. Bank names are as in Fig. 4. The matrix is presented as a heatmap where cells' colour is scaled from green for low values to red for high values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Bank	JPM	CITI	GS	MS	BOA	WF	MIZ	SMBC	HSBC	SS	BNM	USB	RBC	BAR	PNC	TD	NTR	TRST	CRS	CAP	MUFG	CIT	BOK	FITH	AMPR	
JPMORGAN CHASE & CO	669	151	90	90	138	152	91	80	161	100	58	85	49	104	44	105	25	77	43	75	49	37	33	39	105	JPM
CITIGROUP	143	308	86	91	45	42	76	99	115	93	100	78	31	65	96	91	106	71	53	89	53	51	55	57	81	CITI
GOLDMAN SACHS GROUP	108	124	318	68	120	68	115	93	73	78	62	23	132	36	64	80	76	55	5	93	39	75	81	72	72	GS
MORGAN STANLEY	130	117	78	374	125	78	15	96	118	28	69	79	65	120	100	107	65	78	63	88	53	51	58	15	26	MS
BANK OF AMER CORP	185	157	56	76	390	45	60	167	92	79	75	59	98	47	56	83	65	72	53	44	8	90	81	79	32	BOA
WELLS FARGO & CO	142	27	114	66	44	218	81	137	79	30	87	36	63	89	34	82	53	42	25	66	80	71	38	92	12	WF
MIZUHO AMERS LLC	134	106	68	158	65	29	476	110	69	159	81	72	115	103	77	83	73	81	64	85	8	85	41	55	62	MIZ
SMBC AMERICAS	106	73	94	132	90	114	125	258	116	121	38	47	78	27	58	77	48	52	87	59	24	78	76	24	36	SMBC
HSBC N AMER HOLDS	50	67	66	70	97	108	144	65	460	90	84	81	57	49	112	36	28	75	18	60	30	64	40	75	66	HSBC
STATE STREET CORP	94	21	98	101	66	131	111	84	156	173	41	86	27	93	46	104	41	35	45	81	35	42	51	33	53	SS
BANK OF NY MELLON CORP	43	24	90	141	78	55	28	16	52	103	134	73	28	67	85	39	46	29	37	10	19	31	41	15	35	BNM
U.S. BANCORP	71	36	121	118	82	44	71	93	38	71	41	109	44	73	75	50	49	6	17	12	40	45	3	44	16	USB
RBC USA HOLDCO CORP	90	18	74	27	67	80	51	40	137	25	24	11	248	77	41	27	22	13	44	37	31	34	9	42	38	RBC
BARCLAYS US LLC	27	87	45	117	72	37	104	65	44	35	49	69	88	155	42	30	35	16	22	6	24	22	8	22	15	BAR
PNC FNCL SVC GROUP	37	38	88	32	97	104	73	98	33	55	54	58	31	55	179	3	13	4	29	30	34	8	18	11	11	PNC
TD GRP US HOLDS LLC	53	75	116	108	113	50	113	45	43	40	35	39	34	65	37	77	17	25	28	2	20	6	30	3	17	TD
NORTHERN TR CORP	92	49	129	108	52	72	47	107	22	61	47	57	44	33	66	58	119	14	23	18	6	9	10	3	18	NTR
TRUIST FINANCIAL CORP	104	36	19	73	78	54	105	123	66	66	53	50	4	56	30	42	26	28	22	27	43	30	13	31	15	TRST
CREDIT SUISSE HOLD USA	127	22	97	107	37	27	35	108	89	93	38	60	29	29	28	30	45	31	52	25	8	3	23	12	32	CRS
CAPITAL ONE FC	100	113	88	68	102	65	93	69	37	61	21	70	21	24	40	56	7	25	10	49	17	16	6	34	13	CAP
MUFG AMERS HOLDS CORP	91	49	68	55	102	57	98	83	40	86	46	70	78	33	39	54	30	26	10	19	122	32	16	20	22	MUFG
CITIZENS FNCL GRP	132	99	56	62	28	58	96	77	31	97	56	27	12	43	61	52	41	27	19	16	32	89	21	7	21	CIT
BOK FINANCIAL CORP	82	87	53	47	63	36	29	124	86	41	54	6	49	15	44	33	34	12	21	28	15	26	119	10	21	BOK
FIFTH THIRD BANCORP	29	45	97	62	20	105	86	32	54	60	49	35	51	30	28	52	30	11	27	11	14	22	9	51	27	FITH
AMERIPRISE FINANCIAL	66	51	48	45	68	100	121	39	77	122	35	33	35	37	38	15	42	13	36	39	6	24	38	8	65	AMPR

