An Integrated Macroprudential Stress Test of Bank Liquidity and Solvency

Mohamed Bakoush[a,1,*], Enrico Gerding[b,2], Simon Wolfe[a,3],

[a] *Southampton Business School, University of Southampton, UK*
[b] *Electronics and Computer Science, University of Southampton, UK*

Abstract

We develop a macroprudential stress test of banks which integrates liquidity and solvency risks, and estimates the change in both based on the evolution of financial distress within the banking system. We estimate this evolution of financial distress using a new measure of systemic distress called DisressRank which incorporates idiosyncratic and systemic risks in the banking system network. We apply the stress test framework to the U.S. banking system and identify the systemic vulnerability of individual banks and the resilience of the system as a whole to economic risks. We also use this framework to identify and monitor systemic interdependencies between banks.

Keywords: Solvency; Liquidity; Macroprudential Policy; Stress Testing; Systemic Risk; Networks
JEL Classification: G01; G21; G28

[*] Corresponding Author.
[1] Mohamed Bakoush is a PhD Candidate in Financial Economics, Southampton University Business School. (Email: m.bakoush@soton.ac.uk)
[2] Enrico Gerding is an Associate Professor in Computer Science, Southampton University Electronics and Computer Science School. (Email: eg@esc.soton.ac.uk)
[3] Simon Wolfe is a Professor in Banking and Finance, Southampton University Business School.(Email: ssjw@soton.ac.uk)

1. Introduction

The financial crisis of 2007-2008 has revealed the need for better macroprudential policy in order to limit systemic risk and to enhance financial stability. It is widely accepted in the literature that systemic risk is the main threat to financial stability. Impairment of financial stability can impose significant costs on the real economy in terms of economic growth and social welfare. Thus, to protect the real economy from the financial system, it is necessary to detect and to gauge potential sources of systemic risk emerging at the system level. Meanwhile, to protect the financial system from the real economy, it is necessary to assess the robustness of the financial system to macroeconomic shocks. To this end, macroprudential stress tests have been established 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, Drehmann, and Tsatsaronis, 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) provides 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 introduces, with the use of network theory, a new measure of systemic distress that incorporates microprudential as well as macroprudential risks in the banking system network. Our proposed 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 risks at the level of an individual bank and the 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 assessing the vulnerability of banks, it is more appropriate to focus on a bank's systemic distress as compared to 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 level.

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 U.S. 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 provide insights into the possibilities of distress propagation within the system. Applying the proposed framework to the U.S. 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 that is shown here 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 the results of performing 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 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. 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, Maino, and Duma, 2010).

In theory, liquidity and solvency risks interact and can cause each other through the interactions between banks (Diamond and Rajan, 2005). However, empirical evidence on the nexus between liquidity and solvency risks is scarce. Some studies have strived to establish the link between liquidity and solvency in order to be incorporated into macroprudential stress tests. In particular, Schmitz, Sigmund, and Valderrama (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, Liu, and Zhang, 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 follow the same way 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 deposits 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, Souissi, 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). We use the same logic to estimate two types of probabilities 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 assets are derived mainly by the variability of liquid assets. This twist enables us to link liquidity and solvency risks directly as both of them 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, Parigi, and Rochet, 2000). More recent studies support the same notion and emphasize that financial networks can help provide better measurement of systemic risk and financial instabilities (e.g. Gai, Haldane, and Kapadia, 2011; Gai and Kapadia, 2010; Glasserman and Young, 2015; Elliott, Golub, and Jackson, 2014; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 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, Souissi, et al., 2012b; Wong and Hui, 2009; Sole and Espinosa-Vega, 2010) and academic (e.g. Gauthier, Lehar, and Souissi (2012a) and 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, Lehar, and Souissi (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 $N \in \{1, ..., N\}$. 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 is denoted by A_{ij}, 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}, 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 Equation 2 and Equation 3 that the better the liquidity position of a bank as measured by its liquidity coverage ratios, the lower the threat of distress due to illiquidity 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, $\lambda \neq 0$ 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 **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 **D**, which was introduced in Equation 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, Equation 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 **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 i^{th} entry corresponds to the DistressRank of the i^{th} bank. Equation 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 to be used with dynamic networks where the states of banks and the weights of exposures change during a distress propagation process. Here, we use

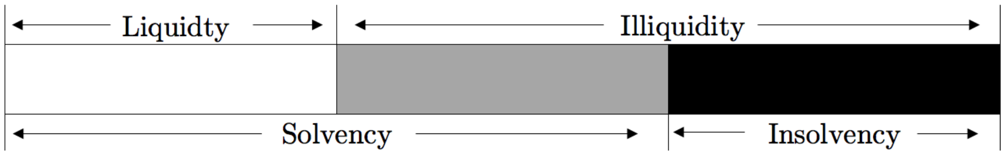


Figure 1: From illiquidity to insolvency. The white area represents a healthy bank that is both liquid and solvent. The grey area represents a stage in which the bank has become illiquid, yet still solvent. The black area represents the stage in which the bank has become both illiquid and insolvent.

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 $E_i \leq 0$.

Figure 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 the system level, the system-wide illiquidity point is the point at which $\sum_i A_i^L = \sum_i L_i^S$. At this point, we can estimate a system-wide liquidity coverage ratio, denoted as ℓ^L, that corresponds to the system-wide illiquidity point as :

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

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 Equation 8. At the system level, it is becomes straightforward that the system-wide insolvency point is the point at which $\sum_i E_i = \sum_i -\Delta A_i^L$. At this point, we can also estimate a system-wide liquidity coverage ratio, denoted as ℓ^S, that corresponds to the system-wide insolvency point as:

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

where $\sum_i E_i$ represents the amount of liquid assets that, if depleted, the system 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). However, unlike distance-to-default, we estimate the distance-to-insolvency using liquid assets and short term liabilities only, instead of total assets and total liabilities, assuming that the change in illiquid assets is trivially small and liabilities are valued at book value. The idea here is to identify how deep into illiquidity a bank can be before the condition in Equation 8 is satisfied and the bank becomes insolvent.

The first step to estimate distance-to-insolvency of a given bank i, denoted as δ_i^S, is to identify the bank's insolvency point, which we derive from Equation 10 above. On average, the insolvency point of a bank i is $\ell^S L_i^S$. Thus, the distance-to-insolvency of bank i can be defined as:

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

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 horizon. It is worth noting from equation Equation 11 that distance-to-insolvency is simply the number of standard deviations that the bank is away form 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.

To estimate the distance-to-illiquidity of a given bank i, denoted as δ_i^L, we start with identifying the average illiquidity point within the system which can be derived from Equation 9 as $\ell^L\ L_i^S$. It then follows that the distance-to-illiquidity of bank i is defined as:

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

Similar to the distance to insolvency, we can interpret the distance to illiquidity as the number of standard deviations that the bank is away form illiquidity. Additionally, 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 Figure 2. Assuming 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), 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 decreases, while χ_i^L and χ_i^S increases 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.

