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Interfaces with Other Disciplines

Do banks change their liquidity ratios based on network characteristics?

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ABSTRACT

By applying interbank network simulation, this paper investigates the impact of interbank network topology on bank liquidity ratios. Whereas regulators have put more emphasis on liquidity requirements since the global financial crisis of 2007–2008, how differently shaped interbank networks affect individual bank liquidity behavior remains an open issue. We look at how banks' interconnectedness within interbank loan and deposit networks affects their decisions to hold more or less liquidity during normal times and distress times. Our sample consists of commercial, investment, and real estate and mortgage banks in 28 European countries and allows us to differentiate large and small networks. Our results show that accounting for bank connections within a network is important to understand how banks set their liquidity ratios. Our findings have critical implications for the implementation of Basel III liquidity requirements and bank supervision more generally.

1. Introduction

One of the most prominent functions of banks in the economy is liquidity creation, which makes them inherently vulnerable (Diamond & Dybvig, 1983). Because they face liquidity shortages or surpluses in their daily operations, banks and other financial institutions are interconnected in different ways based on distinct bilateral transactions in the interbank market. Such linkages enable efficient risk management and risk transfer but are also a potential source of contagion and systemic risk. By incentivizing peer monitoring, interbank lending imposes discipline on banks. On the borrower side, the interbank market charges riskier banks higher rates (Furfine, 2001). On the lender side, higher bank interconnectedness is associated with higher counterparty risk, leading to higher rates and liquidity hoarding during financial crises, as well as possible liquidity freezes (Acharya & Merrouche, 2013).

The global financial crisis of 2007–2008 led bank regulators to impose new liquidity requirements to supplement existing minimum capital ratios. The liquidity standards introduced by the Basel Committee (BCBS, 2010) require banks to hold a sufficient amount of high-quality liquid assets to protect them from liquidity shocks 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). The minimum requirements are independent of the topology and characteristics of the network in which banks operate. However, recent studies such as Glasserman and Young (2015), Huang, Zhuang, Yao and Uryasev (2016), Paltalidis, Gounopoulos, Kizys and Koutelidakis (2015), and Souza, Tabak, Silva and Guerra (2015) highlight the significant role interbank network connectedness plays in systemic risk and the contagion of financial shocks to the economy as a whole. In this paper, we investigate how network simulation algorithms aimed at capturing bank interconnectedness within interbank loan and deposit networks can improve our understanding of how banks set their liquidity ratios during normal times and distress times.

There is an extensive literature on the application of network science in different disciplines (Bekiros, Nguyen, Sandoval Junior & Uddin, 2017; Ben Mohamed, Klibi & Vanderbeck, 2019; Hellsten, Pisinger, Sacramento & Vilhelmsen, 2019; Kao, Simpson, Shao & Lin, 2017; Mazzarisi, Barucca, Lillo & Tantari, 2019; McHale & Relton, 2018; Blas, Simon Martin & Gomez Gonzalez, 2018; van Dorp, 2020). Empirical studies of interbank networks focus on dynamic or static network analysis of interbank markets. On the one hand, dynamic approaches highlight the fragility of the financial system by showing how financial shocks and individual bank defaults could lead to the failure of other institutions and eventually to the collapse of the entire financial system (Brunetti, Harris, Mankad & Michailidis, 2019; Caccioli, Shrestha, Moore & Farmer, 2014; Dungey & Gajurel, 2015; Fry-McKibbin, Martin & Tang, 2014; Souza, deSilva, Tabak & Guerra, 2016). On the other hand, static

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approaches shed light on the importance of interbank connectedness, also called network topology, by determining specific and group characteristics of distinctive financial networks (Craig & Von Peter, 2014; González-Avella, Quadros & Iglesias, 2016; Langfield, Liu & Ota, 2014; Veld & Van Lelyveld, 2014). We follow the latter literature on network topology, which enables us to draw a clear picture of increasingly complex interbank connections and interdependencies. Identifying the type of connections in interbank networks should provide critical information on the strengths and weaknesses of individual banks to access liquidity on different time horizons and in different locations.

By focusing on the network topology approach, we contribute to the literature by examining how local and systemwide bank connectedness affects liquidity management and liquidity ratios of individual banks of different sizes and whether such ratios strongly depend on banks' networks during normal and crisis times. Although there is an extensive banking literature examining the determinants of bank liquidity (Cucinelli, 2013; Distinguin, Roulet & Tarazi, 2013; King, 2013; Mattana & Panetti, 2014; Roman & Şargu, 2014; Vodová, 2011), existing studies neglect the role of interconnectedness among banks in interbank networks. However, one of the specificities of banks is that they have a significant number of direct claims and obligations with one another through their interconnectedness in the interbank market and this source of contagion and systemic risk is not considered in the liquidity requirements. Liquidity requirements limit the possibility that market liquidity risk spreads by requiring the holding of liquid assets and reduce the propagation of funding liquidity risk by imposing limits on short-term liabilities but they do not consider the risk a specific bank brings to the system as a whole through its connectivity (Haldane & May, 2011). By looking at whether the way banks offset their liquidity ratios is affected by their position and strength within the interbank network, we bridge the gap between two strands of the literature. We bring together network science and the banking literature by using simulated interbank networks to compute various network statistics that we, in turn, introduce as additional variables to augment traditional bank liquidity models. Each network variable measures a specific feature of individual bank interconnectedness within the interbank network and thereby reveals its access to interbank liquidity. We hence add to the literature by showing how network simulation algorithms can improve the explanatory power of bank liquidity ratio models. By examining how different states of connectedness influence banks' balance sheet liquidity, we also challenge the validity of imposing uniform minimum liquidity requirements to banks such as those imposed by Basel III.

