Liquidity, Interbank Network Topology and Bank Capital

Aref Mahdavi Ardekani

UNIVERSITÉ PARIS 1 PANTHÉON SORBONNE

Documents de Travail du Centre d'Economie de la Sorbonne

CES Working Papers

CES
Centre d'Économie de la Sorbonne
UMR 8174

Liquidity, Interbank Network Topology and Bank Capital

Aref MAHDAVI ARDEKANI

2020.22R

Version révisée

Maison des Sciences Économiques, 106-112 boulevard de L'Hôpital, 75647 Paris Cedex 13
https://centredeconomiesorbonne.cnrs.fr/
ISSN : 1955-611X

Liquidity, Interbank Network Topology and Bank Capital

Aref Mahdavi Ardekani [a, b]

[a] Université Paris 1 Panthéon-Sorbonne, CES, Paris, France

[b] Université de Limoges, LAPE, Limoges, France

Aref.Mahdavi@univ-paris1.fr

This draft: 04/12/2020

Abstract

By applying the interbank network simulation, this paper examines whether the causal relationship between capital and liquidity is influenced by bank positions in the interbank network. While existing literature highlights the causal relationship that moves from liquidity to capital, the question of how interbank network characteristics affect this relationship remains unclear. Using a sample of commercial banks from 28 European countries, this paper suggests that banks' interconnectedness within interbank loan and deposit networks affects their decisions to set higher or lower regulatory capital ratios when facing higher illiquidity. This study provides support for the need to implement minimum liquidity ratios to complement capital ratios, as stressed by the Basel Committee on Banking Regulation and Supervision. This paper also highlights the need for regulatory authorities to consider the network characteristics of banks.

JEL Classification: G21, G28, L14

Keywords: Interbank network topology, Bank regulatory capital, Liquidity risk, Basel III

Liquidity, Interbank Network Topology and Bank Capital

This draft: 04/12/2020

Abstract

By applying the interbank network simulation, this paper examines whether the causal relationship between capital and liquidity is influenced by bank positions in the interbank network. While existing literature highlights the causal relationship that moves from liquidity to capital, the question of how interbank network characteristics affect this relationship remains unclear. Using a sample of commercial banks from 28 European countries, this paper suggests that banks' interconnectedness within interbank loan and deposit networks affects their decisions to set higher or lower regulatory capital ratios when facing higher illiquidity. This study provides support for the need to implement minimum liquidity ratios to complement capital ratios, as stressed by the Basel Committee on Banking Regulation and Supervision. This paper also highlights the need for regulatory authorities to consider the network characteristics of banks.

JEL Classification: G21, G28, L14

Keywords: Interbank network topology, Bank regulatory capital, Liquidity risk, Basel III

1. Introduction

Following the recent financial crises, much effort has been made by financial regulators to monitor the capital and liquidity of banks in order to enhance the stability of financial markets. Concurrently, the Basel Committee on Banking Regulation and Supervision introduced its unbonded capital and liquidity constraints under the Basel III guideline (BCBS, 2010). While the effectiveness of Basel III has been extensively debated in the literature (e.g., Allahrakha et al., 2018; Le et al., 2020; Merkl & Stolz, 2009; Petersen et al., 2013), recent studies have also pointed to the existence of interrelationships between bank capital and liquidity (Berger & Bouwman, 2009; Bhattacharya & Thakor, 1993; Diamond & Rajan, 2001; Gorton & Winton, 2017; von Thadden, 2004). However, existing studies neglect the role of banks' sophisticated interconnectedness in the interbank market in determining the causal relationship between capital and liquidity.

The most prominent function of banks is liquidity creation by funding long-term illiquid assets with short-term liquid liabilities. This leads banks to hold illiquid assets and provide liquidity to stimulate the whole economy. In addition, however, it makes banks vulnerable to the risk of unexpected withdrawals of short-term liabilities which have been invested in illiquid assets, and consequently raises the probability of bank failure. The interbank market plays a critical role in facilitating liquidity transformation through the channelling of short-term liquid funds between banks with surpluses and those with shortages. It links banks and financial institutions based on their bilateral liquidity needs. Although the mechanism of liquidity redistribution in the interbank market could alleviate such liquidity shocks among banks, access to this market is not equally granted to all banks. Moreover, banks have traditionally been reluctant to cooperate in unsecured interbank markets during turmoil.

Capital and liquidity regulations aim to strengthen bank solvency and liquidity positions. The new capital ratios require banks to maintain a certain amount of Tier 1 and Tier 2 capital against all banks' balance sheets and off-balance sheets exposures to 'constrain the build-up of excessive leverage' in financial institutions. Furthermore, the liquidity constraints require banks to hold a certain amount of liquid assets over a one-month horizon (Liquidity Coverage Ratio, LCR) and to maintain sufficient stable funds over a one-year horizon (Net Stable Funding Ratio, NSFR) to protect them from liquidity shocks. The Basel III capital and liquidity requirements are, however, independent of the banks' network topology or the quality of their interconnectedness in the interbank network.

Ardekani et al. (2020) document that the ways banks set their liquidity ratios are dependent on their interbank network characteristics. Distinguin et al. (2013), Fu et al. (2016) and Horváth et al. (2014) all additionally highlight the causal relationship that moves from liquidity to capital. Accordingly, the relationship between a bank's capital and liquidity might also be influenced by their position in the interbank network.

Literature on the causal relationship between capital and liquidity has often proposed contradictory findings. Distinguin et al. (2013) suggest complementarity between liquidity and capital for large banks and substitutionary effects for small banks. By working on a sample of US and European banks, they find that large (small) banks reduce (increase) their regulatory capital when they face higher illiquidity. Through investigating the causal relationship between liquidity and regulatory capital of banks in Asia-Pacific economies, Fu et al. (2016) find a negative interrelationship between capital and liquidity regardless of bank size. Horváth, Seidler, and Weill (2014) propose substitutionary impacts of liquidity on the capital of Czech banks. They demonstrate that banks enhance their capital ratios when they face higher illiquidity. Because empirical literature does not suggest any clear-cut findings regarding the causal relationship that moves from liquidity to capital, the reason behind these findings remains an open issue. Those findings could possibly be explained by considering the banks' positions in the interbank network. Matz & Neu (2007) argue that higher liquidity creation results in a bank's higher exposure to liquidity risk. Since increasing capital might improve banks' ability to raise more funds from the market or reduce depositor runs, they strengthen their solvency standards when they face higher illiquidity. However, if they are well positioned in the interbank network, they have wider access to the wholesale liquid funds which can reduce their demand for higher capital.

This paper examines how ease of access to the interbank market could influence the interrelationship between banks' capital and liquidity. Specifically, I hypothesise that weakly interconnected banks might target a higher capital ratio to improve their solvency when they face higher illiquidity. Because they have weaker access to interbank funds, they might substitute capital for liquidity to offset their liquidity constraints and to promote their fundraising capacity. Moreover, I suggest that a stronger network position may lead banks to substitute less capital for liquidity, presumably because they believe wider access to wholesale liquidity funds could alleviate the liquidity constraints and soften depositors' requirements for solvency standards. Banks may therefore set different capital ratios depending on their position in the interbank market when they face higher illiquidity. Additionally, banks target different ratios during normal times and distress periods, which could also be differently shaped depending on their network positions.

This study is also related to literature that analyses the topology of bank networks to draw an accurate picture of the significant role played by the shape of interbank network connectedness in bank liquidity risk, systemic risk and the contagion of financial shocks to the economy (Ardekani et al., 2020; Borges et al. 2020; Capponi & Chen, 2015; Glasserman & Young, 2015; Huang et al. 2016; Paltalidis et al. 2015; Souza et al. 2015). Iori et al. (2008), Kuzubaş et al. (2014)

and Soramäki et al. (2007) all investigate the efficiency of banking networks by analysing the topological characteristics of payment systems in different countries. Martinez-Jaramillo et al. (2014) and Rørdam and Bech (2009) assess the network topology of interbank exposure and payment systems in different countries and compare their characteristics. Gabrieli and Georg (2014) suggest that strong network positions would result in higher bank access to the interbank liquidity market. Chinazzi et al. (2013) and Soramäki et al. (2007) highlight the interaction between banks in the interbank market and their willingness to connect with banks of different sizes. This study uses network topology statistics to measure the strength of banks' interconnectedness in the interbank network and to quantify how banks can more or less easily gain access to wholesale liquid funds. This research distinguishes systemwide from local network positions in the interbank market. While local network topology quantifies a bank's immediate access to interbank funds, systemwide network topology measures the crucial role that each bank plays in the whole interbank network.

Although existing literature has addressed the causal relationship between bank capital and liquidity, these studies have neglected the role of interconnectedness among banks in the interbank network. This paper contributes to existing literature by investigating how the interbank network characteristics influence the relationship between a bank's capital and liquidity. My results suggest that, whereas weak interbank interconnectedness strengthens the substitutionary effect of liquidity on capital, broader access to the interbank market works as liquidity insurance and weakens this relationship during normal times. During times of economic distress, my findings suggest that strongly local interconnected banks do not substitute capital for liquidity. This is presumably because they have broader access to the interbank funds, and thus are less pressured by depositor runs. My results do, however, exhibit that strongly system-wide interconnected banks set lower capital ratios when they face higher illiquidity.

The rest of this article is laid out as follows. Section 2 describes the data, variables and methodology of the study, while section 3 presents the results of the study. Robustness checks are reported in section 4. Section 5 provides a conclusion.

2. Sample, Variables and Methodology

2.1. Sample

My sample consists of 506 commercial banks established in 28 European countries[1]. I construct the interbank networks by including all available commercial, investment and real estate banks in the Bankscope database in each country[2]. Therefore, network statistics in this study capture connections of banks in my sample (only commercial) with all possible banks in their respective countries.