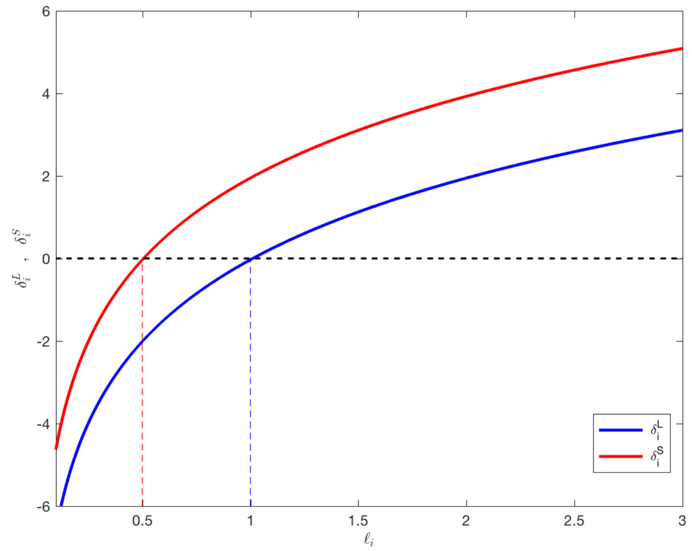
5. A Macroprudential Stress Testing Framework

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 Figure 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) .

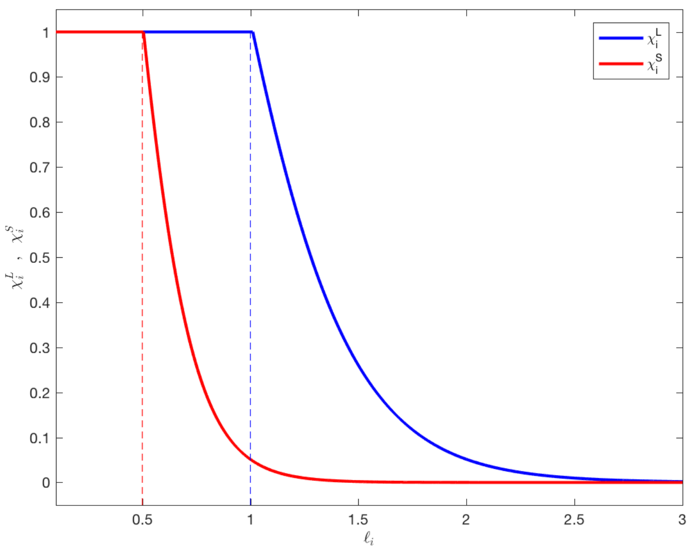
5.1. ***Inputs: Distress Scenario***

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 shocks, 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.



(a) Distance to Illiquidity & Distance to Insolvency



(b) Probability of Illiquidity & Probability of Insolvency

Figure 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.

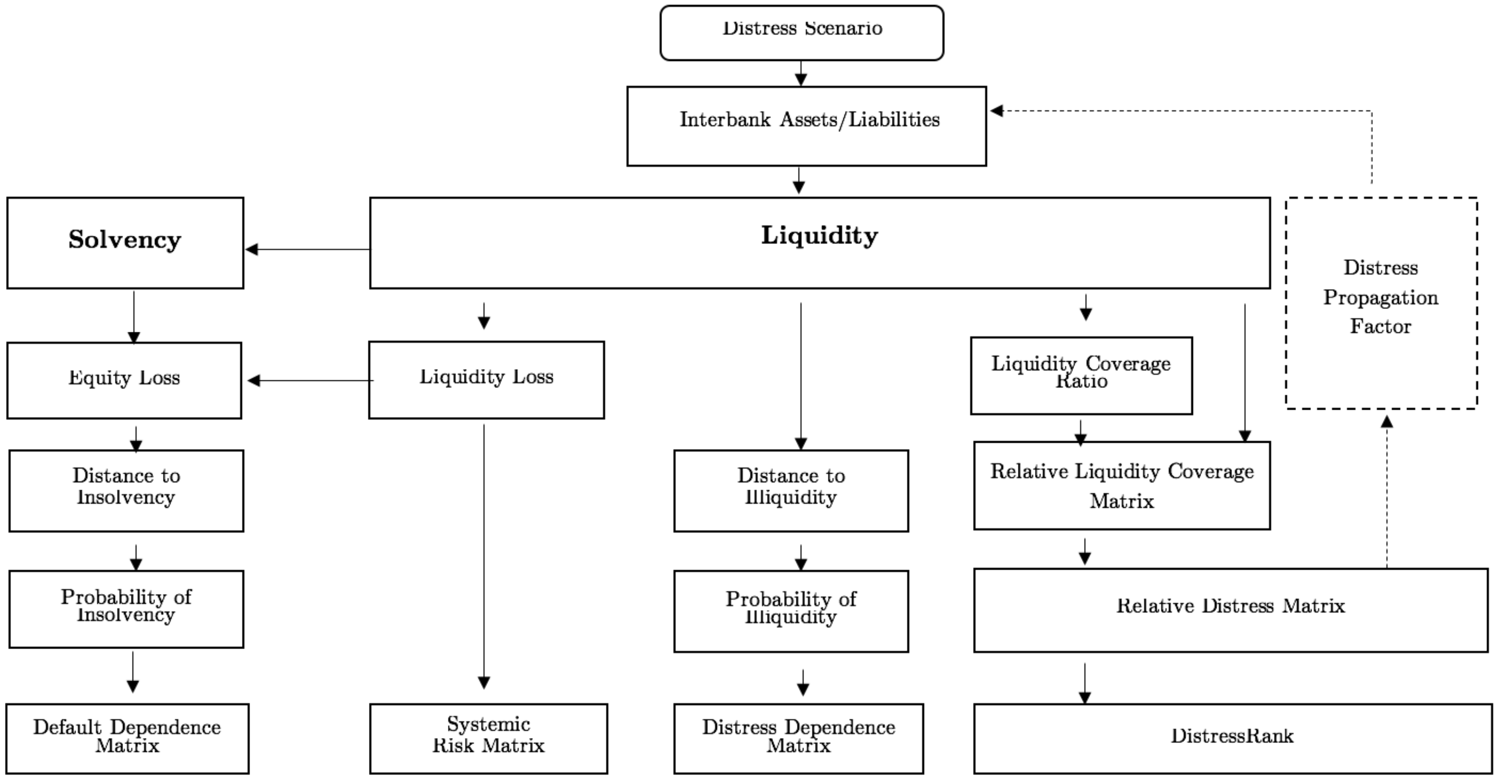


Figure 3: A framework for an integrated macroprudential stress test of liquidity and solvency.

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 and accordingly 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.