Simulation techniques are typically used to evaluate the risk and performance of systems and individual entities. The reasons for performing simulation are either analytical complexity or lack of access to data. Bedoni (1987) and Grubmann (1987) conduct simple bank balance sheet simulations to assist managers in optimum decision making depending on the bank's distinct strategic policies. Grundke and Kühn (2019) employ the bottom-up simulation technique to analyze the influence of Basel III liquidity ratios (NSFR and LCR) on banks. Simaan, Gupta and Kar (2019) conduct a simulation study to illustrate how systemic risk is linked to interconnections of banks in the interbank network. Paisittanand and Olson (2006) evaluate financial risk of credit card operation projects in the Thai banking system using Monte Carlo simulation. Bellini (2013) and Grundke (2010) conduct a comparative study to evaluate simulation approaches for integrated banking risk management. Saha, Subramanian, Basu and Mishra (2009) employ a simulation approach to examine how bank's network is influenced by interest rate volatility. Eventually, by using the tlasso model, Torri, Giacometti and Paterlini (2018) simulate partial correlation networks based on credit default swap data. The interbank market is a complex network of banks with different liquidity needs and confidential OTC[1] contracts. Except in a few countries, banks are not required to report their bilateral exposures to regulatory authorities. Hence, the complexity of banking networks in addition to the unavailibility of data explains why simulation tools are often used. We simulate bilateral transactions in the interbank network by using the Minimum Density algorithm developed by Anand, Craig and von Peter (2015) to fill in the blank using available information on banks' aggregate interbank lendings.

We work on a sample of 1178 banks from 28 European countries encompassing an integrated area under the supervision of a unique monetary authority (the ECB). Such an environment should facilitate transactions among participating countries but also trigger global instability more easily during severe financial distress. European banks experienced the global financial crisis of 2007–2008 and the sovereign debt crisis of 2010–2011, which provides an interesting laboratory to investigate how banks react within distinct interbank network topologies during two different financial meltdowns. Furthermore, because banks may manage liquidity differently in larger or smaller banking sectors due to higher or lower contagion risk in differently scaled networks, we take advantage of the large set of countries in our sample with generally larger and more mature banking sectors in Western Europe than in Eastern Europe.

Our results show that network statistics do play a significant role in explaining liquidity ratios. Small banks and banks in smaller banking sectors mostly consider their local network position to set their liquidity ratios. More precisely, banks that have more direct lenders hold less liquidity presumably because they believe they can have easier access to interbank funds in case of shortage as a result of their ability to diversify their borrowing on the interbank market, while banks with more direct borrowers are more conservative regarding the liquidity they hold. For banks in larger banking sectors and for large and medium-size banks, systemwide network positions mostly matter. A higher systemwide position in the interbank network is associated with lower liquidity ratios. However, counterparty, contagion and systemic risks can arise through these higher systemwide positions. Besides, our results show that during distress times, G-SIFIs take advantage of their network positions by setting lower liquidity ratios when they have stronger systemwide positions in the interbank network. This highlights the need to monitor such banks more closely.

The rest of the paper is laid out as follows. Section 2 describes the data, variables and methodology; Section 3 presents the results of our study. Robustness checks are reported in Section 4. Section 5 concludes.

2. Sample, variables, and method

2.1. Sample

Our sample consists of commercial, investment, and real estate and mortgage banks in 28 European countries.[2] We omit savings, mutual, and cooperative banks due to specificities in terms of interbank relationships. Such banks mainly transact with central institutions within their own systems (BIS, 2001; Boss & Elsinger, 2004; Worms, 2001). Nevertheless, for robustness we also compute network measures based on the entire bank population in each country and investigate the behavior of all banks. The sample period runs from 2001 to 2013. Accounting data (annual financial

[1] Over-the-counter.

[2] 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.

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

Country	Number of banks (Bankscope)	Number of banks (Sample)	Percent of total assets (%)
Austria	102	80	89.37
Belgium	38	22	98.25
Bulgaria	24	20	75.36
Croatia	38	29	91.95
Cyprus	26	11	93.56
Czech republic	29	15	85.53
Denmark	52	46	95.71
Estonia	11	6	98.04
Finland	34	10	97.08
France	173	137	86.46
Germany	215	172	71.03
Greece	17	14	87.27
Hungary	39	25	94.43
Ireland	38	22	78.47
Italy	132	92	76.10
Latvia	25	20	81.28
Lithuania	12	10	94.54
Luxembourg	81	65	91.50
Malta	17	9	85.90
Netherlands	50	28	73.16
Poland	54	42	82.07
Portugal	34	27	88.53
Romania	27	20	86.71
Slovakia	17	9	87.56
Slovenia	18	14	94.01
Spain	70	53	93.40
Sweden	44	31	97.32
United Kingdom	297	149	77.61
Total	1714	1178	83.89

statements) for individual banks are from Bankscope Fitch IBCA. We consider consolidated data but also use unconsolidated data when consolidated balance sheets are not available. Bankscope reports balance sheets and income statements for 1714 banks in the countries in this study. After eliminating banks for which Bankscope does not report information on our variables of interest, our final sample of banks consists of 1178 banks. More than 75% are commercial banks, more than 14% are real estate and mortgage banks, and fewer than 9% are investment banks.