The selected sample period is from 2001 to 2013. Accounting data (annual financial statements) for individual banks are obtained from Bankscope Fitch IBCA. Bankscope reported balance sheets and income statements for 1,238 commercial banks for the countries considered in this study. After eliminating banks for which Bankscope does not report information on variables of interest, the final sample of banks consists of 506 banks.

[Insert Table 1]

2.2. Definition of Variables

This section presents dependent variables, different independent variables reflecting interbank network characteristics and control variables that are introduced in my estimations. Descriptive statistics and definitions of these variables are provided in Table 2. The extreme bank year observations for my dependent and bank-level control variables winsorised (1% lowest and highest values).

[Insert Table 2]

2.2.1. Total Capital Ratio (TCR)

The Basel Committee on Banking Regulation and Supervision has introduced a new capital ratio that requires banks to maintain a certain amount of Tier 1 and Tier 2 capital against all the

[1] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the United Kingdom.

[2] This study omits savings and mutual banks from the sample, subject to their specificities in terms of interbank network relationships (BIS, 2001; Boss & Elsinger, 2004; Worms, 2001).

bank's balance sheet and off-balance sheet exposures in order to 'constrain the build-up of excessive leverage' in financial institutions. The total capital ratio is defined according to Basel III guidelines as Tier 1 plus Tier 2 capital divided by risk-weighted assets (RWA):

$$TCR = \frac{Tier\ 1 + Tier\ 2}{RWA} \qquad (1)$$

Tier 1 capital represents a bank's core capital, which includes a shareholder's equity and non-cumulative preferred shares. Tier 2 capital is defined as complementary capital and consists of hybrid instruments and subordinated debts[3].

2.2.2. Inverse of Structural Liquidity Indicator (I. NSFR)

In addition to the Total Capital Ratio (TCR), the Basel Committee introduced an international framework to assess banks' liquidity. Its longer horizon liquidity requirements, the 'net stable funding ratio' (NSFR) (BCBS, 2010), requires banks to reduce liquidity mismatch by financing their illiquid assets with less risky and more stable funds. It is a structural tool for efficient liquidity measurement, as it scrutinises two sides of the balance sheet and classifies assets and liabilities as illiquid, semi-liquid and liquid, assigning weights to each component. To measure the illiquidity, and consistent with Distinguin et al. (2013), this study uses the inverse of liquidity regulatory ratio. This ratio is defined as[4]:

$$I.NSFR = \frac{Required\ amount\ of\ stable\ funds}{Available\ amount\ of\ stable\ funds} \qquad (2)$$

The available amount of stable funds is the total amount of bank capital; the share of time deposits and stable demand deposits (maturity of less than one year) that would be expected to stay within the bank; and liabilities with a maturity equal or greater than one year. The required amount of stable funding is defined as the amount of assets that are used as collateral for borrowing during a period of liquidity stress, or those that cannot be easily monetised. Basel III requires banks to set their NSFR ratio above 1 (100%). Estimating NSFR according to BCBS (2010) guidelines

[3] For robustness, I replace Tier 1 ratio with TCR (see 4.1).
[4] Following the literature, I consider the NSFR and not the LCR because, due to lack of data, the latter cannot be computed. Additionally, the LCR measurements are based on liquidity shocks over one month (a short horizon). The network statistics variables in my work are computed annually. Hence, their time horizon is in compliance with the NSFR.

is difficult due to the unavailability of data on a detailed breakdown of the balance sheet; therefore, I approximate it with Bankscope data using the weights defined by Vazquez and Federico (2015)[5].

2.2.3. Interbank Network

This paper aims to examine whether the causal relationship between bank capital and liquidity is influenced by interbank network characteristics. To achieve this, network variables are extracted from interbank lending-borrowing relationships. Construction of the interbank network requires an estimation of the bilateral transactions between each pair of banks in the interbank market. A crucial shortcoming when studying the interbank exposure is the unavailability of bilateral transaction data, as financial authorities do not require banks to report such information in most European countries. The only available data is the aggregate interbank loans and deposits in each bank. The most relevant and applied method for constructing the interbank network based on the aggregate interbank transactions is the minimum density (MD) algorithm, proposed by Anand et al. (2015).

A notable point of applying this method is its economic rationality: producing and maintaining extra network linkages in the interbank market is costly and should be minimised. Moreover, it uses known features of the interbank network, as explained in the literature. For instance, Anand et al. (2015) highlight the extreme cost of connections with all possible banks in the network. They also explain that the interbank loan and deposit market has hierarchical attributes. Cocco et al. (2009) suggest that banks connect to counterparties with minimum correlated liquidity shocks, which leads to sparse networks. Chiu et al. (2019) and Cocco et al. (2009) argue that a long-term lending relationship is the base requirement for banks' connections in the interbank network. Building on such work, and by considering the core-periphery characteristics of the interbank network, Craig and Von Peter (2014) show its tiering properties.

Ardekani et al. (2020) construct their interbank exposure network based on an MD algorithm, and examine the relationship between interbank network characteristics and liquidity ratios of European banks. I follow Ardekani et al. (2020) and apply the MD algorithm of Anand

[5] Table B1 presents its detailed weighted components. Vazquez & Federico (2015) explain the departure from Basel III weights. For instance, 100% weight is assigned to total amount of loans, as splitting loans subject to their type or maturity is not possible. An average weight of 35% is assigned to other earning assets, as they are supposed to be more liquid.

et al. (2015) to simulate bilateral exposure network; I then compute my network centrality measurements[6].

The interbank market allows an exchange of short-term funds among banks based on their liquidity preferences and forms complex networks of debtors and creditors. Therefore, it facilitates liquidity transmission in the financial system. To construct my interbank network, I consider each bank as a node N_i and the lending-borrowing relationship between each bank as a directed link L_{ij} that connects node i to node j, where $L_{ij} \neq L_{ji}$. L_{ij} represents a loan from bank i to bank j and L_{ji} denotes deposits from bank j to bank i. In addition to direct linkages between banks, path length of N_i to N_j where denoted by PL_{ij} measures a number of edges between two banks and shows the network distance between two different banks. While there might be several paths from N_i to N_j, d_{ij} quantifies the shortest distance, that is the minimum number of edges between node i and j.

Centrality is a concept developed and used in the social network to identify the importance, influence and power of each entity in the corresponding network. However, growing literature on financial economics (e.g., Boss et al., 2004; Langfield et al., 2014; Minoiu & Reyes, 2013; Rørdam & Bech, 2009) have adopted it to optimally assess the risk, vulnerability and performance of financial networks. This study employs centrality measurements to assess the accessibility of the interbank market funds to each bank by identifying the interconnectedness among banks in the interbank network.

Figure 1 illustrates the configuration of the simulated interbank network in France, a selected European country among my sample in 2013. Each node represents a bank in the interbank network, and the linkages represent the interbank lending-borrowing relationships. Highlighted banks are those with the most significant network interconnectedness among others. In order to capture the interconnectedness of banks in the interbank network, I categorise my network variables into two subgroups: local and system-wide network variables.

2.2.3.1. Local Network Variables

Local network variables measure the immediate connectedness of banks with their counterparts in the interbank network, and are comprised of In-Degree and Out-Degree. In-Degree

[6] A detailed description of the minimum-density algorithm applied for construction of the interbank network is provided in Appendix A.

(3)

quantifies the number of immediate incoming links (direct lenders), and Out-Degree measures the number of immediate outgoing links (direct borrowers).

$$D_j^{in} = \sum_j L_{ji}$$

Where L_{ji} takes a value of one if there is an interbank loan from $bank_j$ to $bank_i$, and zero otherwise.

$$D_j^{out} = \sum_j L_{ij} \qquad (4)$$

Where L_{ij} takes a value of one if there is interbank deposit from $bank_i$ to $bank_j$, and zero otherwise. I define network dummy variables to distinguish between strong and weak local interconnectedness. *HIn-Degree* and *HOut-Degree* dummy variables take a value of one if their values are greater than or equal to the median value.

Banks with strong local network positions in the interbank markets are more specialised for diversifying their interbank borrowing or lending, which helps them to maintain their linkages even in times of economic distress. According to the substitutionary effect of liquidity on capital, banks set higher capital ratios to strengthen their solvency and increase their fundraising capabilities when facing higher illiquidity. I assume that the fundraising capability of illiquid banks is less affected by their solvency if they have higher lending and borrowing diversification in the interbank market. Likewise, I expect that a strong local position in the interbank network weakens this substitutionary effect when banks face higher illiquidity.

2.2.3.2. System-Wide Network Variables

System-wide network variables measure a bank's access to the interbank funds of the whole network. Those variables quantify the network characteristics of each bank compared with all existing banks in the interbank market, and also provide a wider image of a bank's interconnectedness compared with local measurements.

Betweenness Centrality quantifies the systemic position of each bank in the whole network.

$$Betweenness_i = \sum_{j<k} \frac{g_{jik}}{g_{jk}} \qquad (5)$$

Where g_{jik} is defined as the number of geodesic paths between bank j and bank k that pass-through bank i. Eventually, PageRank measures the importance of each bank's counterparties in determining the significant role of a bank in the interbank network.

$$PageRank(i) = \frac{(1-d)}{N} + d \sum_{j \in N-(i)} \frac{PageRank(j)}{TL(j)} \qquad (6)$$

Where for bank i, TL is the total number of links that depart from its out degree, and d is a factor that Winograd (1999) recommended setting at 0.85. I introduce system-wide network dummy variables to differentiate between strong and weak access of banks to the interbank funds in the whole network. *HBetweenness* and *HPageRank* dummy variables take a value of one if their values are greater than or equal to the median value.

A bank's strong system-wide position in the interbank network increases their access to the interbank funds, but is also a potential source of contagion and systemic risk. On that note, the impact of system-wide network variables on the relationship between capital and liquidity depends on the economic situation (crisis vs. normal). Overall, I expect that banks with strong system-wide interconnectedness substitute less capital for liquidity. I also assume that wide accessibility to interbank funds increases banks' fundraising capabilities and reduces pressure to further strengthen their solvency[7].