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 Equation 2 and the relative liquidity coverage matrix as estimated by Equation 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 Equation 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:

$$A^B_{ij}(t) = max \left[0\ , \quad A^B_{ij}(0) \Big(\frac{d_{ij}(0)}{d_{ij}(t)} \Big) \right] \tag{15}$$

where $A^B_{ij}(t)$ and $A^B_{ij}(0)$ 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 $d_{ij}(0)$ 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, Equation 15 assumes a zero recovery rate, an assumption that is widely followed in the financial contagion literature (see Gai and Kapadia, 2010; Markose, Giansante, and Shaghaghi, 2012). The mark to market process is represented by the dashed lines in Figure 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 Figure 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 Equation 11) and the probability of default (see Equation 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 Figure 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 and 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. This amount of expected loss can be estimated in terms of percentage liquidity loss as:

$$V_{ij} = min\left[1 \quad , \quad \frac{\ell_i(0) - \ell_i(T)}{\ell_i(0)}\right] \tag{16}$$

where $\ell_i(T)$ is the amount of liquidity remaining for i at time T after j has become distressed. In dollar terms, the expected loss of bank i relative to bank j is $V_{ij} = \ell_i(0) - \ell_{ij}(T)$. Following the same logic, we can estimate the systemic expected loss of bank i as:

$$V_i = \sum_j \chi_j^L(0) \quad V_{ij} \tag{17}$$

where $\chi_j^L(0)$ is the probability of illiquidity of bank j at $t = 0$. This measure of systemic expected loss represents the systemic vulnerability of bank i measured as the probability-weighted expected loss of bank i due to the distress of any one of the other banks 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 in bank j. We can estimate this amount as:

$$I_{ij} = \frac{\ell_j(0) - \ell_j(T)}{\ell_j(0)} = V_{ji} \tag{18}$$

in dollar terms this amount would be $I_{ij} = \ell_j(0) - \ell_j(T) = V_{ji}$. Needless to say is that this measure is exactly equal to the relative vulnerability of bank j relative to bank i. We also estimate a measure for the systemic impact of bank j as the total expected loss induced in all other banks due to the distress of bank j, which is simply the weighted sum of column j in the systemic risk matrix, and is estimated as:

$$I_i = \sum_j \frac{\ell_j(0)}{\sum_j \ell_j(0)} \quad I_{ij} \tag{19}$$

Finally, we provide a measure of the global system-wide expected loss as:

$$\Phi = \sum_i \chi_i^L(0) \quad I_i \tag{20}$$

where Φ is estimated as the probability-weighted average systemic expected loss. This measure can also be used as an indicator of the system-wide stability. The higher the systemic expected loss, the lower the system stability.

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 U.S. banking system.

6.1. *Data and Interbank Network Construction*

The data used to implement the stress test is related to the largest 25 holding companies in the U.S.[4] For each holding company (bank hence-

[4]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)

forth), 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.[5] 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.[6] 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. The data used to perform the stress test is as of June 30, 2017. This is the most recently available and complete set of data that includes disclosures about the liquidity coverage ratio of the large U.S. banks.

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 derivatives exposures is not observ-

[5] Data is obtained from the Federal Financial Institutions Examination Council's (FFIEC) and is available at https://www.ffiec.gov/nicpubweb/nicweb/nichome.aspx

[6] Data is obtained from the Office of the Comptroller of the Currency (OCC) and is available at https://www.occ.gov/topics/capital-markets/financial-markets/derivatives/derivatives-quarterly-report.html

able, as banks do not provide granular data about their bilateral exposures.

Since information on the the bilateral interbank exposures is essential for our analysis, we estimate this data to fill in the interbank matrix. To this end, we use the Minimum Density (MD) method suggested by Anand, Craig, and Von Peter (2015). The idea behind MD is to distribute each bank's assets and liabilities among the lowest possible number of counterparties. The economic rational for this is that the interbank network appears to be constructed based on relationships and as a result is sparse (Cocco, Gomes, and Martins, 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 United States (Bech and Atalay, 2010) and Germany (Craig and von Peter, 2014).

6.2. ***Results of the Stress Test***

The proposed stress test provides 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 provides 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 U.S. banking system, as of 30 June 2017. Figure 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, JPMorgan Chase is the most vulnerable bank, followed by Goldman Sacks. While the two least vulnerable banks are HSBC North America Holdings and PNC Financial Services Group. The other banks have comparable ranks. The same result can be seen from Figure 5, which shows the exact values of the DistressRank indicator for each bank.

There is a striking observation that can be noticed from Figure 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 US Bank Corporation and Citizens Financial Group.

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 largest interbank assets but rank 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 assessing 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%, which are extreme enough, yet plausible. We can think of a shock as resembling a sever 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, however, we outline some of these metrics below.

Figure 6 shows the number of distressed banks that become illiquid or insolvent following each shock. As would be expected, both numbers increase with the 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 the liquidity position of its counterparties and the severity of the shock. As illustrated, banks are resilient to small shocks up to 4%, while they 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 20%.

Figure 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

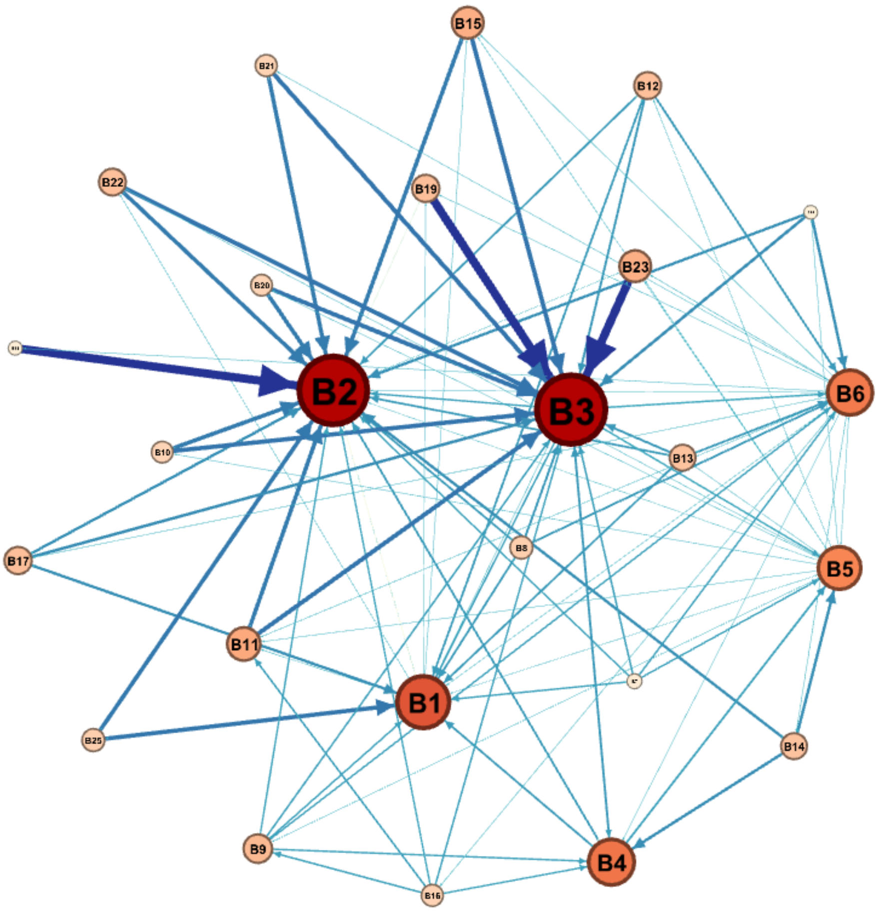


Figure 4: The distress network and DistressRank of individual banks in the system. Nodes represent banks and links represent interbank exposures. The size and color of each node are scaled proportionally to the value of its DistressRank. The width and color of each link are scaled proportionally to the value of relative distress induced from 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: Citi Group, B2: Goldman Sachs Group, B3: JPMorgan Chase, B4: Bank of America, B5: Morgan Stanley, B6: Wells Fargo, B7: HSBC North America, B8: Mizuho America, B9: State Street, B10: RBC USA, B11: Credit Suisse USA, B12: Bank of NY Mellon, B13: Barclays US, B14: PNC Group, B15: US Bancorp, B16: Northern Trust, B17: SunTrust Bank, B18: TD Group US, B19: DB USA, B20: Capital One, B21: MUFG Americas, B22: KeyCorp, B23: Citizens Financial Group, B24: BB&T Corp, B25: Regions Financial Group.