Table B1 in the appendix shows descriptive statistics for the raw sample of 1714 banks and for our final sample of banks. The univariate statistics of these two samples are very similar and on average, the final sample of banks (Table 1) represents more than 83% of the total assets of commercial, investment, and real estate and mortgage banks covered by Bankscope for the sample countries (the lowest is 71.03% for Germany; the highest is 98.25% for Belgium).

2.2. Definition of variables

We present our dependent variable, the independent variables reflecting interbank network characteristics, and the control variables in our estimations. Descriptive statistics and definitions of these variables are in Table 2. Extreme bank-year observations for our dependent and bank-level control variables are winsorized (5% lowest and highest values).

2.2.1. Structural liquidity indicator (NSFR)

The Basel Committee on Banking Regulation and Supervision developed an international framework for liquidity assessment in banking, including the implementation of the net stable funding ratio, or NSFR (BCBS, 2010). It requires banks to finance illiquid assets with more stable and less risky funds, which consequently reduces liquidity mismatch. It is a structural tool for liquidity measurement, as it considers both sides of the balance sheet and categorizes assets and liabilities as liquid, semi-liquid, and illiquid; it then weights each component. This ratio is defined in BCBS (2010) as :[3]

$$NSFR = \frac{Available\ amount\ of\ stable\ funds}{Required\ amount\ of\ stable\ funds} \quad (1)$$

To ensure their liquidity, Basel III expects banks to set this ratio above 100%. The available amount of stable funds is defined as the total amount of bank capital, liabilities with maturities equal to or greater than one year, and the share of stable demand deposits and time deposits with maturities of less than one year that the bank expects to retain. The required amount of stable funding is the amount of assets that cannot be easily monetized or used as collateral for secured borrowing during a liquidity stress period. Because calculating NSFR based on BCBS (2010) is difficult due to unavailable detailed balance sheet breakdowns, we approximate it with Bankscope data using the weights defined in Vazquez and Federico (2015).[4]

2.2.2. Interbank network

We investigate the relationship between individual bank network statistics and the NSFR ratio. A first step towards estimating this relationship is the construction of the network based on the lending-borrowing relationships in the interbank loan and deposit market. Subsequently, we create bank-level network variables based on bank specific characteristics in the interbank markets. A substantial drawback is the difficulty of accessing bilateral exposure data for individual banks, as banks are not required to report this to regulatory authorities in most of the European countries. Balance sheets only provide information on a bank's aggregate loans to and deposits from all other banks. Therefore, to scrutinize network characteristics at the bank level, we have to predict these bilateral relationships by applying mathematical algorithms.

Several studies, such as Anand et al. (2015); Elsinger, Lehar and Summer (2006); and Upper and Worms (2004), introduce and extend the ways to predict missing values and fill in blanks. Common techniques are maximum entropy (ME) and minimum density (MD) algorithms. However, maximum entropy is not an appropriate estimation method for this study, because it assumes that each bank diversifies its loan-deposit portfolio as evenly as possible with all the other banks in the network, thereby leading to a complete network, which is too far from reality. ME could be a suitable method for predicting a network if there were no information on banks' state of interconnectedness. However, the literature outlines some steady features of interbank networks. Chiu, Eisenschmidt and Monnet (2019) and Cocco, Gomes and Martins (2009), for example, show that banks' connections in the interbank market are based on long-term lending relationships. Cocco et al. (2009) suggest that a bank constructs a linkage to other banks with whom its liquidity shocks are less correlated, which leads to sparse networks. Craig and von Peter (2014) highlight tiering properties of the interbank network by considering its core-periphery features. They explain how the majority of banks (called "periphery") connect to few banks (called "core") depending on their own needs and characteristics. Anand et al. (2015) explain that interacting with all possible banks is too costly based on information refinement and operational risk. They also highlight the hierarchical attributes of the interbank loan-deposit market, which show that

[3] We follow the literature and consider NSFR but not LCR, which cannot be computed due to lack of data. Besides, the LCR is expected to protect banks from liquidity shocks over a short horizon (one month). In our work, the network statistics variables are computed annually (same time horizon as the NSFR).

[4] The detailed components and their weights are in Table B2. The departures from the Basel III weights are detailed in Vazquez and Federico (2015). For example, as it is not possible to split loans according to type or maturity, a weight of 100% is assigned to total loans. As other earning assets are supposed to be more liquid, an average weight of 35% is assigned.

Table 2
Descriptive statistics and variable definitions.