2.2.3.3. Validity of the Simulated Network

Anand et al. (2018) compare a variety of methods for reconstructing networks for 25 distinct financial markets, and suggest that the best method to preserve the structure of links is Minimum Density. I further prove this simulation technique's validity by analysing whether the simulated interbank network has characteristics in common with the interbank network in the real world.

Small world and scale-free properties are the common features of the real-word interbank network, as suggested by the empirical literature. A network has the scale-free properties when its Degree distribution follows the power law. By analysing the network topology of the interbank market in several different countries, Boss and Elsinger (2004), Iori et al. (2008), Lenzu and

[7] The centrality measurements are calculated based on the methods of Bastian and Heymann (2009).

Tedeschi (2012), Martinez-Jaramillo et al. (2014), Rönnqvist and Sarlin (2016) and Xu et al. (2016) highlight that interbank Degree distribution follows the power law. In this study, I investigate whether my simulated network has the common feature of the real-world interbank network by testing whether its Degree distribution fits the power law. The probability distribution function of networks that obey power law is:

$$P(x) \propto x^{-\alpha} \qquad (7)$$

Where α is a scaling parameter with typical value that usually lies in the range $2<\alpha<3$ (sporadic exceptions are allowed).

The first step to test whether data distribution fits the power law is determination of the lower-bound value of the data X_{min}, and to subsequently test the distribution for the value greater than X_{min}. To estimate X_{min} and consequently the scaling parameter α, I follow Clauset et al. (2007). Finally, to show whether the Degree distribution of my simulated network fits power law, I estimate goodness-of-fit between power law and my data. I reject the hypothesis that Degree follows the power law distribution if the p-value is less than or equal to 0.1.

The Degree log-log plots are illustrated in Figures 2 and 3. Section A shows the plots for the whole sample (28 European countries), and section B illustrates the plot for six selected European countries. Table 3 presents the results for the power-law fits and the corresponding p-values, and shows that the Degree distribution of my simulated interbank network obeys power law.

[Insert Table 3]

2.2.4. Control Variables

My study also includes a set of control variables known to affect the capital and liquidity of banks. In my capital equation, I control for bank size by introducing the logarithm of total assets (Size); loan loss provision to net interest income (*LLP_NIR*) as a proxy of the riskiness of bank assets; and the *Z-Score*, which is an indicator of a bank's distance to bankruptcy in my regressions.

$$Zscore = \frac{ROAmma3+\left(\frac{Equity}{TA}\right)mma3}{ROAsdma3} \qquad (8)$$

Where ROAmma3 is the three-year rolling window average return on assets defined as the ratio of net income to average total assets, (Equity/TA)mma3 represents the three-year rolling window average of equity to total assets and ROAsdma3 represents the three-year rolling window standard deviation of the Return on Assets. I also include the Return on Equity (*ROE*). My country-level control variable comprises the Natural logarithm of GDP per capita (*GDPperCa*). GDPperCa is a country's gross domestic product per capita. Given that European banks have recently weathered both the global financial crisis of 2007-2009 and the European sovereign debt crisis of 2010-2012, I construct a dummy variable to capture the effects of both crises. This dummy variable takes the value of one in the aforementioned crisis years, and zero otherwise.

In the liquidity equation, I control for bank network characteristics by using the network dummy (HNetwork). I also consider the Net Interest Margin (NIM) as a proxy of bank profitability, the ratio of bank total assets to country total assets as a proxy for market power (MKT_POW) and the Central Bank policy rate (CB_Policy) as a proxy for monetary policy. Eventually, I include crises dummy.

The correlation matrix is presented in Table 4. The correlation coefficients between independent variables are low except between bank size, as measured by the natural logarithm of total assets (Size) and some network measures. To check whether such correlation affects my results, I perform a robustness test. I replace Bank Size with a size dummy variable which is not correlated with my network measures. All the specifications yield qualitatively similar results (see 4.3). Thus, all the results presented below are those obtained with Bank Size and network variables introduced simultaneously[8].

[Insert Table 4]

2.3. Methodology

In this paper, I question whether bank network topology could influence the interrelationship between bank liquidity and capital. Specifically, I use individual bank network indicators based on their loans to other banks and deposits from other banks and test how their interactions with liquidity affect banks' capital ratios. However, the causal relationship between

[8] I also perform multicollinearity checks among all variables by running a VIF test. The results of the VIF test in Tables 4 and 5 indicate low multicollinearity.

capital and liquidity as documented in the literature poses potential serial correlation and endogeneity issues. To tackle these issue, I follow Distinguin et al. (2013) and Sclip et al. (2019) in using the GMM simultaneous equations model. GMM is more efficient than 2SLS (two-stage least squares) regression because it considers the heteroskedasticity of errors. Additionally, it is robust to the error distribution (Distinguin et al., 2013; Hall, 2005).

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} \\ \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t} \quad (9)$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 TCR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} \\ + \alpha_5 Crises_t + \varepsilon_{i,t} \quad (10)$$

In the capital equation, I regress capital ratio on the interaction between the inverse of Basel-III liquidity ratio *(I.NSFR)* and interbank network topology, and also a set of controls identified in the previous literature. Where $TCR_{i,t}$ is a Total Capital Ratio, α_0 is a constant, $I.NSFR_{i,t}$ is the inverse of Net Stable Funding Ratio, $HNetw(x)$ is a network dummy variable that is either *HIn-degree, HOut-degree, HBetweenness, or HPageRank*. $HNetw(x)$ takes a value of one if the network measurement is greater than or equal to the median value. $B_{i,t-1}$ is a vector of bank-level control variables including *Size*, *Z-score*, Loan Loss Provision to Net Interest Revenue (*LLP_NIR*) and the Return on Equity *(ROE*). $C_{j,t}$ is a vector of country-level control variable that comprises the Natural logarithm of GDPperCa. $Crises_t$ is crisis dummy variable that takes the value of one for the 2007-2012 period (global financial crisis and sovereign debt crisis). $\varepsilon_{i,t}$ is an error term.

In the liquidity equation, I regress the illiquidity ratio on the *TCR* and a set of controls identified in previous literature. $B_{i,t-1}$ is a vector of bank-level control variables including Net Interest Margin *(NIM)* and Market Power *(MKT_POW)*. $C_{j,t}$ is a vector of country-level control variable that comprises the Central bank Policy rate *(CB_Policy)*. Standard errors are clustered at the bank level. To deal with possible endogeneity, and consistent with Distinguin et al. (2013) and Sclip et al. (2019), I replace all bank-level controls with their one-year lagged value in both equations. Subsequent to testing for cross-section and time random versus fixed effects, I apply random effect estimations using the Huber-White estimator in both equations. Using the Huber-

White estimator results in standard errors that are robust within panel correlation and to cross-sectional heteroscedasticity. Finally, I include time and cross-section fixed effects in the regressions.

3. Results

I first investigate the link between illiquidity and capital of European banks with different interbank network positions. I then look at how this interrelationship is influenced by network topology during both normal times and crisis times.

3.1 Impact of Network Topology on Causal Relationships between Bank Liquidity and Capital

To determine whether the relationship between liquidity and capital is affected by bank topology in the interbank network, I first investigate this interrelationship without considering the interbank network interactions (column 1 of Table 5). Higher illiquidity pushes banks to raise their capital ratios. Banks that face higher illiquidity are more inclined to strengthen their solvency standards and consequently improve their fundraising abilities. Likewise, concerning liquidity equation and consistent with the 'Risk Absorption' theory, a higher regulatory capital ratio is associated with higher illiquidity. Bhattacharya and Thakor (1993) and von Thadden (2004) show that higher capital allows banks to absorb greater risk, which results in higher liquidity creation. These results highlight that banks consider capital as a substitute for liquidity when facing higher illiquidity. Columns 2 through 5 of Table 5 present results of the effect of bank network topology on the liquidity-capital relationship.

Banks with a small number of immediate interbank borrowers (*Out-Degree*) or lenders (*In-Degree*) substitute capital for liquidity. Because they have less access to interbank funds, they strengthen their solvency to improve their fundraising abilities. There is no significant evidence for the impact of illiquidity on capital for banks with strong local network positions, which may indicate that these banks do not substitute capital for liquidity. The broader local access to the interbank market and stronger ability of interbank lending-borrowing diversification works as liquidity insurance and weakens (or eradicates) the substitutionary effect. Indeed, they might easily raise funds without compromising their solvency.

Concerning system-wide network measures and similar to my findings for local network variables, banks that face higher illiquidity strengthen their solvency when they are characterised by weak *PageRank*. Because of weak linkages to highly connected counterparties, they might be less confident in their liquidity funding capabilities in the interbank network. Therefore, they strengthen their solvency to improve their external fundraising capabilities. However, illiquidity does not significantly influence the capital of banks with weak *Betweenness*. Surprisingly, banks with strong intermediation role in the interbank market (*Betweenness*) or banks that are strongly interconnected with centrally positioned peers (*PageRank*) set lower capital ratios when facing higher illiquidity. Increasing global accessibility to wholesale liquid funds might strengthen bank fundraising abilities, which could explain the negative sign of the relationship.

Concerning control variables, the most relevant factor that explains regulatory capital is *Bank Size*. A negative and significant effect of *Bank Size* on *TCR* demonstrates that larger banks set a lower capital ratio. In regards to liquidity determinants, *NIM*, *CB_Policy* and *Crises_Dummy* are the most relevant factors. Results show that more profitable banks set lower liquidity ratios. Additionally, raising central bank policy rates or emergent financial crises correspond with banks' decision to set lower liquidity ratios.

In summary, I find that a strong system-wide position leads banks to set a lower capital ratio when they face higher illiquidity. By contrast, banks with weak local network positions and banks that are weakly interconnected with centrally positioned peers strengthen their solvency standards.