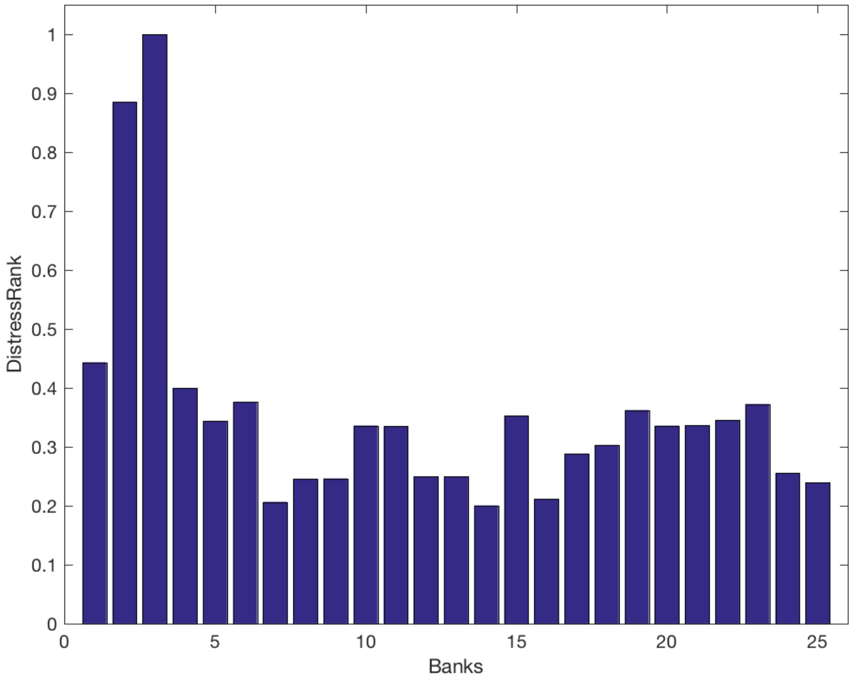


Figure 5: The DistressRank of individual banks in the system. Number of banks is 25. Banks' names are coded from 1 to 25 where 1: Citi Group, 2: Goldman Sachs Group, 3: JPMorgan Chase, 4: Bank of America, 5: Morgan Stanley, 6: Wells Fargo, 7: HSBC North America, 8: Mizuho America, 9: State Street, 10: RBC USA, 11: Credit Suisse USA, 12: Bank of NY Mellon, 13: Barclays US, 14: PNC Group, 15: US Bancorp, 16: Northern Trust, 17: SunTrust Bank, 18: TD Group US, 19: DB USA, 20: Capital One, 21: MUFG Americas, 22: KeyCorp, 23: Citizens Financial Group, 24: BB&T Corp, 25: Regions Financial Group.

at 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 Figure 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

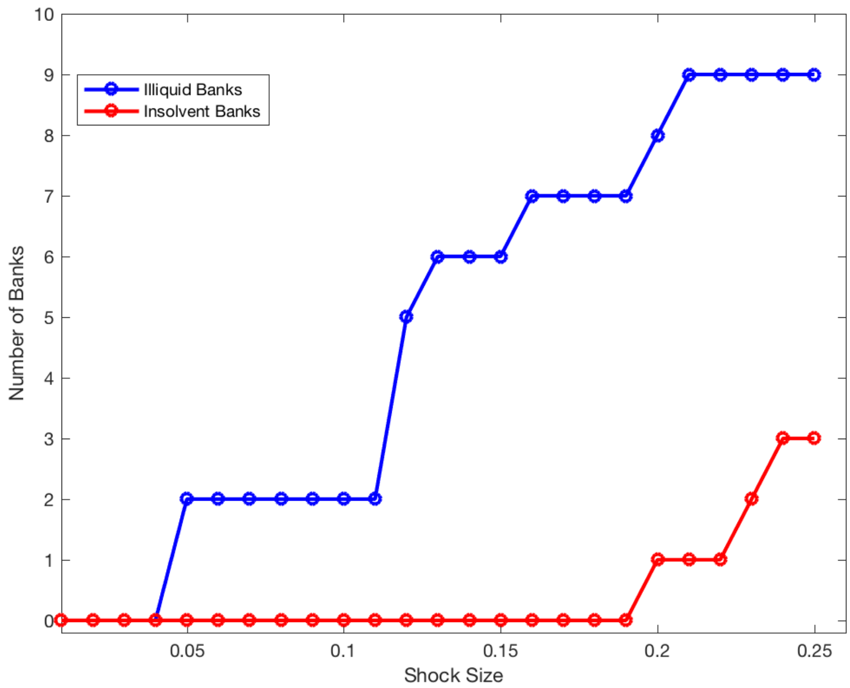


Figure 6: Number of Illiquid and Insolvent Banks due to a specific shock to the interbank assets. Shock size ranges from 1% to 25% of interbank assets.

that is significant at a 95% significance level with adjusted R^2 of 61%. This result confirms the importance of considering interconnectedness in designing macroprudential stress tests.

Finally, we can 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. Figure 9 and Figure 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 increases 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 have their probability of insolvency nearly doubled following the shock.

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

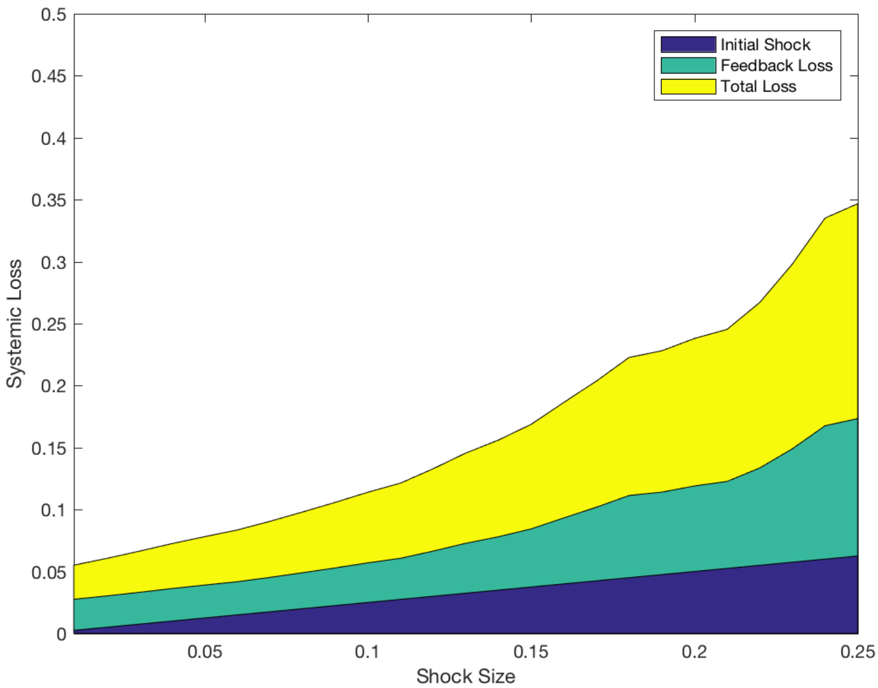


Figure 7: Decomposition of systemic loss into first round loss due to the initial shock and feedback loss occurring during second and upper rounds. Shock size ranges from 1% to 25% of interbank assets. Systemic loss is estimated at the system level as the total reduction in the value of banks' assets.