Variables	Definition	Mean	S.d.	Min.	Median	Max
Dependent variable						
NSFR	Net stable funding ratio	0.792	0.620	0.046	0.744	2.449
Network variables						
In-degree	Total number of interbank lenders to bank	1.884	3.660	0.000	1.000	61.000
Out-degree	Total number of interbank borrowers from bank	1.863	3.186	0.000	1.000	53.000
ClusteringCo	Connection density of each bank's direct neighbors	0.186	0.295	0.000	0.000	1.000
Hub	Importance of each bank according to its out-degree compared to other banks in the network	0.026	0.039	0.000	0.010	0.385
Authority	Importance of each bank according to its in-degree compared to other banks in the network	0.026	0.042	0.000	0.009	0.500
Betweenness	The ratio of links between bank j and bank k that pass through bank i, compared to the total number of links between bank j and bank k	0.050	0.132	0.000	0.002	1.000
Closeness	A measure of how close each bank is to other banks in the network based on interbank distance	0.315	0.132	0.000	0.290	1.000
PageRank	Ratio that indicates to what extent the importance of counterparties could determine the importance of each bank	0.026	0.051	0.000	0.008	0.475
Bank-level controls						
Bank-size	Natural logarithm of bank's total assets	14.423	1.968	10.639	14.274	18.201
Z-score	Indicator of bank distance to bankruptcy	69.456	80.357	3.284	38.345	311.580
NIM	Net interest margin	2.289	1.647	0.132	1.951	7.026
ROA	Return on assets	0.654	1.061	−1.942	0.508	3.597
Cost_inc	Cost-Income ratio	63.589	22.568	21.563	62.960	118.519
Eq_TA	Equity to total assets	11.031	10.711	2.050	7.667	53.252
Country-level controls						
CB_policyrate	The central bank policy rate	2.089	1.375	0.000	2.000	7.750
GDPperCa	Natural logarithm of GDP per capita	27.253	1.574	22.235	27.957	30.790
Inflation	Inflation rate	2.411	1.877	−4.480	2.117	34.468
HHI_TA	Herfindahl-Hirschman index (HHI), calculated as the sum of the squared market shares (based on total assets) of all banks in each country	0.174	0.089	0.054	0.161	0.771
Dummy variables						
Investment	Dummy variable for investment banks. Equals 1 if the bank belongs to the investment specialization.	0.098	0.297	0.000	0.000	1.000
Realestate	Dummy variable for real estate and mortgage banks. Equals 1 if the bank specializes in mortgages & real estate.	0.143	0.350	0.000	0.000	1.000
Crisis_subprime	Dummy variable for global financial crisis of 2007–2008 (subprime mortgage crisis). Equals 1 during the 2007–2008 period.	0.157	0.363	0.000	0.000	1.000
Crisis_sovereign	Dummy variable for sovereign debt crisis of 2010–2011. Equals 1 during the 2010–2011 period.	0.164	0.370	0.000	0.000	1.000
Sector-size	Dummy variable for large banking sectors. Equals 1 if the size of the country's banking sector is greater than the annual median value of the whole sample.	3.492	3.423	0.002	2.694	18.019
Small-size	Dummy variable for small banks. Equals 1 if bank's total assets are less than 1 billion euros.	0.409	0.492	0.000	0.000	1.000
G-SIFIs	Dummy variable for G-SIFIs. Equals 1 if the bank belongs to the list of G-SIFIs published by FSB.	0.012	0.111	0.000	0.000	1.000
Instruments						
BDepsFB_CDepsFB	Bank deposits from other banks as a share of total interbank deposits in each country	0.001	0.004	0.000	0.000	0.083
BLAATB_CLAATB	Bank loans to other banks as a share of total interbank loans in each country	0.027	0.078	0.000	0.002	0.890
BIB_CIB	Bank interbank transactions as a share of total interbank transactions in each country	0.029	0.078	0.000	0.002	0.864
FD_CLAATB_CDepsFB	First difference of country interbank loans to deposits ratio	−0.021	0.321	−3.401	−0.015	1.753
CDegree_Popul	Total number of banks' degree in each country, scaled by population	4.528	3.364	0.089	3.592	10.925
BCredit_BDeposits	The financial resources provided to the private sector by domestic money banks as a share of total deposits	124.919	49.690	17.795	121.545	360.77
Concentration	Assets of the three largest commercial banks in the country as a share of total commercial banking assets	64.732	16.577	29.246	64.841	100

most banks are interested in interacting with a limited number of other banks whose preferences conveniently match theirs. Thus, we use the minimum density algorithm introduced by Anand et al. (2015) to build our network. A notable point of applying this method is its economic rationality: producing and maintaining extra interbank links is costly and should be minimized.[5]

To study banking network topology, we first need to characterize its features by defining each bank as a node indexed by $i = 1$ to N and the links that connect node i to j by a_{ij}. The interbank market is a directed network such that if node i has a link with node j, it is not necessary that node j link with i; in other words $a_{ij} \neq a_{ji}$.

Another important feature is the path length of node i to j, which denotes the number of links from i to j and shows that not all nodes connect to each other directly. It also illustrates the possibility of an indirect link between two different nodes through others. The shortest possible distance between two given nodes, i and j, is called a geodesic path and is denoted by g_{ij}. Sometimes there is more than one geodesic path between a pair of nodes.

[5] A detailed description of the construction of the banking networks by applying the minimum-density algorithm is provided in Appendix A.

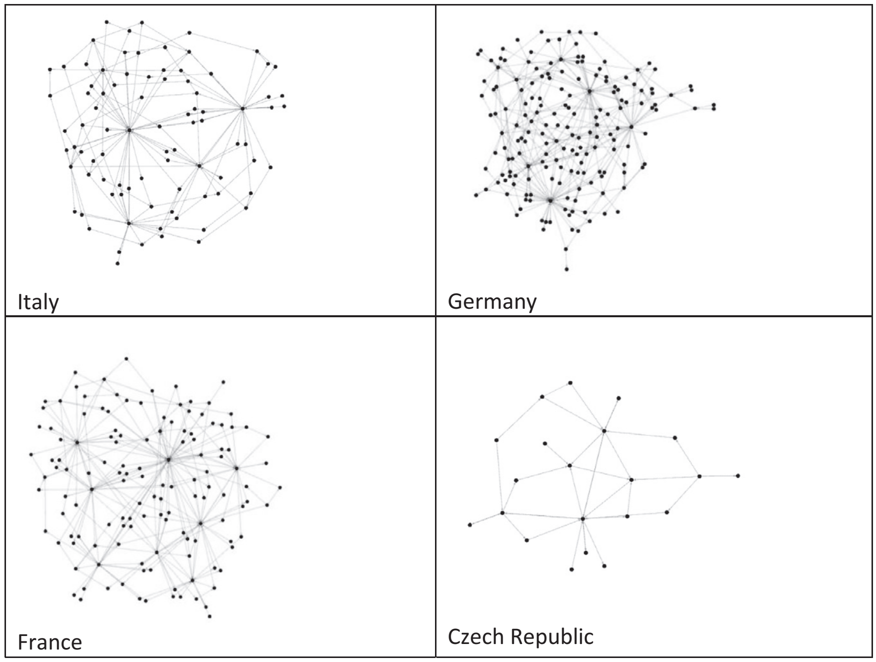

Fig. 1. Interbank network configurations of four selected European countries.