[Insert Table 5]

3.2. Impact of Network Topology on Causal Relationships between Bank Liquidity and Capital During Normal and Crisis Times

I consider the impact of interbank network topology on the interrelationship between bank liquidity and capital ratio within crisis periods by looking at both the global financial crisis of 2007-2009 and the European sovereign debt crisis of 2010-2012. Both crises significantly influenced the interconnectedness of European banks, as banks were reluctant to deal with each other on unsecured interbank markets during these periods and preferred to interact through the

Eurosystem. Under such circumstances, the role played by network interconnectedness is expected to change dramatically.

Moreover, the financial crisis had a severe impact on bank fundraising ability. It raised bank funding costs and liquidity risks. Schanz (2011) argues that depositors are more risk-averse during crisis times. They force banks to strengthen their solvency and offer a higher deposit rate to induce them to roll their funds over. These depositor requirements (higher bank solvency and higher deposit rate) could possibly raise the substitutionary impact of liquidity on capital. In this section, I examine how the ease of a bank's accessibility to the interbank market might impact the substitutionary effects of liquidity on capital during both normal and crisis times.

The results presented in Table 6 show that banks with strong local interconnectedness do not substitute capital for liquidity during normal times or crisis times. By contrast, banks with weak local positions set higher capital ratios when they face illiquidity during both periods.

During normal times, banks with low system-wide access to the interbank market substitute capital for liquidity. The broader system-wide position, however, works as liquidity insurance and weakens these substitutionary effects. Crises weaken the substitutionary effects of liquidity on capital for banks with a weak system-wide position. Although a weak system-wide position indicates less access to the interbank liquid funds, it could also be interpreted as fewer counterparty and systemic risks during crisis times. However, banks with strong system-wide access to the interbank market start targeting lower capital ratios when they face higher illiquidity. Because of the too-interconnectedness-to-fail status, bailout expectations are higher for such interconnected intermediaries during crisis times. These expectations boost the confidence their interbank peers have in these highly interconnected banks, leading them to take advantage of their system-wide network positions during crises which enables them to benefit from lower fluctuations in interbank borrowing rates. Consequently, bank managers might consider interbank funds as stable, and substitute them for capital when they face higher illiquidity. Therefore, by targeting a lower capital ratio, they might achieve higher profits.

[Insert Table 6]

4. Robustness Checks

To check the robustness of my results, I conduct several sensitivity analyses as described in the following sections.

4.1. Alternative Capital Ratio

To check the robustness of my results, I conduct regression by replacing TCR with the Tier-1 capital ratio defined as Tier-1 capital divided by risk-weighted assets (RWA). As presented in Table C1, the results are consistent with my baseline model.

4.2. Alternative Measure of Strong Network Interconnectedness

I also determine whether the interrelationship between liquidity and capital is influenced by extremely strong interconnectedness in the interbank network. For this purpose, I replace my network dummy with $EHNetw(x)$, which takes a value of one if the value of the network variable is greater than or equal to the value of the 90th percentile. As shown in Table C2, the results remained unchanged.

4.3. Size Dummy Variable

With the exception of *HPageRank*, the logarithm of bank total assets (*Bank Size*) and network dummy variables are correlated (ranging from 47% to 56%). To ensure that this correlation do not affect my results, I perform a robustness test by replacing *Bank Size* with a dummy variable (*Size_Dummy*) that takes the value of one for small banks (banks with total assets less than one billion Euro) and zero otherwise. As shown in Table C3, the main results remain unchanged.

4.4. Additional Controls

To check the robustness of the simultaneous equations and correspondent to the literature, I also add controls for *Bank Size* and *GDPperCap* on the liquidity equation. The results remain unchanged[9].

[9] The results are available upon request.

4.5. Estimation of NSFR with Different Weights

To check the robustness of the *NSFR* ratio estimation, I apply minimum, maximum and extreme case weights (0.5, 0.85 or 1) for demand and savings deposits, as documented by the Basel accords. The conclusion remained unchanged[9].

5. Conclusion

Existing literature has thus far neglected to address how the causal relationship between bank liquidity and capital is influenced by its network characteristics. In this paper, I augment traditional capital-liquidity relationship models with network statistics to assess whether and how this relationship depends on a bank's local and system-wide network characteristics in the interbank market. Using a GMM simultaneous equations approach applied to a dataset of listed and unlisted banks from 28 European countries, my study shows that bank capital ratio is not only explained by the macro environment and the individual bank characteristics outlined in the literature, but also by the relationship between liquidity and interbank network topology. My findings suggest that while banks with weak local or system-wide interbank positions improve their solvency when they face higher illiquidity, those with strong local interconnectedness do not substitute capital for liquidity. Likewise, strongly system-wide interconnected banks set a lower capital ratio when they face higher illiquidity.

In addition, my findings highlight that, in times of financial crisis, banks with a strong system-wide position in the interbank network weaken their solvency when they face higher illiquidity; this is presumably because of higher bailout expectations. As the higher system-wide interconnectedness leads banks to set lower liquidity ratios during crisis times (Ardekani et al., 2020), these banks are more exposed to the insolvency and liquidity risks than others during turmoil. My findings support the need to implement minimum liquidity ratios in complement with capital ratios, as stressed by the Basel Committee on Banking Regulation and Supervision. However, my findings also cast doubt on the current uniform liquidity and capital requirements for banks with different interbank topology. Adding liquidity ratios to capital ratios could be more relevant for institutions with strong system-wide positions than for weakly interconnected ones. Presumably, strong system-wide interconnected banks might underestimate liquidity and insolvency risk because of their too-interconnected-to-fail status.

References:

Allahrakha, M., Cetina, J., & Munyan, B. (2018). Do higher capital standards always reduce bank risk? The impact of the Basel leverage ratio on the U.S. triparty repo market. *Journal of Financial Intermediation*, *34*(January), 3–16. https://doi.org/10.1016/j.jfi.2018.01.008

Anand, K., Craig, B., & von Peter, G. (2015). Filling in the blanks: network structure and interbank contagion. *Quantitative Finance*, *15*(4), 625–636. https://doi.org/10.1080/14697688.2014.968195

Anand, K., van Lelyveld, I., Banai, Á., Friedrich, S., Garratt, R., Hałaj, G., … de Souza, S. R. S. (2018). The missing links: A global study on uncovering financial network structures from partial data. *Journal of Financial Stability*, *35*, 107–119. https://doi.org/10.1016/j.jfs.2017.05.012

Ardekani, A. M., Distinguin, I., & Tarazi, A. (2020). Do banks change their liquidity ratios based on network characteristics? *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2020.02.011

Basel Committee on Banking Supervision. (2010). International regulatory framework for banks (Basel III). *Bank of International Settlements*. Retrieved from http://www.bis.org/bcbs/basel3.htm

Basel Committee on Banking Supervison. (2010). *Basel III: International framework for liquidity risk measurement, standards and monitoring, December 2010*. *Supervision*.

Berger, A. N., & Bouwman, C. H. S. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*(9), 3779–3837. https://doi.org/10.1093/rfs/hhn104

Bhattacharya, S., & Thakor, A. (1993). Contemporary banking theory. *Journal of Financial Intermediation*, *3*(1), 2–50.

BIS. (2001). *Marrying the Macro- and Micro-Prudential Dimensions of Financial Stability*. *Working Paper Series*. https://doi.org/10.2139/ssrn.1165494

Borges, M. R., Ulica, L., & Gubareva, M. (2020). Systemic risk in the Angolan interbank payment system–a network approach. *Applied Economics*, *52*(45), 4900–4912. https://doi.org/10.1080/00036846.2020.1751052

Boss, M., & Elsinger, H. (2004). An empirical analysis of the network structure of the Austrian interbank market. *Financial Stability Report*, 77–87.

Boss, M., Elsinger, H., Summer, M., & Thurner, S. (2004). Network topology of the interbank market. *Quantitative Finance*, *4*(6), 677–684. https://doi.org/10.1080/14697680400020325

Capponi, A., & Chen, P.-C. (2015). Systemic risk mitigation in financial networks. *Journal of Economic Dynamics and Control*, *58*, 152–166. https://doi.org/10.1016/j.jedc.2015.06.008

Chinazzi, M., Fagiolo, G., Reyes, J. A., & Schiavo, S. (2013). Post-mortem examination of the international financial network. *Journal of Economic Dynamics and Control*, *37*(8), 1692–1713. https://doi.org/10.1016/j.jedc.2013.01.010

Chiu, J., Eisenschmidt, J., & Monnet, C. (2019). Relationships in the interbank market. *Review of Economic Dynamics*, *1*, 1–22. https://doi.org/10.1016/j.red.2019.06.003

Clauset, A., Young, M., & Gleditsch, K. S. (2007). On the frequency of severe terrorist events. *Journal of Conflict Resolution*, *51*(1), 58–87. https://doi.org/10.1177/0022002706296157

Cocco, J. F., Gomes, F. J., & Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, *18*(1), 24–48. https://doi.org/10.1016/j.jfi.2008.06.003

Craig, B., & Von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, *23*(3), 322–347. https://doi.org/10.1016/j.jfi.2014.02.003

Diamond, D. W., & Rajan, R. G. (2001). Liquidity Risk , Liquidity Creation , and Financial Fragility : A Theory of Banking. *Journal of Political Economy*, *109*(2), 287–327.

Distinguin, I., Roulet, C., & Tarazi, A. (2013). Bank regulatory capital and liquidity: Evidence from US and European publicly traded banks. *Journal of Banking and Finance*, *37*(9), 3295–3317. https://doi.org/10.1016/j.jbankfin.2013.04.027

Fu, X. M., Lin, Y. R., & Molyneux, P. (2016). Bank capital and liquidity creation in asia pacific. *Economic Inquiry*, *54*(2), 966–993. https://doi.org/10.1111/ecin.12308

Gabrieli, S., & Georg, C.-P. (2014). A network view on interbank market freezes. *Banque de France Working Paper*, (531).