Fig. 12. Default dependence matrix. Each cell in the matrix represents the percentage change in the probability of insolvency of the bank in the row given that the bank in the column has become illiquid. The diagonal represents the implied percentage change in the probability of insolvency of a given bank when it becomes illiquid. Bank names are as in Fig. 4. The matrix is presented as a heatmap where cells' colour is scaled from green for low values to red for high values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

representing more interconnectedness and/or higher probabilities of distress.

Another interesting finding from the systemic risk matrix is related to the relationship between systemic impact (SysImpact row) and systemic vulnerability (SysVul column) of each bank. We illustrate this relationship in Fig. 14. While most banks seem to be vulnerable to shocks from other banks as measured by their expected loss, not all banks have significant systemic impact as the systemic impact values of smaller banks seem to be negligible. Only big banks in the sample have systemic impact levels that are comparable to their systemic vulnerability levels. In addition, banks do not have the same ranking based on systemic impact and systemic vulnerability indicators. This finding has important implications for designing a macroprudential stress test that aims to consider interconnectedness. In particular, using measures of systemic impact is not sufficient to identify the vulnerabilities within a system. A comprehensive analysis of interconnectedness should consider systemic vulnerability as well as systemic impact of the financial institutions in the system.

7. Conclusion

This paper proposes a macroprudential stress testing approach and illustrates its empirical application on a data set of the US banking system. The innovative features of the proposed macroprudential stress test were inspired by the recent regulatory recommendations to strengthen the systemic focus and to more deeply consider the interactions between liquidity and solvency risks in designing effective macroprudential stress tests. In particular, the proposed approach provides a tool for the banking system supervisors to analyse the current