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 probability of illiquidity of the bank in the row relative to the bank in the column. In Figure 11, we present the distress dependence matrix estimated for the group of 25 U.S. banks included in the stress test. In this matrix, each cell represents the change in the probability of illiquidity of the bank in the row given that the bank in the column has become illiquid. For better illustration, we provide the matrix as a heatmap.

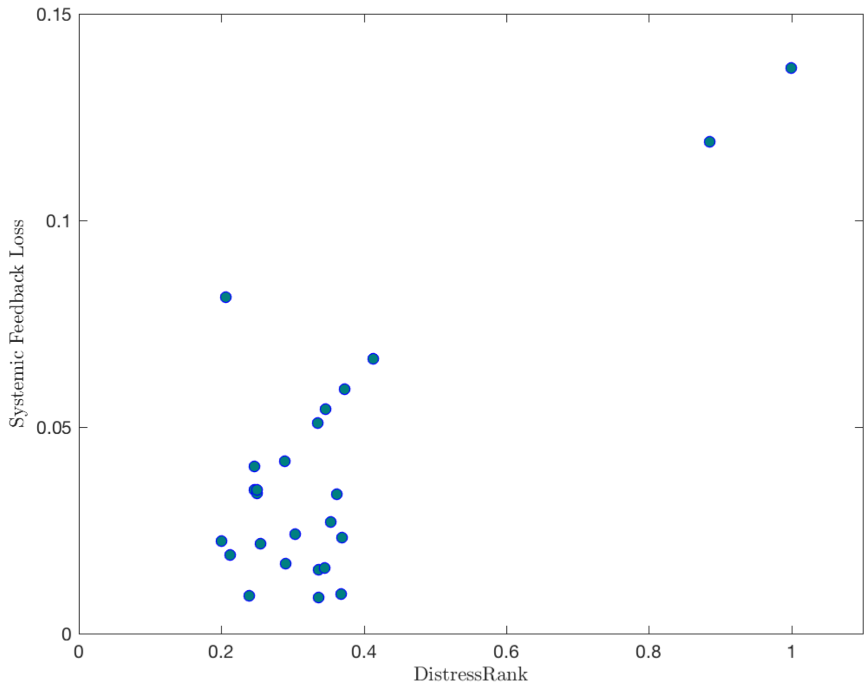


Figure 8: DistressRank and Systemic Feedback Loss. A bank's systemic feedback loss is estimated as its share in the total feedback loss at the system level due to a specific shock. Shock size is 10% of interbank assets. Each circle in the figure represents a bank.

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, Citi Group is more vulnerable to the distress of Goldman Sachs, JP Morgan and Bank of America compared to other banks in the sample. Another interesting observation is that, the four most vulnerable banks, namely Goldman Sachs, Morgan Stanley, Citi Group and Bank of America, stem their vulnerability from each other. This is explained by the fact that the exposure of these banks to each other represent 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 resilient to the distress of each other mainly due to the fact that they have limited exposures to each other.

B- Systemic Default Dependence

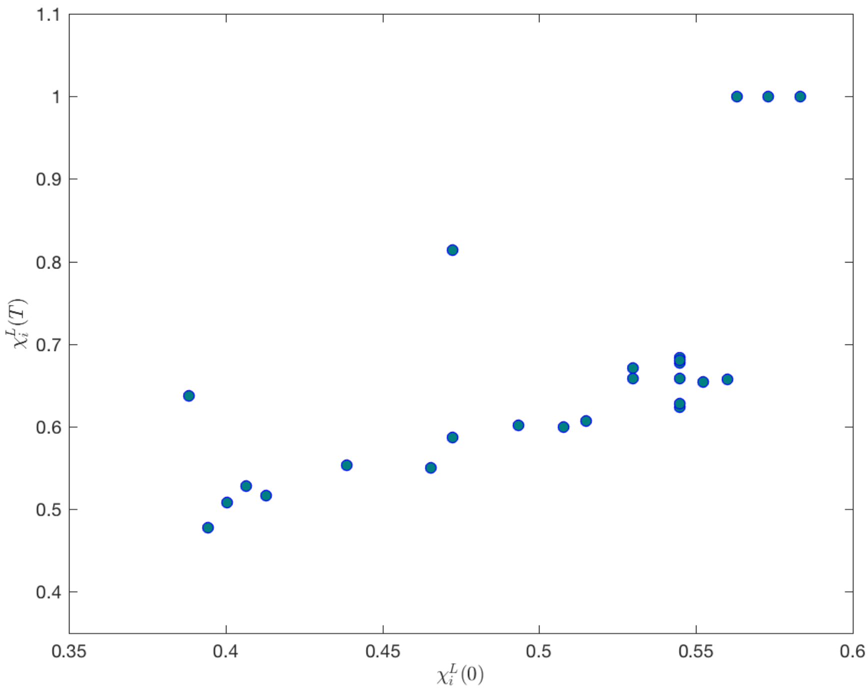


Figure 9: Change in Probability of Illiquidity for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^L(0)$ and $\chi_i^L(T)$ are the probability of illiquidity of bank i before and after applying the shock to the system, respectively. Each circle in the figure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

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 Figure 12 where each row represents the change in the probability of insolvency of the bank in the row given that the bank in the column has become illiquid. Again, each cell can be viewed as the conditional probability of insolvency of the bank in the row relative to the bank in the column. For better illustration, the matrix is shown as a heatmap.

The same observations on the distress dependence matrix apply also 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, Goldman Sachs

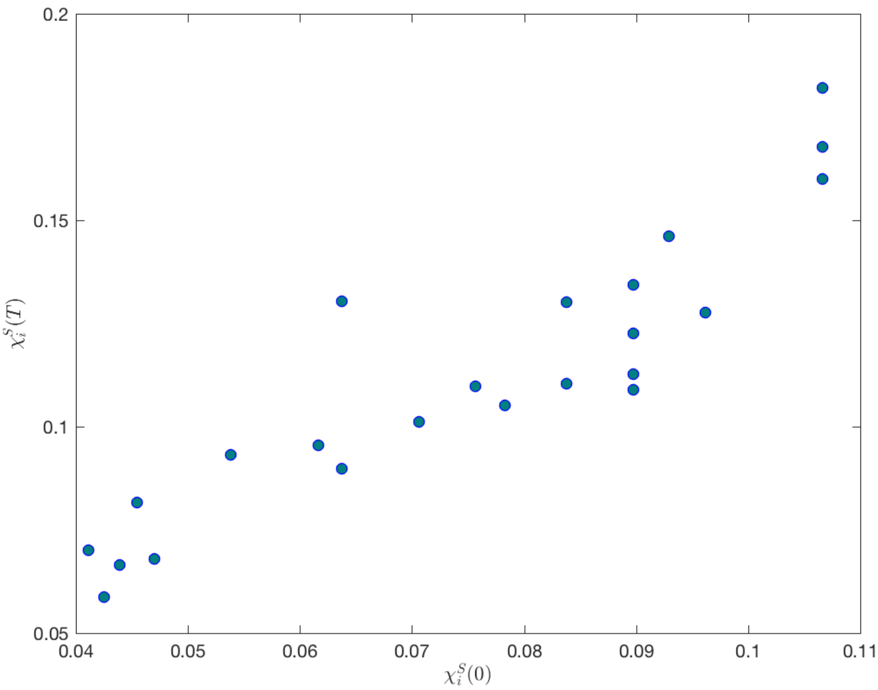


Figure 10: Change in Probability of Insolvency for each bank in the system due to a specific shock. Shock size is 10% of interbank assets. $\chi_i^S(0)$ and $\chi_i^S(T)$ are the probability of insolvency of bank i before and after applying the shock to the system, respectively. Each circle in the figure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