Glasserman, P., & Young, H. P. (2015). How likely is contagion in financial networks? *Journal of Banking and Finance*, *50*, 383–399. https://doi.org/10.1016/j.jbankfin.2014.02.006

Gorton, G., & Winton, A. (2017). Liquidity provision, bank capital, and the macroeconomy. *Journal of Money, Credit and Banking*, *49*(1). Retrieved from https://scholar.google.com/scholar?q=%28Gorton+and+Winton%2C+2000%29&btnG=&hl=en&as_sdt=0%2C5

Hall, A. R. (2005). *Advanced Texts in Econometrics: Generalized Method of Moments*. *Oxford University Press, Oxford, UK.*

Horváth, R., Seidler, J., & Weill, L. (2014). Bank Capital and Liquidity Creation: Granger-Causality Evidence. *Journal of Financial Services Research*, *45*(3), 341–361. https://doi.org/10.1007/s10693-013-0164-4

Huang, W.-Q., Zhuang, X.-T., Yao, S., & Uryasev, S. (2016). A financial network perspective of financial institutions' systemic risk contributions. *Physica A: Statistical Mechanics and Its Applications*, *456*, 183–196. https://doi.org/10.1016/j.physa.2016.03.034

Iori, G., G., D. M., Precup, O. V., Gabbi, G., & Caldarelli, G. (2008). A network analysis of the Italian overnight money market. *Journal of Economic Dynamics and Control*, *32*(1), 259–278. https://doi.org/10.1016/j.jedc.2007.01.032

Kuzubaş, T. U., Ömercikoğlu, I., & Saltoğlu, B. (2014). Network centrality measures and systemic risk: An application to the Turkish financial crisis. *Physica A: Statistical Mechanics and Its Applications*, *405*, 203–215. https://doi.org/10.1016/j.physa.2014.03.006

Langfield, S., Liu, Z., & Ota, T. (2014). Mapping the UK interbank system. *Journal of Banking and Finance*, *45*(1), 288–303. https://doi.org/10.1016/j.jbankfin.2014.03.031

Le, T. N. L., Nasir, M. A., & Huynh, T. L. D. (2020). Capital requirements and banks performance under Basel-III: A comparative analysis of Australian and British banks. *Quarterly Review of Economics and Finance*, 1–12. https://doi.org/10.1016/j.qref.2020.06.001

Lenzu, S., & Tedeschi, G. (2012). Systemic risk on different interbank network topologies. *Physica A: Statistical Mechanics and Its Applications*, *391*(18), 4331–4341. https://doi.org/10.1016/j.physa.2012.03.035

M. Bastian, S. Heymann, M. J. et al. (2009). Gephi: an open source software for exploring and manipulating networks. *Proceedings of International AAAI Conference on Web and Social Media*, 361–362.

Martinez-Jaramillo, S., Alexandrova-Kabadjova, B., Bravo-Benitez, B., & Solórzano-Margain, J. P. (2014). An empirical study of the Mexican banking system's network and its implications for systemic risk. *Journal of Economic Dynamics and Control*, *40*, 242–265. https://doi.org/10.1016/j.jedc.2014.01.009

Matz, L., & Neu, P. (2007). *Liquidity Risk Measurement and Management Liquidity Risk Measurement and Management*. John Wiley & Sons (Asia) Pte. Ltd.

Merkl, C., & Stolz, S. (2009). Banks' regulatory buffers, liquidity networks and monetary policy transmission. *Applied Economics*, *41*(16), 2013–2024. https://doi.org/10.1080/00036840802360245

Minoiu, C., & Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability*, *9*(2), 168–184. https://doi.org/10.1016/j.jfs.2013.03.001

Paltalidis, N., Gounopoulos, D., Kizys, R., & Koutelidakis, Y. (2015). Transmission Channels of Systemic Risk and Contagion in the European Financial Network. *Journal of Banking & Finance*, *61*, 36–52. https://doi.org/10.1016/j.jbankfin.2015.03.021

Petersen, M. A., Maruping, J. B., Mukuddem-Petersen, J., & Hlatshwayo, L. N. P. (2013). A Basel perspective on bank leverage. *Applied Financial Economics*, *23*(17), 1361–1369. https://doi.org/10.1080/09603107.2013.818210

Rönnqvist, S., & Sarlin, P. (2016). Bank networks from text: interrelations, centrality and determinants. *ECB Working Paper Series*, *1876*(1). https://doi.org/10.1111/j.1467-629x.1984.tb00054.x

Rørdam, K. B., & Bech, M. L. (2009). The topology of Danish interbank money flows. *Banks and Bank Systems*, *4*(4), 48–65.

Schanz, J. (2011). A joint calibration of bank capital and liquidity ratios. *Bank of England Working Paper Series*.

Sclip, A., Girardone, C., & Miani, S. (2019). Large EU banks' capital and liquidity: Relationship and impact on credit default swap spreads. *British Accounting Review*, *51*(4), 438–461. https://doi.org/10.1016/j.bar.2018.10.001

Soramäki, K., Bech, M. L., Arnold, J., Glass, R. J., & Beyeler, W. E. (2007). The topology of interbank payment flows. *Physica A: Statistical Mechanics and Its Applications*, *379*(1), 317–333. https://doi.org/10.1016/j.physa.2006.11.093

Souza, S. R. S., Tabak, B. M., Silva, T. C., & Guerra, S. M. (2015). Insolvency and contagion in the Brazilian interbank market. *Physica A: Statistical Mechanics and Its Applications*, *431*(July 2011), 140–151. https://doi.org/10.1016/j.physa.2015.03.005

Tonzer, L. (2015). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability*, *18*, 19–32. https://doi.org/10.1016/j.jfs.2015.02.002

Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance*, *61*, 1–14. https://doi.org/10.1016/j.jbankfin.2015.08.023

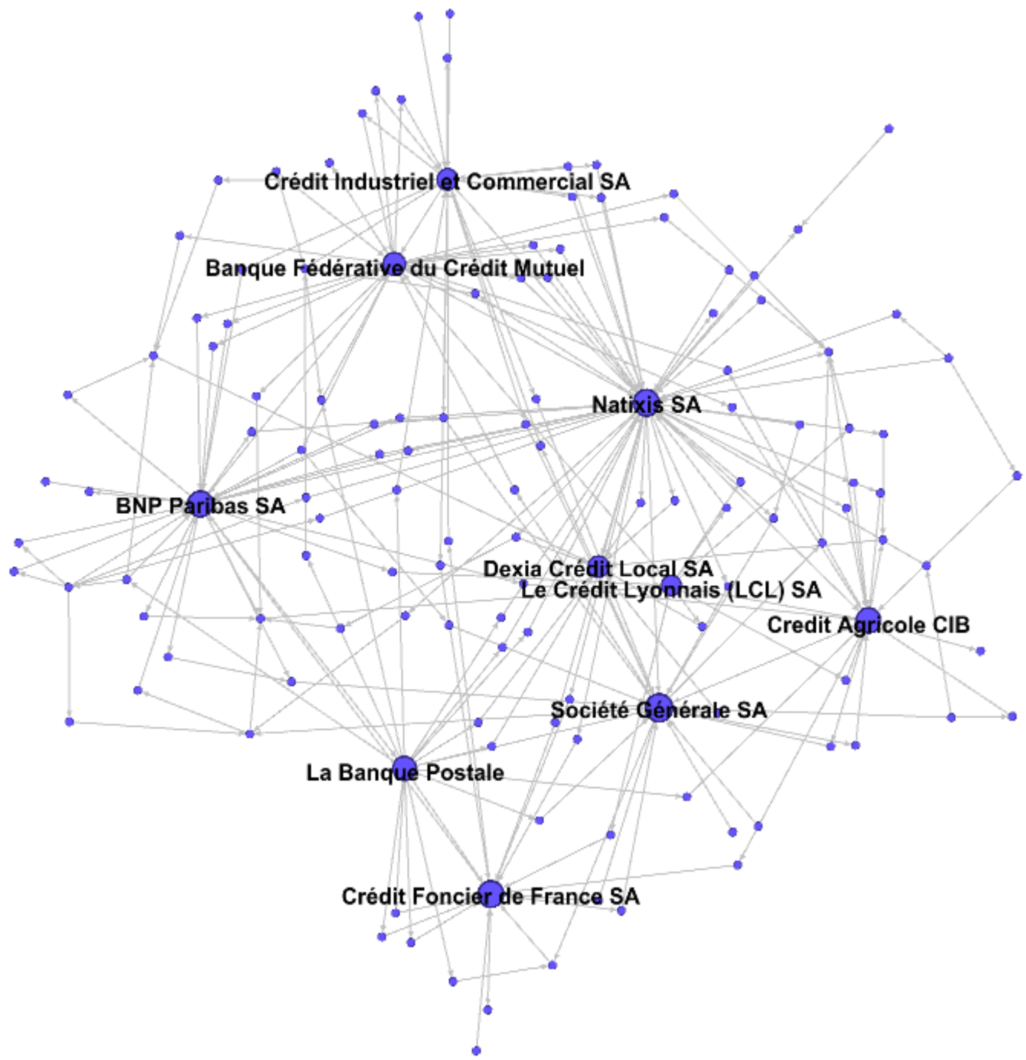
von Thadden, E. L. (2004). Bank capital adequacy regulation under the new Basel accord. *Journal of Financial Intermediation*, *13*(2), 90–95. https://doi.org/10.1016/j.jfi.2003.04.002

Winograd, L. P. B. M. (1999). The PageRank Citation Ranking: Bringing Order to the Web. *Technical Report. Stanford InfoLab*, *9*(1), 1–14. https://doi.org/10.1.1.31.1768

Worms, A. (2001). The reaction of bank lending to monetary policy measures in Germany. *ECB Working Paper Series*.