Bank	JPM	CITI	GS	MS	BOA	WF	MIZ	SMBC	HSBC	SS	BNM	USB	RBC	BAR	PNC	TD	NTR	TRST	CRS	CAP	MUFG	CIT	BOK	FITH	AMPR	SysVul	
JPMORGAN CHASE & CO	3.73	0.58	1.53	0.23	2.32	2.15	0.03	0.01	0.08	0.00	0.02	0.05	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	1.92	JPM
CITIGROUP	0.81	2.42	0.97	1.19	2.33	0.38	0.26	0.01	0.29	0.05	0.01	0.47	0.02	0.28	0.05	0.01	0.00	0.01	0.01	0.02	0.00	0.02	0.00	0.00	0.03	0.83	CITI
GOLDMAN SACHS GROUP	2.91	0.80	2.25	0.35	0.62	0.40	0.09	0.03	0.32	0.01	0.11	0.06	0.01	0.03	0.06	0.02	0.00	0.01	0.05	0.02	0.03	0.02	0.01	0.02	0.00	1.21	GS
MORGAN STANLEY	0.31	0.26	2.90	2.40	0.20	0.16	0.03	0.01	0.12	0.00	0.03	0.02	0.00	0.01	0.01	0.04	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.01	0.00	1.20	MS
BANK OF AMER CORP	2.85	1.18	0.64	0.70	2.61	0.25	0.73	0.00	0.07	0.01	0.01	0.09	0.01	0.05	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.70	BOA
WELLS FARGO & CO	0.26	0.41	0.15	0.10	0.15	0.86	0.02	0.00	0.05	0.00	0.00	0.09	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	WF
MIZUHO AMERS LLC	1.29	0.10	0.25	0.26	0.04	0.03	2.13	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	MIZ
SMBC AMERICAS	2.61	0.20	0.50	0.53	0.08	0.07	0.01	1.99	0.03	0.00	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	SMBC
HSBC N AMER HOLDS	0.50	1.41	0.22	0.26	0.34	0.08	0.05	0.06	2.93	0.01	0.00	0.10	0.00	0.06	0.01	0.06	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.06	HSBC
STATE STREET CORP	0.04	0.05	0.02	0.02	0.18	0.01	0.02	0.02	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SS
BANK OF NY MELLON COR	0.31	0.20	0.08	0.09	0.18	0.03	0.02	0.02	0.01	0.00	1.40	0.02	0.00	0.01	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	BNM
U.S. BANCORP	0.13	0.33	0.06	0.07	0.35	0.03	0.04	0.04	0.01	0.00	0.00	0.86	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	USB
RBC USA HOLDCO CORP	0.08	0.20	0.04	0.05	0.22	0.13	0.02	0.03	0.01	0.00	0.00	0.01	0.77	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	RBC
BARCLAYS US LLC	0.08	0.27	0.05	0.05	0.16	0.12	0.02	0.02	0.01	0.00	0.00	0.02	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	BAR
PNC FNCL SVC GROUP	0.30	0.04	0.06	0.07	0.12	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	PNC
TD GRP US HOLDS LLC	0.21	0.92	0.12	0.15	0.22	0.05	0.03	0.04	0.04	0.01	0.00	0.06	0.00	0.04	0.01	1.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	TD
NORTHERN TR CORP	0.19	0.08	0.04	0.05	0.02	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NTR
TRUIST FINANCIAL CORP	0.25	0.33	0.08	0.09	0.13	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	TRST
CREDIT SUISSE HOLD USA	0.38	0.28	0.10	0.11	0.07	0.02	0.01	0.01	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.00	0.00	0.00	0.02	CRS
CAPITAL ONE FC	0.03	0.12	0.02	0.02	0.04	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	CAP
MUFG AMERS HOLDS CORP	0.11	0.47	0.07	0.08	0.11	0.17	0.02	0.02	0.02	0.00	0.00	0.03	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.58	0.00	0.00	0.00	0.00	0.01	MUFG
CITIZENS FNCL GRP	0.25	0.33	0.08	0.09	0.13	0.02	0.02	0.02	0.02	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.00	0.00	CIT
BOK FINANCIAL CORP	0.30	0.02	0.06	0.06	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.01	BOK
FIFTH THIRD BANCORP	0.03	0.02	0.01	0.01	0.15	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	FITH
AMERIPRISE FINANCIAL	0.04	0.19	0.03	0.03	0.04	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	AMPR
SysImpact	1.54	0.68	1.31	0.72	0.99	0.66	0.12	0.03	0.15	0.01	0.04	0.12	0.02	0.05	0.02	0.02	0.00	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	6.58	

Fig. 13. Systemic risk matrix. Each cell in the matrix represents the expected loss of the bank in the row given that the bank in the column has become illiquid. SysImpact stands for systemic impact of the bank in the column. SysVul stands for systemic vulnerability of the bank in the row. The cell in the intersection of SysImpact and SysVul represents the systemic loss. To enable comparability, SysVul and SysImpact are estimated as a percent of the total liquid assets in the system. Bank names are as in Fig. 4. The matrix is presented as a heatmap where cells' colour is scaled from green for low values to red for high values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