appears to be the most vulnerable bank to shocks from its counterparties and specially from Citi Group and Morgan Stanley. If Citi Group becomes illiquid, the probability of insolvency of Goldman Sachs increase by a factor of 3.78 times. Any distress that arises with Citi Group will definitely lead to a serious liquidity problem with any one of 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 interdependencies 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 matrix is shown in Figure 13. For better illustration, we provide the matrix as a heatmap.

The systemic risk matrix confirms the same results obtained by analysing

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	
CITIGROUP	1.06	0.15	0.34	0.56	0.05	0.04	0.01	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	CITI
GOLDMAN SACHS	0.87	0.75	0.21	0.32	0.67	0.09	0.04	0.00	0.05	0.01	0.00	0.10	0.00	0.05	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	GS
JPMORGAN CHASE	0.18	0.18	0.57	0.07	0.13	0.08	0.01	0.00	0.05	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	JPM
BANK OF AMERICA	0.07	0.07	0.52	0.67	0.05	0.04	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BOA
MORGAN STANLEY	0.84	0.33	0.14	0.17	1.24	0.06	0.13	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MS
WELLS FARGO	0.06	0.10	0.03	0.02	0.04	0.20	0.00	0.00	0.01	0.00	0.00	0.02	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	WF
HSBC N AMERICA	0.22	0.02	0.03	0.04	0.01	0.01	0.25	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	0.00	0.00	HSBC
MIZUHO	0.44	0.03	0.07	0.09	0.01	0.01	0.00	0.23	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	0.00	MIZ
STATE STREET	0.10	0.30	0.04	0.05	0.06	0.01	0.01	0.00	0.59	0.00	0.00	0.02	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	SS
RBC USA HOLDCO	0.01	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	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	RBC
CREDIT SUISSE	0.06	0.04	0.01	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CRS
BANK OF NY MELLON	0.03	0.07	0.01	0.02	0.07	0.01	0.01	0.00	0.00	0.00	0.00	0.16	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	BNM
BARCLAYS	0.02	0.04	0.01	0.01	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BAR
PNC FNCL SVC	0.02	0.05	0.01	0.01	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	PNC
U S BC	0.05	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	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	0.00	USP
NORTHERN TR	0.04	0.18	0.02	0.03	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NTR
SUNTRUST	0.03	0.02	0.01	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	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SUN
TD GRP US	0.03	0.01	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	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	TD
DB USA	0.09	0.07	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	DB
CAPITAL ONE	0.01	0.02	0.00	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	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	CAP
MUFG AMERS	0.02	0.11	0.01	0.02	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	MUFG
KEYCORP	0.05	0.06	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	KEY
CITIZENS FNCL	0.05	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	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	CIT
BB&T	0.01	0.00	0.00	0.00	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	0.00	0.00	0.03	0.00	BBT
REGIONS	0.01	0.03	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	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	REG

Figure 11: Distress Dependence Matrix. Each cell in the matrix represents the change in the probability of illiquidity of the bank in the row given that the bank in the column has become illiquid. Bank names are as in Figure 4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values.

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	
CITIGROUP	3.91	0.37	0.96	1.91	0.13	0.10	0.01	0.00	0.03	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CITI
GOLDMAN SACHS	3.78	2.90	0.54	0.87	2.46	0.21	0.10	0.00	0.12	0.02	0.01	0.23	0.01	0.12	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	GS
JPMORGAN CHASE	0.48	0.50	2.28	0.18	0.35	0.20	0.03	0.01	0.13	0.00	0.04	0.03	0.00	0.01	0.02	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.01	0.00	JPM
BANK OF AMERICA	0.17	0.15	1.73	2.50	0.11	0.08	0.01	0.00	0.05	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	BOA
MORGAN STANLEY	3.59	0.92	0.33	0.44	4.05	0.13	0.31	0.00	0.03	0.00	0.00	0.04	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	MS
WELLS FARGO	0.14	0.25	0.07	0.05	0.08	0.53	0.01	0.00	0.02	0.00	0.00	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	WF
HSBC N AMERICA	0.73	0.04	0.09	0.12	0.02	0.01	0.88	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	0.00	0.00	HSBC
MIZUHO	1.99	0.09	0.20	0.25	0.04	0.03	0.00	0.78	0.01	0.00	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	0.00	0.00	MIZ
STATE STREET	0.26	0.98	0.09	0.13	0.16	0.04	0.02	0.00	2.74	0.00	0.00	0.04	0.00	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SS
RBC USA HOLDCO	0.02	0.02	0.01	0.01	0.08	0.00	0.01	0.00	0.00	0.09	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	RBC
CREDIT SUISSE	0.15	0.10	0.03	0.04	0.08	0.01	0.01	0.00	0.00	0.00	0.61	0.01	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	CRS
BANK OF NY MELLON	0.07	0.18	0.03	0.04	0.18	0.01	0.01	0.00	0.01	0.00	0.00	0.42	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	BNM
BARCLAYS	0.04	0.10	0.02	0.02	0.11	0.06	0.01	0.00	0.00	0.00	0.00	0.01	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	BAR
PNC FNCL SVC	0.04	0.14	0.02	0.02	0.07	0.05	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	PNC
U S BC	0.14	0.02	0.02	0.03	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	USP
NORTHERN TR	0.10	0.53	0.05	0.07	0.10	0.02	0.01	0.00	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NTR
SUNTRUST	0.09	0.04	0.02	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	SUN
TD GRP US	0.05	0.01	0.02	0.02	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	TD
DB USA	0.21	0.16	0.04	0.05	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.00	0.00	0.00	0.00	0.00	0.00	DB
CAPITAL ONE	0.01	0.06	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	CAP
MUFG AMERS	0.06	0.27	0.03	0.04	0.06	0.08	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	MUFG
KEYCORP	0.12	0.16	0.03	0.04	0.06	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	KEY
CITIZENS FNCL	0.13	0.01	0.02	0.03	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	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	CIT
BB&T	0.01	0.01	0.00	0.01	0.07	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	0.00	0.00	0.09	0.00	BBT
REGIONS	0.02	0.09	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	REG

Figure 12: Default Dependence Matrix. Each cell in the matrix represents the change in the probability of insolvency of the bank in the row given that the bank in the column has become illiquid. Bank names are as in Figure 4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values.