Xu, T., He, J., & Li, S. (2016). A dynamic network model for interbank market. *Physica A: Statistical Mechanics and Its Applications*, *463*, 131–138. https://doi.org/10.1016/j.physa.2016.07.013

Figure-1: Interbank network configurations of selected European country (France-2013):



Highlighted nodes represent banks with extreme number of direct linkages

Figure-2: Degree log-log plot for the whole sample. This figure illustrates the cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for Degree distribution of all 28 European countries.

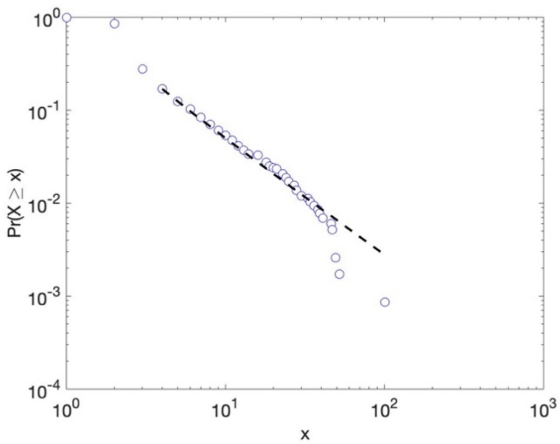
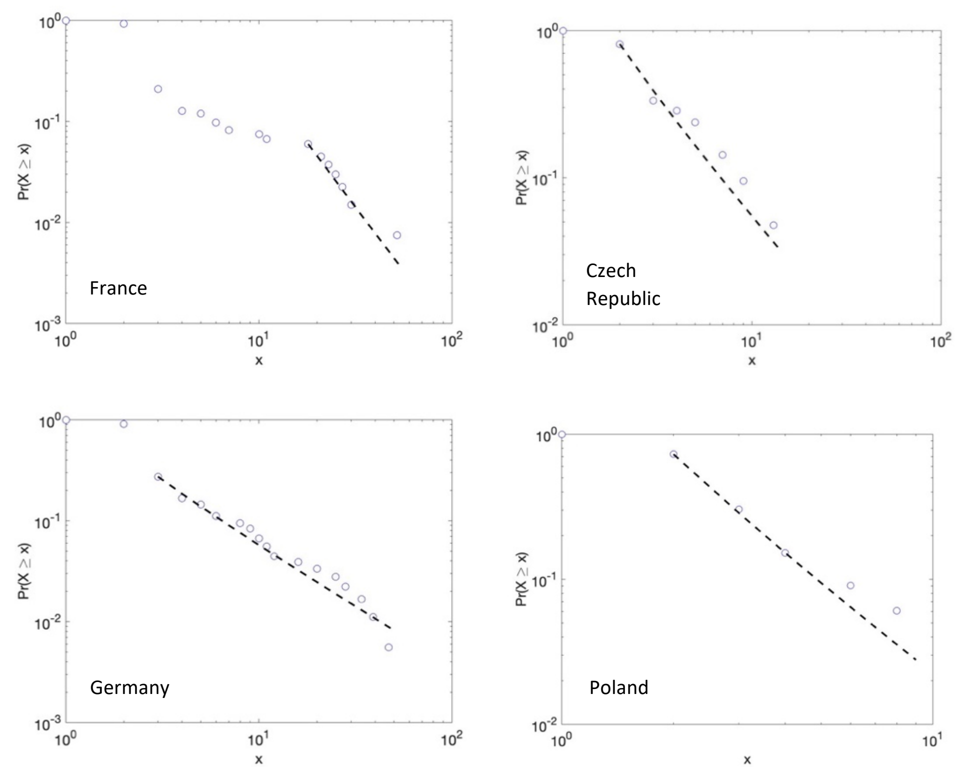


Figure-3: Degree log-log plot for six selected European countries. It consists of three large size banking industry (France, Germany and Italy) and three small size banking industry (Czech Republic, Poland and Slovenia). This figure shows the cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for Degree distribution of four selected European countries.



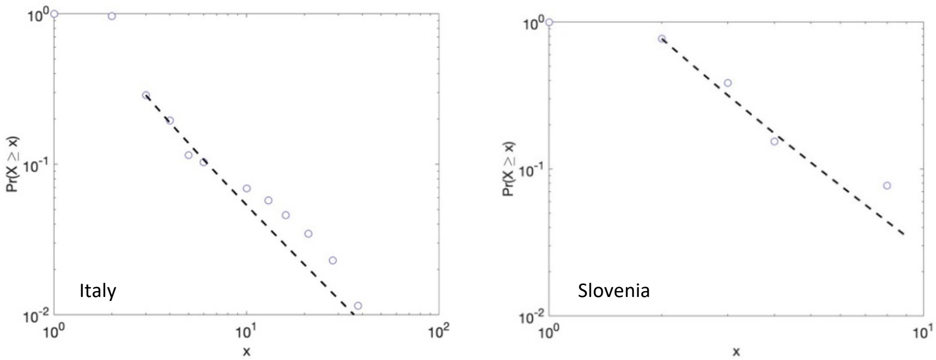


Table 1: Distribution of banks and representativeness of the final sample

Country Name	No. Obs
AUSTRIA	136
BELGIUM	75
BULGARIA	89
CROATIA	65
CYPRUS	50
CZECH REPUBLIC	58
DENMARK	400
ESTONIA	36
FINLAND	48
FRANCE	164
GERMANY	183
GREECE	75
HUNGARY	60
IRELAND	62
ITALY	608
LATVIA	38
LITHUANIA	41
LUXEMBOURG	86
MALTA	15
NETHERLANDS	131
POLAND	88
PORTUGAL	70
ROMANIA	81
SLOVAKIA	22
SLOVENIA	101
SPAIN	107
SWEDEN	101
UNITED KINGDOM	236
Total	3226

Table 2: Descriptive Statistics and definitions of my variables

Variables	Definition	Mean	Sd	Min	Median	Max
	Capital measure					
TCR	Total Capital Ratio	15,022	6,065	9,000	13,400	40,230
	Liquidity measure					
I.NSFR	Inverse of Net stable funding ratio	2,619	4,561	0,155	1,198	43,728
	Network Variables					
In-Degree	Total numbers of interbank lenders to bank					
HIn-Degree	Dummy variable that takes a value of one if bank's In-Degree is greater than or equal to the mean value of Country's In-Degree	0,369	0,483	0,000	0,000	1,000
Out-Degree	Total numbers of interbank borrowers from bank					
HOut-Degree	Dummy variable that takes a value of one if bank's Out-Degree is greater than or equal to the mean value of Country's Out-Degree	0,355	0,479	0,000	0,000	1,000
Betweenness	The ratio of links between bank j and bank k that passed through bank i compared to the total number of links between bank j and bank k.					
HBetweenness	Dummy variable that takes a value of one if bank's Betweenness is greater than or equal to the mean value of Country's Betweenness	0,428	0,495	0,000	0,000	1,000
PageRank	Ratio that indicates to what extent the importance of counterparties could determine the importance of each bank					
HPageRank	Dummy variable that takes a value of one if bank's PageRank is greater than or equal to the mean value of Country's PageRank	0,704	0,456	0,000	1,000	1,000
	Controls					
Bank Size	Logarithm of total assets	15,393	1,974	10,639	15,423	18,201
Z-Score	Indicator of bank distance to bankruptcy	60,235	70,053	3,284	34,356	311,580
ROE	Return on Equity	7,392	10,547	-19,134	7,925	28,440
LLP_NIR	Loans loss provisions to net interest revenue	23,691	27,148	-13,684	15,632	100,562
MKT_POW	Market power measured by bank total assets divided by country total assets	0,070	0,123	0,000	0,010	0,874
NIM	Net Interest Margin	2,620	1,528	0,132	2,388	7,026
GDPperCa	Natural logarithm of GDP per capita	27,136	1,598	22,235	27,969	30,790
Policy_Rate	ECB policy rates	1,911	1,316	0,000	2,000	7,750
Crises	Dummy variable for crisis times. Takes a value of one for the persiods of 2007-2009 (Global Financial Crisis) & 2010-2012(European Sovereign Debt Crisis)	0,542	0,498	0,000	1,000	1,000

Table 3: Power-law fits

	X_{min}	α	Goodness of Fit	p-value	Log-Likelihood
France	18	3,5	0,1246	0,619	-25,8138
Germany	3	2,18	0,0694	0,421	-128,743
Italy	3	2,27	0,08	0,469	-62,3853
Czech	2	2,49	0,089	0,505	-30,0925
Slovenia	2	2,83	0,0871	0,673	-14,6528
Poland	2	2,93	0,0383	0,896	-33,3666
All Sample	4	2,23	0,0311	0,469	-565,1287

This table provides *X*min as a lower-bound for Degree, the parameters for power-law fits, the goodness-of-Fits and its corresponding *p*-value and α as the scaling parameter.