Fig. 1 synthesizes the simulated interbank network configuration of four selected European countries (Italy, Germany, France and Czech Republic) among our sample in 2013. Each node represents a bank in the network and the links represent the lending-borrowing relationships.

The network tools for capturing connectedness between the nodes in this study are based on degree and centrality measurements, which are described below.

We divide the network measurements in two categories:

(1) *Local* statistics measure bank access to interbank funds via their immediate counterparties. Banks with high local lending-borrowing positions have more relationships and more local counterparties.
(2) *Systemwide* statistics assess the interbank network interconnectedness based on each bank's position in the whole network. They measure each bank's access to the interbank market compared with all existing banks in the network and provide a wider image of banks' interconnectedness, as well as of the possible counterparty, contagion, and systemic risks that would arise through this interconnectedness.

Local network variables: Local network statistics comprise *In-degree*, *Out-degree*, and *ClusteringCo*, which quantify each bank's interconnectedness to its local neighbors.

In-degree, in network science, is the number of incoming links to each node. In our study, it corresponds to the number of banks that have deposits in bank *i*. Thus, it is a measure of the bank's ability to diversify its borrowing on the interbank market.

$$D_j^{in} = \sum_j a_{ji} \tag{2}$$

Out-degree is the number of outgoing links from each node. It corresponds to the number of banks that have a loan from bank *i*. Thus, it is a measure of the bank's ability to diversify its lending on the interbank market.

$$D_j^{out} = \sum_j a_{ij} \tag{3}$$

In-Degree and *Out-Degree* can thus be interpreted as the immediate risk for a bank to catch whatever is flowing through the network (Kuzubaş, Ömercikoğlu & Saltoğlu, 2014).

The clustering coefficient (*ClusteringCo*) measures how often triangular connections occur, or the probability a bank has counterparties that are themselves connected. For bank *i*, it measures the probability of a connection between bank *j* and *k* if both are connected to bank *i*. To describe the clustering coefficient, consider a binary network defined by graph $G = (A, N)$, in which N is the number of banks and A is its adjacency matrix that contains a_{ij}. $a_{ij} = 1$ if there is a direct link between bank i and j; it equals zero otherwise. Assume D_i is the degree of bank i, which is the number of its neighbors. We measure the percentage of i's pair neighbors that are themselves neighbors based on the ratio of bank i triangles to all possible triangles produced by graph G; we then form the clustering coefficient measure. It measures the density of connections around a single node. It is a measure of connectedness between a node's neighbors.

$$ClusteringCo_i(A) = \frac{\frac{1}{2}\sum_{j\neq i}\sum_{h\neq(i,j)} a_{ij}a_{ih}a_{jh}}{\frac{1}{2}D_i(D_i - 1)} \tag{4}$$

A high clustering coefficient means that any two banks that already transact with a third bank are more likely to have interbank connections with one another than to establish new connections with any other bank in the network. Indeed, banks might be interested in some diversification of interbank links. However, keeping a link is also costly (Boss, Elsinger, Summer & Thurner, 2004).

Systemwide network variables: Systemwide network statistics correspond to variables named *Betweenness*, *Closeness*, *Hub*, *Authority*, and *PageRank*.

Two important statistics (*Betweenness* and *Closeness*) capture noteworthiness of banks' positions in the network and show which banks are more central than others.

Betweenness centrality measures the number of shortest paths among all banks that pass through a specific bank. Technically, it depicts the ratio of links between bank *j* and bank *k* that pass through bank *i*, compared to the total number of links between bank *j* and bank *k*. Likewise, increasing bank *i*'s *Betweenness* shows an increasing intermediary role of bank *i* in the network, because every relationship between j and k should pass through i, giving i the power to strengthen or dampen a relationship. Banks characterized by higher *Betweenness* ratios are dominant intermediary banks in the system:

$$B_i = \sum_{j<k} \frac{g_{jik}}{g_{jk}} \tag{5}$$

where g_{jik} is the number of geodesic paths between bank j and k that pass through bank i.

Closeness centrality measures how close each bank is to the other banks in the network based on distance.[6] *Closeness* captures to what extent bank i could signal to other banks more directly and with less distance. So, banks with a high *Closeness* ratio could have more access to the interbank market, as they can lend or borrow more directly to and from other banks. They can facilitate the spread of liquidity as well as the spread of shocks. It is calculated by measuring the reverse distance of each bank to all other banks:

$$C_i = \frac{1}{\sum_j \sum_{j=1}^{g} d_{ij}} \tag{6}$$

In which d_{ij} is the shortest distance between banks i and j. Banks with high *Betweeneness* or *Closeness* can facilitate the spread of liquidity as well as the spread of shocks.

Three statistics (*Hub*, *Authority* and *PageRank*) take into account the importance of the banks to whom the bank is connected.

Authority and *Hub* measure the importance of each bank's total number of interbank lenders (borrowers) relative to the other banks in the network but also consider the strength of its lenders (borrowers) based on their outgoing (incoming) links. Therefore, banks with strong *Authority* (*Hub*) are those that are connected to strong *Hubs* (*Authorities*) in the network. *Hub* and *Authority* are calculated based on the HITS algorithm (Kleinberg, 1999).