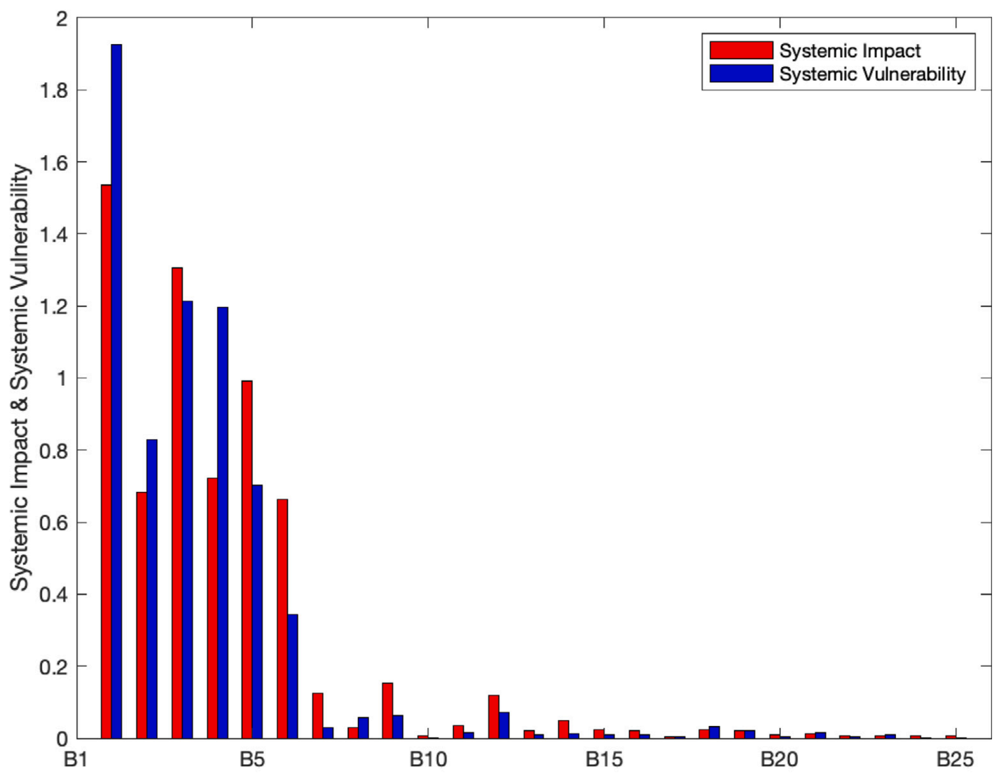


Fig. 14. The systemic impact and systemic vulnerability of individual banks.

state of the system stability. The empirical application of the stress test shows how it can be effectively used to identify the systemic vulnerability of individual banks as well as the resilience of the system as a whole to economic risks. The findings confirm the need to consider interconnectedness in designing macroprudential stress tests. At the bank level, the results confirm that interlinkages play a significant role in identifying individual banks' vulnerability. On this premise, we propose DistressRank as a measure of the systemic distress of a bank. The results show that a bank's DistressRank is associated with its systemic feedback loss. At the system level, the systemic loss due to feedback loops was shown to be significant compared to the direct loss that results from the initial shock to the system. Ignoring these feedback effects may lead to a significant underestimation of systemic loss.

Moreover, the proposed approach provides a tool for the banking system supervisors to monitor the evolution of contagion and systemic

Table A.1
Balance sheets of banks.

	Assets			Liabilities			
	A^B	A^O	A^F	L^B	L^O	L^F	E
Bank 1	20	20	60	30	2.5	55.5	12
Bank 2	25	15	60	25	5	56	14
Bank 3	30	20	50	20	10	54	16
Sum	75	55	170	75	17.5	165.5	42

risk within the system due to endogenous or exogenous shocks. Applying the stress test framework to the US banking system shows how it can be effective for monitoring and assessing interdependence among banks. Our findings provide an insight into the possibilities of distress propagation within the system. An important finding that is shown here is that banks that are not directly connected together through interbank assets or liabilities are still subject to distress from each other through common counterparties. These findings can form the basis for intervention by policy makers in case a specific bank has become distressed and there is a need to identify banks that are likely to be affected the most.

Although the framework demonstrated here was applied using a reconstructed network of interbank exposures, these data were sufficient to highlight the merit of the proposed stress test framework. However, we have to acknowledge that using granular supervisory bank data (e.g. FR 2052a daily liquidity report in the US) may change the results related to risks of individual banks in our sample even though we would expect to obtain similar results on systemic vulnerabilities in the banking system. Also, given that this stress test aims to identify the raw systemic impact of the proposed stress scenarios, it does not consider some important risk mitigation techniques in the interbank market. This includes collateralization requirements in interbank repo transactions that could limit the systemic impact of some shocks. Also, the existence of central counterparties could help reduce counterparty credit risk in the interbank market due to the daily initial and variation margins. This stress testing framework also takes the perspective of the banking system supervisor as it aims to help in making the intervention decisions related to which banks to support and by how much. Therefore, it identifies the systemic impact without considering the role of the central bank in providing liquidity to the banks and markets.