Table 4: Correlation matrix of explanatory and control variables

	TCR	I.NSFR	HInDegree	HOutDegree	HBetweenness	HPageRank	Size	Size_Dummy	Z-Score	LLP_NIR	ROE	GDPperCap	crises	NIM	MKT_POW	CB_Policy
TCR	1.0000															
I.NSFR	0.0861	1.0000														
HInDegree	-0.1812	-0.0136	1.0000													
HOutDegree	-0.1351	-0.0686	0.4873	1.0000												
HBetweenness	-0.1584	-0.0821	0.6449	0.6034	1.0000											
HPageRank	-0.1212	-0.1218	0.3671	0.2338	0.4617	1.0000										
Bank Size	-0.3136	-0.0839	0.5629	0.5606	0.4710	0.1822	1.0000									
Size_Dummy	0.2848	0.0688	-0.3788	-0.3581	-0.3133	-0.0739	-0.7428	1.0000								
Z-Score	-0.0261	0.0866	-0.0432	-0.0506	-0.0847	-0.1065	0.0111	-0.0500	1.0000							
LLP_NIR	-0.0205	0.0571	0.0293	-0.0106	0.0281	0.0153	0.0234	0.0010	-0.2021	1.0000						
ROE	-0.0886	-0.0766	0.0805	0.1099	0.1054	0.0994	0.0739	-0.0830	0.0717	-0.5108	1.0000					
GDPperCap	-0.0459	0.1230	-0.0482	-0.0754	-0.1500	-0.3176	0.1192	-0.0772	0.1560	-0.0865	-0.0375	1.0000				
crises	0.0327	0.0463	-0.0121	-0.0202	-0.0104	-0.0549	0.0573	-0.0502	-0.1156	0.1300	-0.1211	0.0159	1.0000			
NIM	0.0391	-0.1308	-0.1869	-0.1808	-0.1205	0.0348	-0.4527	0.3651	-0.0890	0.0278	0.1593	-0.0969	-0.0701	1.0000		
MKT_POW	-0.1278	-0.0874	0.4612	0.4928	0.4716	0.3004	0.4738	-0.2737	-0.0836	0.0039	0.1566	-0.2595	-0.0557	-0.0055	1.0000	
CB_Policy	-0.1325	-0.1136	0.0247	0.0368	0.0289	0.0644	-0.0307	0.0225	0.0903	-0.3178	0.3403	-0.0352	-0.2407	0.0875	0.0570	1.0000

Table 5: Baseline GMM model of interaction between network topology and liquidity on bank capital ratio

	1	2	3	4	5
VARIABLES		HIn-Degree	HOut-Degree	HBetweenness	HPageRank
Capital Equation					
I.NSFR (1)	2.552***	2.838***	2.600***	0.606	2.513**
	(0.963)	(0.621)	(0.553)	(0.771)	(1.088)
HNetw		6.363***	7.305***	6.146***	4.778***
		(1.703)	(1.702)	(1.821)	(1.802)
HNetw*I.NSFR (2)		-2.883***	-2.599***	-0.847	-2.627**
		(0.628)	(0.553)	(0.771)	(1.102)
Bank Size	-1.100***	-0.591**	-0.915***	-1.190***	-0.578***
	(0.369)	(0.261)	(0.278)	(0.198)	(0.211)
Z-score	-0.000376	-0.00577*	-0.00269	-0.000721	-0.00421
	(0.00240)	(0.00305)	(0.00254)	(0.00281)	(0.00317)
LLP_NIR	-0.0244	-0.0288**	-0.0142	-0.0137	-0.0145
	(0.0215)	(0.0132)	(0.0106)	(0.0113)	(0.0130)
ROAE	-0.0728	-0.0614*	-0.0380	-0.0590**	-0.0245
	(0.0603)	(0.0328)	(0.0271)	(0.0278)	(0.0267)
GDPperCa	-2.139	-1.111**	-0.861*	0.556	-1.497
	(1.379)	(0.529)	(0.516)	(0.718)	(1.220)
Crises	0.170	0.285	0.455	0.854*	-0.380
	(0.645)	(0.404)	(0.405)	(0.449)	(0.754)
Constant	84.51**	48.76***	45.86***	15.10	59.69*
	(40.39)	(16.14)	(15.95)	(19.50)	(32.74)
Liquidity Equation					
TCR	0.528*	0.284**	0.206**	0.223	0.313***
	(0.282)	(0.113)	(0.0981)	(0.287)	(0.108)
HNetw		0.515*	-0.467*	-0.933	-0.0517
		(0.305)	(0.240)	(2.916)	(0.300)
NIM	-0.400**	-0.196***	-0.245***	-0.336***	-0.327***
	(0.164)	(0.0724)	(0.0719)	(0.102)	(0.105)
MKT_POW	0.692	-0.330	1.084	1.816	0.496
	(1.548)	(1.186)	(1.124)	(4.717)	(1.276)
CB_Policyrate	-0.0170	-0.167**	-0.197***	-0.144	-0.0973
	(0.190)	(0.0709)	(0.0659)	(0.170)	(0.0941)
Crises	-0.406**	-0.353**	-0.334**	-0.333	-0.365**
	(0.207)	(0.165)	(0.161)	(0.205)	(0.174)
Constant	-4.038	-0.912	0.707	0.823	-0.913
	(4.193)	(1.720)	(1.479)	(5.438)	(1.545)
Wald-test					
1+2		-.044	.001	-.240***	-.113**
Observations	3,226	3,226	3,226	3,226	3,226
No. Banks	506	506	506	506	506
VIF Test	1.42	1.5	1.51	1.47	1.48
Hansen's J	0.653703	4.28696	4.19729	2.91254	2.57347
Hansen's J p-value	0.7212	0.3686	0.3800	0.2331	0.4622

This table presents regression results using GMM simultaneous equations model for an unbalanced panel of European commercial banks over the 2001-2013 period by introducing the interaction the network dummy and I.NSFR. employ two steps GMM estimator with robust standard error:

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t}$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 TCR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} + \alpha_5 Crises_t + \varepsilon_{i,t}$$

TCR is capital ratio and I.NSFR is my illiquidity measurement, Network statistics dummies (*HNetw*) include *HIn-degree, HOut-degree*, *HBetweenness* and *HPageRank*. $B_{i,t-1}$ is a vector of bank-level control. C_j is a vector of country-level control variables. *Crises* is a dummy variable for financial crises (2007-2012). I include time and cross-section fixed effects in the regressions and I use the Huber-White estimator. Hansen Test is used. VIF test reports multicollinearity checks among all variables. All dependent and bank-level control variables are winsorized at 1% - 99%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6: GMM model of interaction between network topology and liquidity on bank capital ratio during normal times and crisis times

	1	2	3	4	5
VARIABLES		HIn-Degree	HOut-Degree	HBetweenness	HPageRank
Capital Equation					
I.NSFR (1)	4.253***	6.759***	5.397***	6.755***	4.853***
	(1.630)	(2.563)	(1.639)	(1.974)	(1.285)
HNetw		9.248	9.043**	7.592***	4.976***
		(6.713)	(4.374)	(2.498)	(1.105)
HNetw*I.NSFR (2)		-7.364	-5.729*	-6.211***	-4.601***
		(5.049)	(3.196)	(1.831)	(1.208)
Crises*I.NSFR (3)	-4.209**	-6.296***	-5.076***	-6.411***	-4.618***
	(1.638)	(2.349)	(1.527)	(1.897)	(1.245)
HNetw*I.NSFR *Crises (4)		6.369	4.879*	5.186***	3.470***
		(4.408)	(2.785)	(1.510)	(0.984)
Liquidity Equation					
TCR	0.533*	0.188	0.229	0.164	0.357***
	(0.284)	(0.309)	(0.263)	(0.254)	(0.0972)
Wald-test					
1+2	.044	-.605	-.331	.544***	.252**
1+3		.462*	.321**	.344***	.234***
1+2+3+4		-.531	-.527	-.680*	-.895***
Observations	3,226	3,226	3,226	3,226	3,226
No. Banks	506	506	506	506	506
VIF Test	1.71	2.21	2.05	2.05	2.08
Hansen's J	1.17504	2.66928	1.97063	2.94736	3.09101
Hansen's J p-value	0.5557	2.66928	0.1604	0.3998	0.5427
Bank-Level Controls	Yes	Yes	Yes	Yes	Yes
Country-level Controls	Yes	Yes	Yes	Yes	Yes

This table presents regression results for crisis times and normal times using GMM simultaneous equations model for an unbalanced panel of European commercial banks over the 2001-2013 period by introducing the interaction the network dummy, crises dummy and I.NSFR. I employ two steps GMM estimator with robust standard error:

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 Crises(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_5 HNetw(x)_{i,j,t} * I.NSFR_{i,t} * Crises(x)_{i,j,t} + \alpha_6 B_{i,j,t-1} + \alpha_7 C_{j,t} + \alpha_8 Crises_t + \varepsilon_{i,t}$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 TCR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} + \alpha_5 Crises_t + \varepsilon_{i,t}$$

TCR is capital ratio and I.NSFR is my illiquidity measurement, Network statistics dummies (*HNetw*) include *HIn-degree, HOut-degree*, *HBetweenness* and *HPageRank*. $B_{i,t-1}$ is a vector of bank-level control. C_j is a vector of country-level control variables. *Crises* is a dummy variable for financial crises (2007-2012). I include time and cross-section fixed effects in the regressions and I use the Huber-White estimator. Hansen Test is used. VIF test reports multicollinearity checks among all variables. All dependent and bank-level control variables are winsorized at 1% - 99%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Appendix A

Minimum Density

Introduced by Anand et al. (2015), minimum density (MD) is an efficient and streamlined method and is consistent with total observed interbank lending and borrowing for each bank. The main assumption of MD is that producing and maintaining the extra linkages is costly for banks. The first step to conducting an MD approach is to solve the constrained optimisation problem:

$$\min_{IE} c \ \sum_i^N \sum_j^N 1\left[IE_{ij} > 0\right] \qquad s.t$$

$$\sum_{j=1}^{N} IE_{ij} = IL_i \quad \forall i = 1,2,\dots,N \tag{11}$$

$$\sum_{i=1}^{N} IE_{ij} = ID_j \quad \forall j = 1,2,\dots,N$$

$$IE_{ij} \geq 0$$

IE: A matrix of interbank exposure.

c: Fixed cost for establishing the extra linkages.

Integer function 1: Equals 1 if and only if bank *i* lends to bank *j*.

The bank's lending-borrowing capacity in this approach is constrained by the total amount of interbank loans (*IL)* and deposits (*ID*), which are considered marginals.