PageRank centrality is based on Google's algorithm proposed in Page, Brin, Motwani and Winograd (1998). This variable considers WWW (World Wide Web) as a digraph. The feature that makes it a unique and significant network parameter is its capability to consider the extent to which the importance of neighbors determines the importance of each bank. It is defined as:

$$PR(i) = \frac{(1-d)}{N} + d \sum_{j \in N-(i)} \frac{PR(j)}{L(j)} \tag{7}$$

where i is the set of banks, L is the number of linkages that depart from its out degree, and d is a factor that Winograd (1999) recommends setting at 0.85. Thus, *PageRank* considers the number of banks that provide liquidity to the considered bank but also the relative importance of the lenders i.e. the more important the lenders are, the higher will be *PageRank* (Kaltwasser & Spelta, 2019).

All of these network variables are calculated based on software developed by Bastian and Heymann (2009).

Banks with easier access to interbank funds store less liquidity because borrowing money is cheaper than holding costly liquid assets (Bhattacharya &, Gale,1987). We hence expect a negative relationship between banks' liquidity ratios and the network variables, except for *Out-degree*, *ClusteringCo* and *Hub*. We expect banks with more local borrowers (*Out-degree*), significant lending position in the whole network (*Hub*) or more local peers with higher connection densities (*ClusteringCo*) to store more liquidity, as they are more likely to share the burden of a potential default.

Validity of our simulated network: Anand et al. (2018) compare different network-reconstruction methods for 25 distinct financial markets and show that minimum density is the best method to preserve the structure of links. We further justify the validity of this simulation technique by investigating whether simulated network has a common feature with real world interbank network.

The empirical literature in the financial network suggests that interbank network topology has small world and scale-free properties. A scale-free network is a network whose Degree[7] distribution follows power law. Boss et al. (2004), Iori, Precup, Gabbi & Caldarelli (2008), Lenzu & Tedeschi (2012), Martinez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benitez & Solórzano-Margain (2014), Rönnqvist & Sarlin (2016), Xu, He & Li (2016) investigate the interbank network topology of different countries and exhibit that interbank Degree distribution follows power-law. Accordingly, we test whether the Degree distribution of our simulated network fits power-law distribution following. The Degree distribution obeys power-law if its probability distribution function is:

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

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

Normally, empirical data obey power-law distribution for values greater than some minimum or lower-bound value $X_{\min}$. Therefore, the first step is to find the proper lower-bound value and then estimating the scaling parameter α. Following Clauset, Shalizi and Newman (2009), we apply Clauset, Young and Gleditsch (2007) method to estimate $X_{\min}$ and maximum likelihood method to estimate the scaling parameter α. Eventually, we calculate goodness-of-fit between our data and power-law to illustrate whether the power-law is likely to fit to our simulated data. If the p-value is less than or equal to 0.1, we reject the hypothesis that our data follow the power-law distribution.

Figs. 2 and 3 illustrate the Degree log-log plots for the whole sample (28 European countries) and four selected European countries. The results for the power-law fits and the corresponding p-values are presented in Table 3. The results confirm that the Degree distribution of our simulated interbank network obeys power-law.

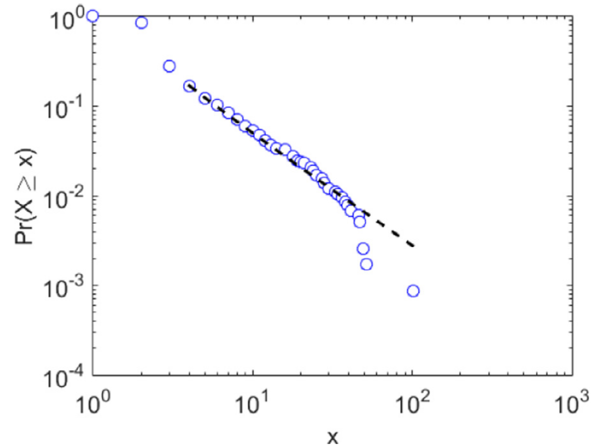

Fig. 2. Degree log-log plot (All sample). This figure illustrates the cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for Degree distribution of all 28 European countries.

[6] Distance is measured based on the number of intermediate banks between two banks.

[7] *Degree*, in network science, is the total number of incoming and outgoing links to and from each node. For interbank networks, it corresponds to the number of banks that have deposits in or a loan from bank i.