Bank	CITI	GS	JPM	BOA	MS	WF	HSBC	MIZ	SS	RBC	CRS	BNM	BAR	PNC	USP	NTR	SUN	TD	DB	CAP	MUFG	KEY	CIT	BBT	REG	SysVul	
CITIGROUP	0.46	0.07	0.16	0.25	0.03	0.02	0.00	0.00	0.01	0.00	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	0.00	0.00	0.43	CITI
GOLDMAN SACHS	0.36	0.31	0.10	0.14	0.28	0.04	0.02	0.00	0.03	0.00	0.00	0.05	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.58	GS
JPMORGAN CHASE	0.10	0.10	0.30	0.04	0.08	0.05	0.01	0.00	0.03	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.33	JPM
BANK OF AMERICA	0.04	0.03	0.23	0.29	0.02	0.02	0.00	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	0.00	0.00	0.00	0.00	0.00	0.29	BOA
MORGAN STANLEY	0.35	0.15	0.07	0.08	0.52	0.03	0.06	0.00	0.01	0.00	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	0.00	0.00	0.53	MS
WELLS FARGO	0.03	0.05	0.02	0.01	0.02	0.10	0.00	0.00	0.00	0.00	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	0.00	0.00	0.11	WF
HSBC N AMERICA	0.16	0.01	0.03	0.03	0.00	0.00	0.18	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	0.00	0.00	0.21	HSBC
MIZUHO	0.32	0.03	0.05	0.06	0.01	0.01	0.00	0.17	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	0.00	0.30	MIZ
STATE STREET	0.06	0.18	0.02	0.03	0.04	0.01	0.00	0.00	0.35	0.00	0.00	0.01	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	0.34	SS
RBC USA HOLDCO	0.01	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	RBC
CREDIT SUISSE	0.04	0.03	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.13	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	0.14	CRS
BANK OF NY MELLON	0.02	0.04	0.01	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.09	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	0.09	BNM
BARCLAYS	0.01	0.03	0.00	0.01	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	BAR
PNC FNCL SVC	0.01	0.04	0.00	0.01	0.02	0.01	0.00	0.00	0.00	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	0.00	0.00	0.07	PNC
U S BC	0.04	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	USP
NORTHERN TR	0.03	0.12	0.01	0.02	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	NTR
SUNTRUST	0.02	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	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	SUN
TD GRP US	0.02	0.01	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	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	TD
DB USA	0.05	0.04	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	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.08	DB
CAPITAL ONE	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	CAP
MUFG AMERS	0.01	0.06	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.08	MUFG
KEYCORP	0.03	0.04	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.07	KEY
CITIZENS FNCL	0.04	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	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.04	CIT
BB&T	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	BBT
REGIONS	0.01	0.02	0.00	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	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	REG
SysImpact	0.173	0.089	0.136	0.129	0.093	0.038	0.010	0.001	0.016	0.001	0.003	0.013	0.002	0.005	0.002	0.002	0.000	0.002	0.002	0.001	0.001	0.001	0.000	0.001	0.001	0.30	

Figure 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. Bank names are as in Figure 4. The matrix is presented as a heatmap where cells colors are scaled from green for low values to red for high values. SysImpact stands for Systemic Impact of the bank in the column and is estimated as in Equation 19. SysVul stands for Systemic Vulnerability of the bank in the row and is estimated as in Equation 17. The cell in the intersection of SysImpact and SysVul represents the Systemic Loss which is estimated as in Equation 20.

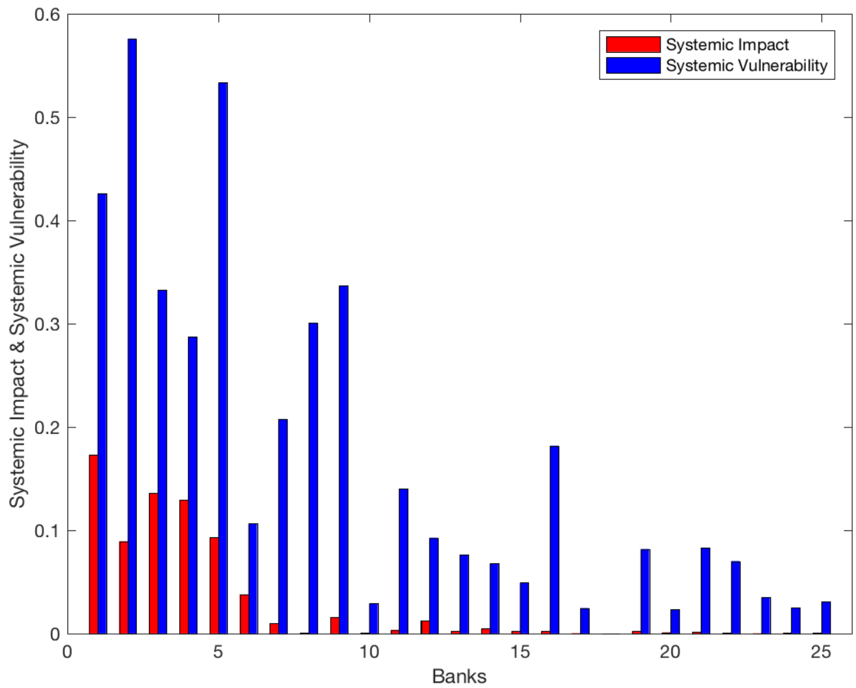


Figure 14: The Systemic Impact and Systemic Vulnerability of banks. Systemic Impact of individual banks is estimated as in Equation 19. Systemic Vulnerability of individual banks is estimated as in Equation 17.

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 others. If Citi Group becomes illiquid, it induces a 17.3% system wide expected loss. Goldman Sachs is the most vulnerable bank with an expected loss of nearly 58%. The expected systemic loss is 30% which represents a system wide stability measure. The higher this indicator is the more fragile the system is, 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 Figure 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 have systemic impact levels that are significant enough to be comparable to their systemic vulnerability. 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 reveal 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 U.S. 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.

The proposed approach provides a tool for the banking system supervisors to analyse the current 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 risk within the system due to endogenous or exogenous shocks. Applying the stress test framework to the U.S. banking system shows how it can be effective for monitoring and assessing interdependencies 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 will be affected the most.

In conclusion, the proposed macroprudential stress test is able to reveal the systemic vulnerabilities in a banking system, giving policymakers insight into the system resilience. Although the framework demonstrated here was applied using a reconstructed network of interbank exposures, this data was sufficient to highlight the merit of the proposed stress test framework. The availability of granular bank data would only increase the robustness of the analysis. 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.

References

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. (2015) "Systemic risk and stability in financial networks." *The American Economic Review*, 105(2):564–608.

Allen, Franklin and Douglas Gale.(2000) "Financial contagion." *Journal of Political Economy*, 108(1):1–33.

Anand, Kartik, Ben Craig, and Goetz Von Peter. (2015) "Filling in the blanks: Network structure and interbank contagion." *Quantitative Finance*, 15(4):625–636.

Aymanns, Christoph, Carlos Caceres, Christina Daniel, and Liliana B Schumacher. (2016) "Bank solvency and funding cost." Working Paper No 16-64. International Monetary Fund.