In the second step, the link-generating algorithm imposes a penalty upon each bank for deviations from the marginal borrowing and lending capacity:

$$IL\_D_i \equiv \left(IL_i - \sum_j IE_{ij}\right) \tag{12}$$

$$ID\_D_i \equiv \left(ID_i - \sum_j IE_{ji}\right) \tag{13}$$

Current deviation of bank *i*'s from marginal lending and borrowing are measured by IL_D_i *and* ID_D_i respectively. Therefore, the model maximises the value of sparse matrix *IE*, which minimises marginal deviations when the above criterion is added to the objective function:

$$\mathrm{V(IE)} = -c \sum_{i=1}^{N} \sum_{j=1}^{N} 1\left[IE_{ij} > 0\right] - \sum_{i=1}^{N} (\propto_i IL_i^2 + \delta_i ID_i^2) \tag{14}$$

I define a set of probabilities Q that captures disassortative characteristics of an interbank network:

$$Q_{ij} \propto \max\left\{\frac{IL_{-D\,i}}{ID_{-D\,j}}, \frac{ID_{-D\,j}}{IL_{-D\,i}}\right\} \quad (15)$$

Consistent with the probability Q, there is an increase in the lending probability of *i* to *j* if *i* is a small lender to a large borrower *j or i* is a large lender to a small borrower *j*. The selection process continues by highest value loading a matrix of exposure following the like-selection priority determination:

$$IE_{ij} = \mathrm{Min}\ \{IL\_D_i, ID\_D_j\} \quad (16)$$

Eventually, the interbank network is produced by this maximisation function:

$$Max \sum_{IE} P(IE)V(IE) + \theta\ R(P \parallel Q) \quad (17)$$

P(IE): The probability distribution for all plausible network formations.

R: The relative entropy function.

θ: A scaling parameter (reflecting the finding solutions' weight with similar features to the prior matrix Q.[10]

[10] This algorithm has been constructed and run with a Matlab programme. The heuristic process that executes this method is fully described in Anand et al. (2015).

Appendix B

Table B1: Stylized Balance Sheet and Weights to Compute the NSFR

ASSETS	Weight	LIABILITIES+EQUITY	Weight
1 Total Earning Assets		**1** Deposits &Short-term funding	
1.A Loans	100%	**1.A** Customer Deposits	
1.A.1 Total Customer Loans		**1.A.1** Customer Deposits- Current	85%
Mortgages Loans		**1.A.2** Customer Deposits-Savings	70%
Other Mortgage Loans		**1.A.3** Customer Deposits-Term	70%
Other Consumer/Retail Loans Corporate		**1.B** Deposits from Banks	0%
&Commercial Loans Other Loans		**1.C** Other Deposits and Short-term Borrowings	0%
1.A.2 Reserves for Impaired Loans/NPLs			
1.B Other Earning Assets		**2** Other interest bearing liabilities	
1.B.1 Loans and Advances to Banks	35%	**2.A** Derivatives	0%
1.B.2 Derivatives		**2.B** Trading Liabilities	0%
1.B.3 Other Securities		**2.C** Long-term funding	100%
Trading securities Investment securities		**2.C.1** Total Long Term Funding	100%
		Senior Debt	
1.B.4 Remaining earning assets		Subordinated Borrowing	
2 Fixed Assets	100%	Other Funding	100%
3 Non-Earning Assets		**2.C.2** Pref. Shares and Hybrid Capital	
3.A Cash and due from banks		**3** Other (Non-Interest bearing)	100%
3.B Goodwill	0%	**4** Loan Loss Reserves	100%
3.C Other Intangibles	100%	**5** Other Reserves	100%
3.D Other Assets	100%		
	100%	**6** Equity	100%

This table presents a stylized bank balance sheet, together with the weights assigned to different assets and liabilities for the computation of the net stable funding ratio defined in Vazquez and Federico (2015).

Appendix C

Table C1: Baseline GMM model of interaction between network topology and liquidity on Tier-1 capital ratio

	1	2	3	4
VARIABLES	HIn-Degree	HOut-Degree	HBetweenness	HPageRank
Capital Equation				
I.NSFR (1)	3.262***	3.063***	0.273	2.878**
	(0.740)	(0.673)	(0.818)	(1.323)
HNetw	7.277***	8.558***	6.966***	4.921**
	(2.008)	(2.066)	(1.989)	(2.179)
HNetw*I.NSFR (2)	-3.325***	-3.075***	-0.616	-3.036**
	(0.754)	(0.679)	(0.827)	(1.345)
Liquidity Equation				
Tier 1	0.249***	0.176**	0.262	0.280***
	(0.0947)	(0.0836)	(0.229)	(0.0905)
Wald-test				
1+2	-.062	-.011	-.342***	-.158***
Observations	3,226	3,226	3,226	3,226
No. Banks	506	506	506	506
Hansen's J	4.8908	4.93067	2.0234	1.86548
Hansen's J p-value	0.2987	0.2945	0.3636	0.6008
Bank-level Controls	Yes	Yes	Yes	Yes
Country-level Controls	Yes	Yes	Yes	Yes

This table presents regression results using GMM simultaneous equations model for an unbalanced panel of European commercial banks over the 2001-2013 period by introducing the interaction the network dummy and I.NSFR. I employ two steps GMM estimator with robust standard error:

$$Tier-1_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t}$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 Tier-1_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} + \alpha_5 Crises_t + \varepsilon_{i,t}$$

Tier-1 is capital ratio and I.NSFR is my illiquidity measurement, Network statistics dummies (*HNetw*) include *HIn-degree, HOut-degree*, *HBetweenness* and *HPageRank*. $B_{i,t-1}$ is a vector of bank-level control. C_j is a vector of country-level control variables. *Crises* is a dummy variable for financial crises (2007-2012). I include time and cross-section fixed effects in the regressions and I use the Huber-White estimator. Hansen Test is used. All dependent and bank-level control variables are winsorized at 1% - 99%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C2: Baseline GMM model of interaction between network topology and liquidity on TCR capital ratio: Network dummy is defined based on 90-percentile value.

	1	2	3	4
VARIABLES	HIn-Degree	HOut-Degree	HBetweenness	HPageRank
Capital Equation				
I.NSFR (1)	2.408***	2.240***	0.122	4.092
	(0.510)	(0.457)	(0.795)	(2.996)
HNetw	6.294***	6.808***	3.955**	6.086
	(1.535)	(1.570)	(1.764)	(3.941)
HNetw*I.NSFR (2)	-2.450***	-2.296***	-0.426	-4.314
	(0.522)	(0.466)	(0.804)	(3.098)
Liquidity Equation				
TCR	0.242**	0.201**	0.101	0.330***
	(0.101)	(0.0989)	(0.294)	(0.113)
Wald-test				
1+2	-.0428	-.0562	-.304***	-.221*
Observations	3,226	3,226	3,226	3,226
No. Banks	506	506	506	506
Hansen's J	5.24486	5.62496	2.22564	2.62603
Hansen's J p-value	0.2631	0.2290	0.3286	0.4529
Bank-level Controls	Yes	Yes	Yes	Yes
Country-level Controls	Yes	Yes	Yes	Yes

This table presents regression results using GMM simultaneous equations model for an unbalanced panel of European commercial banks over the 2001-2013 period by introducing the interaction the network dummy and I.NSFR. I employ two steps GMM estimator with robust standard error:

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t}$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 TCR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} + \alpha_5 Crises_t + \varepsilon_{i,t}$$

TCR is capital ratio and I.NSFR is illiquidity measurement, Network statistics dummies (*HNetw*) include *HIn-degree, HOut-degree*, *HBetweenness* and *HPageRank*. $B_{i,t-1}$ is a vector of bank-level control. C_j is a vector of country-level control variables. *Crises* is a dummy variable for financial crises (2007-2012). I include time and cross-section fixed effects in the regressions and I use the Huber-White estimator. Hansen Test is used. VIF test reports multicollinearity checks among all variables. All dependent and bank-level control variables are winsorized at 1% - 99%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table C3: Baseline GMM model of interaction between network topology and liquidity on TCR capital ratio – replace logarithm of total assets by size dummy

	1	2	3	4
VARIABLES	HIn-Degree	HOut-Degree	HBetweenness	HPageRank
Capital Equation				
I.NSFR (1)	2.600***	2.339***	-0.103	1.989**
	(0.565)	(0.500)	(0.980)	(0.965)
HNetw	5.532***	6.059***	4.532**	3.890**
	(1.461)	(1.421)	(2.260)	(1.618)
HNetw*I.NSFR (2)	-2.634***	-2.347***	-0.155	-2.097**
	(0.571)	(0.502)	(0.984)	(0.976)
Liquidity Equation				
TCR	0.276**	0.201**	0.223	0.313***
	(0.112)	(0.0980)	(0.287)	(0.108)
Wald-test				
1+2	-.0339	-.0079	-.258***	-.107**
Observations	3,226	3,226	3,226	3,226
No. Banks	506	506	506	506
Hansen's J	4.67287	4.5542	2.91254	2.57347
Hansen's J p-value	0.3225	0.3362	0.2331	0.4622
Bank-level Controls	Yes	Yes	Yes	Yes
Country-level Controls	Yes	Yes	Yes	Yes

This table presents regression results using GMM simultaneous equations model for an unbalanced panel of European commercial banks over the 2001-2013 period by introducing the interaction the network dummy and I.NSFR. I employ two steps GMM estimator with robust standard error:

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t}$$

$$I.NSFR_{i,t} = \alpha_0 + \alpha_1 TCR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 B_{i,j,t-1} + \alpha_4 C_{j,t} + \alpha_5 Crises_t + \varepsilon_{i,t}$$

TCR is capital ratio and I.NSFR is my illiquidity measurement, Network statistics dummies (*HNetw*) include *HIn-degree, HOut-degree*, *HBetweenness* and *HPageRank*. $B_{i,t-1}$ is a vector of bank-level control. C_j is a vector of country-level control variables. *Crises* is a dummy variable for financial crises (2007-2012). I include time and cross-section fixed effects in the regressions and I use the Huber-White estimator. Hansen Test is used. VIF test reports multicollinearity checks among all variables. All dependent and bank-level control variables are winsorized at 1% - 99%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.