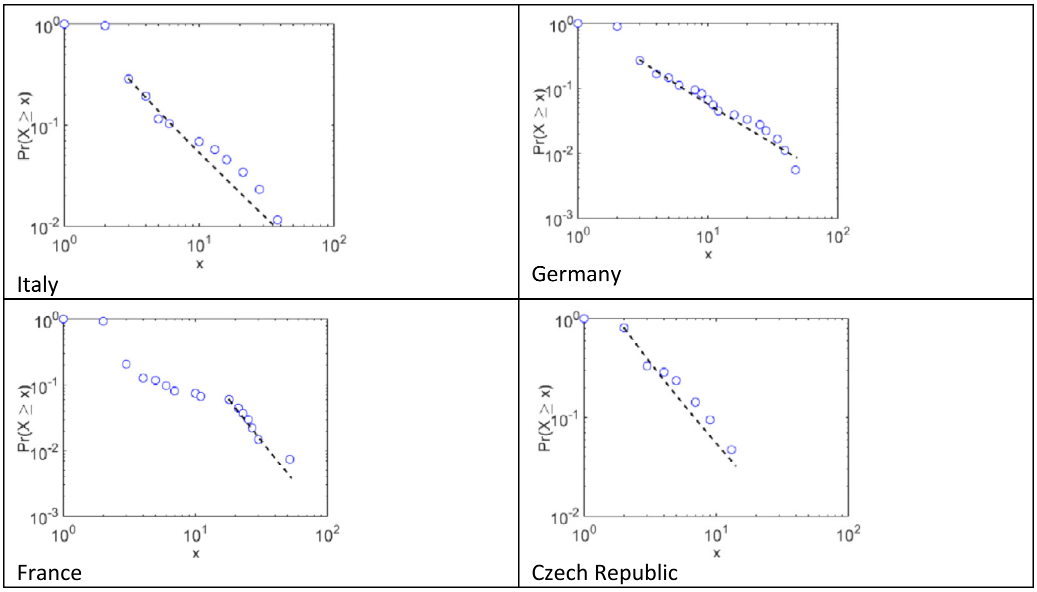

Fig. 3. Degree log-log plot (four selected European countries). This figure illustrates the cumulative distribution functions $P(x)$ and their maximum likelihood power-law fits for Degree distribution of four selected European countries.

Table 3
Power-law fits.

	X_{min}	α	Goodness of Fit	p-value	log-likelihood
All sample	4	2.320	0.031	0.461	−565.129
Germany	3	2.180	0.069	0.422	−128.743
France	18	3.500	0.125	0.636	−25.814
Italy	3	2.270	0.080	0.456	−62.385
Czech Republic	2	2.490	0.089	0.497	−30.093

This table presents the power-law fits parameters and corresponding p-value of the goodness-of-Fits. X_{min} is lower-bound for Degree, α is the scaling parameter.

2.2.3. Control variables

We include a set of control variables known to affect bank liquidity (DeYoung & Jang, 2016; Dietrich, Hess & Wanzenried, 2014; Distinguin et al., 2013).

We first control for bank size by introducing the natural logarithm of total assets (*Bank-size*) in our regressions. Larger banks are indeed expected to have easier access to liquidity in the interbank market than small banks, but they can also benefit from stronger support from lenders of last resort for safety-net considerations.

We also introduce *Z-score*, which is an indicator of a bank's likelihood of bankruptcy. The higher this ratio is, the lower the probability of default. *Z-score* in this study is calculated as:

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

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* stands for the three-year rolling window standard deviation of return on assets. All the ratios are in percentages. The expected relationship between *Z-score* and NSFR is negative. Banks with lower default probability can thus increase their revenue by funding their assets with less stable liabilities (Horvath, Seidler & Weill, 2016).

We also include return on assets (*ROA*) and net interest margin (*NIM*). The expected signs for the coefficients of these variables are ambiguous. *ROA* measures the bank's overall profitability and could be positively (Chen, Chou, Chang & Fang, 2015) or negatively (Bonfim & Kim, 2012) associated with bank liquidity. On one hand, banks with higher overall profitability could adopt riskier liquidity-management strategies to boost income. On the other hand, banks that are more profitable might hold more liquidity, possibly to reduce the likelihood of a fire sale of illiquid assets. *NIM* measures the portion of a bank's profitability generated by its traditional intermediation activities. Similar to *ROA*, we expect either a positive or a negative coefficient for *NIM*. We consider the cost to income ratio (*Cost-income*) as proxy of bank cost efficiency. We expect a negative coefficient for *Cost-income*, as banks with higher cost efficiency (lower *Cost-income*) on average store more liquidity (Bonfim & Kim, 2012). We also consider the ratio of equity to total assets (*Eq_TA*) as a proxy of bank leverage. We expect a positive impact of *Eq_TA* on bank liquidity, as lower bank leverage reduces liquidity risk (Dietrich et al., 2014)).

Our country-level control variables include the central bank policy rate (*CB_policyrate*), the natural logarithm of GDP per capita (*GDPperCa*), *Inflation*, banking sector size (*Sector-size*) and HHI index, which is calculated based on banks' total assets (*HHI_TA*). The CB policy rate is a proxy of monetary policy. When the central bank's policy rate is relatively low, credit supply increases (Berger & Bouwman, 2017; Bernanke & Blinder, 1992), which negatively affects bank liquidity. In line with Distinguin et al. (2013), we expect a positive relationship between *CB_policyrate* and bank liquidity. GDP per capita is a country's gross domestic product per capita. An increase in GDP per capita induces higher investment opportunities that lead banks to lend more and store less liquidity. Distinguin et al. (2013) find that economic growth positively affects bank illiquidity. We thus expect a negative relationship between GDP per capita and bank liquidity. Inflation is another control variable in this study. Higher inflation lessens money value and raises a bank's opportunity cost of storing liquidity. Hence, we expect that inflation negatively affects bank liquidity. We also use the ratio of banking sector size to GDP to account for differences in financial development across the countries in our sample. We expect a positive relationship between banking sector size and bank liquidity. Higher financial development reduces a bank's investment opportunity due to higher bank competition and leads to higher bank liquidity. To control for market concentration, we include the Herfindahl-Hirschman index (*HHI_TA*). It is the sum of the squared market shares (based on total assets) of all banks in each country. When market concentration is higher, banks have more freedom to diversify their loan portfolios, offer flexible interest rates, and attract more funds (Petersen & Rajan, 1995). They thereby may store less liquidity. We hence expect a negative relationship between *HHI_TA* and bank liquidity.