In conclusion, the proposed macroprudential stress test can reveal the systemic vulnerabilities in a banking system, giving policymakers insights into the system resilience. Extending the analysis to include additional banks would provide a tool for policymakers to more comprehensively monitor and regulate the interdependencies in the banking system and the resilience of the system as a whole. Another avenue for extending the work done here is to consider the reactions of banks to shocks and the possibilities of deleveraging and its impact on the magnitude of systemic loss.

Appendix. Toy model

This appendix provides an illustration of the stress test framework based on simulated data of three banks. Appendix A.1 outlines the banking system profile. Appendices A.2 and A.3 provide the results of the two stress scenarios discussed in Section 5.1.

A.1. System profile

Table A.1 provides information on the balance sheet of three banks that represent the banking system. These banks interact with each other and have a network of interbank assets A^B and liabilities L^B. Table A.2 further decomposes the interbank assets and liabilities of banks where the value of each cell represents an asset of the bank in the row and a liability for the bank in the column.

Table A.2
Interbank assets and liabilities matrix.

	Bank 1	Bank 2	Bank 3
Bank 1		15	5
Bank 2	10		15
Bank 3	20	10	

Table A.3
Liquidity coverage matrix.

	Liquidity coverage matrix			Liquidity coverage ratio
	Bank 1	Bank 2	Bank 3	
Bank 1		0.25	1.13	1.23
Bank 2	1.00		0.50	1.33
Bank 3	1.00	1.67		1.67

Table A.4
Distress matrix.

	Distress matrix			DistressRank
	Bank 1	Bank 2	Bank 3	
Bank 1		1.00	1.00	0.55
Bank 2	4.00		0.60	0.83
Bank 3	0.89	2.00		0.64

Table A.5
System stability profile.

	Illiquidity point	Insolvency point	Probability of illiquidity	Probability of insolvency
Bank 1	1	0.63	24.02%	0.54%
Bank 2	1	0.53	15.25%	0.02%
Bank 3	1	0.47	9.95%	0.03%

Table A.6
Interbank assets and liabilities matrix following stress scenario 1.

	Bank 1	Bank 2	Bank 3
Bank 1		13.5	4.5
Bank 2	9		13.5
Bank 3	18	9	

Table A.7
Balance sheets of banks following stress scenario 1.

	Assets			Liabilities			
	A^B	A^O	A^F	L^B	L^O	L^F	E
Bank 1	18	20	60	30	2.5	55.5	10
Bank 2	22.5	15	60	25	5	56	11.5
Bank 3	27	20	50	20	10	54	13
Sum	67.5	55	170	75	17.5	165.5	34.5

Table A.8
Liquidity coverage matrix following stress scenario 1.

	Liquidity coverage matrix			Liquidity coverage ratio
	Bank 1	Bank 2	Bank 3	
Bank 1		0.20	1.05	1.17
Bank 2	0.90		0.40	1.25
Bank 3	0.80	1.53		1.57

Table A.9
Distress matrix following stress scenario 1.

	Distress matrix			DistressRank
	Bank 1	Bank 2	Bank 3	
Bank 1		1.11	1.25	0.66
Bank 2	5.00		0.65	0.91
Bank 3	0.95	2.50		0.76

Table A.10
System stability profile following stress scenario 1.

	Illiquidity point	Insolvency point	Probability of illiquidity	Change in probability of illiquidity	Probability of insolvency	Change in probability of insolvency
Bank 1	1	0.69	30.84%	28.38%	0.95%	76.67%
Bank 2	1	0.62	22.14%	45.15%	0.05%	157.75%
Bank 3	1	0.57	13.40%	34.69%	0.05%	90.06%

The information from balance sheets are then used to estimate the overall liquidity coverage ratio and relative liquidity coverage matrix as illustrated in Table A.3. Further, the distress matrix is then estimated based on the liquidity coverage matrix and DistressRank is estimated based on Eq. (6) and the results are shown in Table A.4. We then outline the system stability profile in Table A.5 where the illiquidity and insolvency points based on Eqs. (9) and (10), respectively. Also, the probabilities of illiquidity and insolvency are estimated based on Eqs. (12) and (14), respectively. As the system profile shows, while Bank 1 has the highest insolvency point which is associated with the highest probability of illiquidity and insolvency, Bank 3 seems to be the most stable bank with the lowest insolvency point and probability of illiquidity and very low probability of insolvency. Bank 2 comes in between based on these stability measures.