Basel Committee on Banking Supervision. (2013a) "The Liquidity Coverage Ratio and liquidity risk monitoring tools." Basel Committee on Banking Supervision.

Basel Committee on Banking Supervision. (2013b) "Global systemically important banks-updated assessment methodology and the higher loss absorbency requirement, revised version July 2013". Basel Committee on Banking Supervision.

Basel Committee on Banking Supervision. "Making supervisory stress tests more macroprudential:Considering liquidity and solvency interactions and systemic risk." Working Paper No 29, Basel Committee on Banking Supervision,

Bech, Morten L and Enghin Atalay. (2010) "The topology of the federal funds market." *Physica A: Statistical Mechanics and its Applications*, 389(22):5223–5246.

Black, Fischer and Myron Scholes. (1973) "The pricing of options and corporate liabilities." *Journal of Political Economy*, 81(3):637–654.

Blaschke, Winfrid, Maria Soledad Martinez Peria, Giovanni Majnoni, and Matthew T Jones. (2001) "Stress testing of financial systems: an overview of issues, methodologies, and FSAP experiences." Working Paper No 01-88, International Monetary Fund.

Bohn, Jeff and Peter Crosbie. (2003) "Modeling default risk." KMV Corporation.

Borio, Claudio, Mathias Drehmann, and Kostas Tsatsaronis. (2014) "Stress-testing macro stress testing: does it live up to expectations?" *Journal of Financial Stability*, 12:3–15.

Buncic, Daniel and Martin Melecky. (2013) "Macroprudential stress testing of credit risk: A practical approach for policy makers." *Journal of Financial Stability*, 9(3):347–370.

Bunn, Philip, Alastair Cunningham, and Mathias Drehmann. (2005) "Stress testing as a tool for assessing systemic risk." *Bank of England Financial Stability Review*, 18:116–26.

Čihák, Martin. (2007) "Introduction to applied stress testing." Working Paper No 07-59, International Monetary Fund.

Cocco, Joo F., Francisco J. Gomes, and Nuno C. Martins. (2009) "Lending relationships in the interbank market." *Journal of Financial Intermediation*, 18(1):24 – 48.

Craig, Ben and Goetz von Peter. (2014) "Interbank tiering and money center banks." *Journal of Financial Intermediation*, 23(3):322 – 347.

Diamond, Douglas W and Raghuram G Rajan. (2005) "Liquidity shortages and banking crises." *The Journal of Finance*, 60(2):615–647.

Drehmann, Mathias, Steffen Sorensen, and Marco Stringa. (2010) "The integrated impact of credit and interest rate risk on banks: A dynamic framework and stress testing application." *Journal of Banking & Finance*, 34(4):713–729.

Elliott, Matthew, Benjamin Golub, and Matthew O Jackson. (2014) "Financial networks and contagion." *The American Economic Review*, 104 (10):3115–3153.

Freixas, Xavier, Bruno M Parigi, and Jean-Charles Rochet. (2000) "Systemic risk, interbank relations, and liquidity provision by the central bank." *Journal of Money, Credit and Banking*, 32(3):611–638.

Gai, Prasanna and Sujit Kapadia. (2010) "Contagion in financial networks." In Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 466(2120):2401-2423. The Royal Society.

Gai, Prasanna, Andrew Haldane, and Sujit Kapadia. (2011) "Complexity, concentration and contagion." *Journal of Monetary Economics*, 58(5): 453–470.

Gauthier, Céline, Alfred Lehar, and Moez Souissi. (2012a) "Macroprudential capital requirements and systemic risk." *Journal of Financial Intermediation*, 21(4):594–618.

Gauthier, Céline, Moez Souissi, et al. (2012) "Understanding systemic risk in the banking sector: A macrofinancial risk assessment framework." *Bank of Canada Review*, Spring, 29–38.

Glasserman, Paul and H Peyton Young. (2015) "How likely is contagion in financial networks?" *Journal of Banking & Finance*, 50:383–399.

Glasserman, Paul and Peyton Young. (2016) "Contagion in financial networks." *Journal of Economic Literature*, 54(3):779–831.

Gray, Dale and Andreas Jobst. (2010) "New directions in financial sector and sovereign risk management." *Journal of Investment Management*, 8:18–31, 03.

Gray, Dale and Samuel Malone. (2008) *Macrofinancial risk analysis*. John Wiley & Sons.

Hasan, Iftekhar, Liuling Liu, and Gaiyan Zhang. "The determinants of global bank credit-default-swap spreads." *Journal of Financial Services Research*, 50(3):275–309.

International Monetary Fund. (2014) "Review of the Financial Sector Assessment Program: Further Adaptation to the Post Crisis Era." International Monetary Fund.

Lee, Seung Hwan. "Systemic liquidity shortages and interbank network structures." *Journal of Financial Stability*, 9(1):1–12.

Levy-Carciente, Sary, Dror Y. Kenett, Adam Avakian, H. Eugene Stanley, and Shlomo Havlin. (2015) "Dynamical macroprudential stress testing using network theory." *Journal of Banking & Finance*, 59(Supplement C):164 – 181.

Markose, Sheri, Simone Giansante, and Ali Rais Shaghaghi. (2012) "'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk." *Journal of Economic Behavior & Organization*, 83(3):627–646.

Merton, Robert C. (1974) "On the pricing of corporate debt: The risk structure of interest rates." *The Journal of Finance*, 29(2):449–470.

Meyer, Carl D. (2000) *Matrix analysis and applied linear algebra*, volume 2. SIAM.

Newman, Mark.(2010) *Networks: an introduction.* Oxford University Press.

Ong, Li, Rodolfo Maino, and Nombulelo Duma. (2010) "Portfolio credit risk and macroeconomic shocks: Applications to stress testing under data-restricted environments." Working Paper No 10-282. International Monetary Fund.

Ong, Lilian and Martin Čihák. (2014) "Stress Testing at the International Monetary Fund: Methods and Models." In A Guide to IMF Stress Testing : Methods and Models. International Monetary Fund.

Pierret, Diane. (2015) "Systemic risk and the solvency-liquidity nexus of banks." *International Journal of Central Banking*, 11(3):193–227.

Schmitz, Stefan W, Michael Sigmund, and Laura Valderrama. (2017) "Bank solvency and funding cost: New data and new results." Working Paper No 17-116. International Monetary Fund.

Scott, John. (2017) *Social network analysis.* Sage.

Segoviano, Miguel A and Charles Albert Eric Goodhart. (2009) "Banking stability measures." Working Paper No 09-4. International Monetary Fund.

Segoviano, Miguel A and Pablo Padilla. (2006) "Portfolio credit risk and macroeconomic shocks: Applications to stress testing under data-restricted environments." Working Paper No 6-283. International Monetary Fund.

Sole, Juan and Marco A Espinosa-Vega. (2010) "Cross-border financial surveillance: a network perspective." Working Paper No 10-105, International Monetary Fund.

Tarullo, Daniel K. (2016) "Next steps in the evolution of stress testing." In Remarks at the Yale University School of Management Leaders Forum.

Wong, TC and Cho-Hoi Hui. (2009) "A liquidity risk stress-testing framework with interaction between market and credit risks." Working Paper 06-2009, Hong Kong Monetary Authority.