A.2. Stress scenario 1

Stress scenario 1 aims to study the overall system stability by applying a uniform shock to all banks in the system. We apply this by exposing the three banks to a shock that reduces their interbank assets by 10%. The affected interbank assets and liabilities matrix is shown in Table A.6. This leads to modified balance sheets as shown in Table A.7. We follow the same procedure as in Appendix A.1 above to estimate the liquidity coverage matrix (Table A.8), and the distress matrix together with the DistressRank (Table A.9).

The main results of the first stress scenario are shown in Table A.10. As can be seen, the 10% shock has led to impairment of the stability of all the three banks as shown by the increases in insolvency point, probability of illiquidity and probability of insolvency. However, on a relative basis, it seems that Bank 2 was affected the most by the shock as it has the highest percentage change in its probabilities of illiquidity (+45.15%) and insolvency (+157.75%). The second most affected was Bank 3, and the least affected was Bank 1. These results are very interesting as they follow the same order as the estimates of the systemic distress of the three banks as measured by DistressRank (see Table A.4). This shows that the systemic distress that results from the feedback loop in the interbank assets/liabilities network is the determining factor in the overall impact of uniform shock to the system.

A.3. Stress scenario 2

Stress scenario 2 aims to evaluate the systemic interdependence in the system. We apply this by sequentially exposing the three banks to a shock that reduces their interbank assets by a sufficient amount to make the bank illiquid. For example, Banks 1 is exposed to a 37% decline in its interbank assets which is sufficient to make this bank illiquid. Similarly, Bank 2 and Bank 3 are exposed to a 40% and 67% decline in their interbank assets, respectively. Similar to stress scenario 1, the affected interbank assets and liabilities matrix, the balance sheets, the liquidity coverage matrix, and the distress matrix are estimated for each bank. In order to avoid repetition and due to limited space, we only show the main results here.

Table A.11 shows the systemic distress dependence matrix where each cell shows the change in the probability of illiquidity of the bank in the row when the bank in the column becomes illiquid under stress scenario 2. Similarly, Table A.12 shows the systemic default dependence matrix where each cell shows the change in the probability of insolvency of the bank in the row when the bank in the column becomes illiquid under stress scenario 2. These two matrices are useful to highlight the interdependence among the banks in the system. For example, the results show that Bank 1 illiquidity affects Bank 3 more than Bank 2, while Bank 3 is affects Bank 2 more than Bank 1. This is again in line with the initial systemic distress profile of the three banks as measured by DistressRank.

Table A.11
Systemic distress dependence matrix: Change in the probability of illiquidity following stress scenario 2.

	Bank 1	Bank 2	Bank 3
Bank 1	316.26%	98.92%	50.29%
Bank 2	71.73%	555.70%	262.19%
Bank 3	105.21%	48.49%	905.19%

Table A.12
Systemic default dependence matrix: Change in the probability of insolvency following stress scenario 2.

	Bank 1	Bank 2	Bank 3
Bank 1	672.81%	432.88%	157.95%
Bank 2	305.63%	4119.85%	4197.11%
Bank 3	396.35%	135.96%	8529.38%

Table A.13
Systemic risk matrix: Expected loss in liquid assets following stress scenario 2.

	Bank 1	Bank 2	Bank 3	Sys. Vulnerability
Bank 1	4.44%	2.29%	0.83%	7.57%
Bank 2	2.22%	3.81%	2.50%	8.53%
Bank 3	3.56%	1.22%	4.00%	8.77%
Sys. Impact	10.22%	7.32%	7.33%	24.87%

Another way to evaluate the systemic interdependence in the system is by estimating the expected loss in liquid assets of banks when a given bank becomes illiquid as shown in Table A.13. The main cells in this table shows the expected loss in liquid assets of the bank in the row when the bank in the column becomes illiquid under stress scenario 2. In addition, the total of each row shows the systemic vulnerability of the bank at the left of this row, while the total of each column shows the systemic impact of the bank at the top of this column. The results are still in line with the initial distress profile of the system. These results complement the estimates of change in probabilities of illiquidity and insolvency by providing a measure of economic loss in value.

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