Given that European banks experienced both the global financial crisis of 2007–2008 and the European sovereign debt crisis of 2010–2011, we construct two dummy variables to capture the effects of both crises. Each dummy variable equals 1 in the aforementioned crisis years and zero otherwise. We also introduce bank specialization dummy variables, including *Investment* and *Realestate*, in the regressions.

2.3. Methodology

In this paper, we question whether interbank network topology affects bank liquidity ratios. Specifically, we use individual bank network indicators based on their loans to other banks and deposits from other banks and test how they affect NSFR. Because specific factors (such as the size and shape of the industry in each country at each point in time, the type of interaction with the central bank, or other environmental or individual bank factors) likely determine such network variables, to address possible endogeneity issues we conduct 2SLS instrumental variable estimations:

$$\begin{aligned} NSFR_{i,t} = {} & \alpha_0 + \alpha_1 Netw(x)_{i,t} + \alpha_2 B_{i,t-1} + \alpha_3 C_{j,t} \\ & + \alpha_4 Crisis\_Subprime_t + \alpha_5 Crisis\_Sovereign_t \\ & + \alpha_6 Investment_i + \alpha_7 Realestate_i + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where α_0 is a constant, $Netw(x)$ is a network variable that is either *In-degree, Out-degree, Betweenness, Closeness, Hub, Authority, PageRank* or *ClusteringCo* .[8] $B_{i,t-1}$ is a vector of bank-level control variables including *Bank-size*, *Z-score*, net interest margin (*NIM*), return on assets *(ROA)*, cost to income ratio (*Cost_inc*), and equity to total assets (*Eq_TA*). To deal with possible endogeneity, we replace all bank-level controls by their one-year lagged value. $C_{j,t}$ is a vector of country-level control variables that comprise central bank policy rate (*CB_policyrate*), the natural logarithm of GDP per capita (*GDPperCa*), *Inflation*, banking sector size to GDP ratio (*Sector-size*), and HHI index, which is calculated based on banks' total assets (*HHI_TA*). $Crisis\_subprime_t$ is a global, subprime-mortgage-crisis dummy variable that equals 1 for the 2007–2008 period. $Crisis\_sovereign_t$ is a European sovereign crisis dummy variable that equals 1 for the period 2010–2011. $Investment_t$ and $Realestate_t$ are bank specialization dummy variables for investment and real estate banks. μ_i is bank fixed effects and $\varepsilon_{i,t}$ is an error term. We use robust standard errors in our model and we cluster standard errors at the bank level.

To deal with endogeneity of the network variables, we instrument our systemwide network variables with the share of each bank's interbank transactions in the country, the first difference of country interbank loans to deposits ratio, and a measure of bank concentration.[9] Banks representing a high proportion of interbank transactions (the sum of interbank loans and deposits) at the country level should have better positions in the network. The first difference of country-level aggregate interbank loans-to-deposit ratio captures the dynamic nature of each country's interbank network, which could influence each bank's systemwide network characteristics. Eventually, bank concentration could influence the global structure of the interbank network. In a country with higher bank concentration, a few large banks could have high central positions in the network, but in a less concentrated banking sector more banks could have a strong systemwide position in the network.

Because our local network variables measure direct interconnectedness, we introduce other instruments. We instrument all the local network variables with country-level Degree[10] scaled by population and the country-level bank-credit-to-bank-deposits ratio. Banks' direct interconnectedness in the interbank networks should be higher in countries with higher numbers of bank connections. Also, in a country with higher bank-credit-to-bank-deposit ratios, counterparties perceive banks as riskier and less liquid because of higher systemic liquidity risk. This should result in a declining number of direct interbank lenders and borrowers in such countries. For *In-degree*, we add each bank's share of the country's total interbank deposits; for *Out-degree*, we add each bank's share of the country's total interbank loans; and for *ClusteringCo*, we add each bank's share of the country's total interbank transactions. Indeed, a higher share of interbank deposits or loans in a country should result in a higher number of lenders or borrowers, respectively, while a higher share of interbank transactions should imply a higher number of linkages regardless of their directions.

We employ the Hansen J (Overidentification), Under-Identification (Kleibergen-Paap rk LM), and Weak-Identification (Kleibergen-Paap rk Wald F statistic) tests to assess the validity of our instruments.

3. Results

We first investigate the link between interbank network connectedness and bank NSFR ratios. We then look at how factors such as bank size and crises affect such a relationship.

3.1. Impact of network topology on bank liquidity ratios

The instrumental variable (IV) panel regression results are presented in Table 4.

As shown in Table 4 regarding local network statistics, when banks have more direct lenders (*In-degree*), they hold less liquidity presumably because they believe they will have easier access to interbank funds in case of a shortage as a result of their ability to diversify their borrowing on the interbank market. Concerning systemwide network measures, our findings highlight that banks that play a major role in the interbank network, either as dominant direct lenders (*Hub*) or borrowers (*Authority*), have lower NSFR ratios. Although we expect a positive relationship between *Hub* and NSFR, the too interconnected to fail status of those banks might explain this negative relationship. Because of their critical lending role in that market, they are more likely to set lower liquidity ratios and strengthen their interbank lending power presumably because they have higher bailout expectations. A stronger intermediation role in the whole network, measured by *Betweenness,* also has a negative influence on the NSFR ratio, indicating that such banks rely less on liquid assets and stable funds to cover unexpected liquidity shocks; in turn, they are more likely to rely on interbank debt possibly because bailout expectations are higher for such interconnected intermediaries. Similarly, higher accessibility to the rest of the network via a decreasing number of intermediating banks between pair entities (*Closeness*) leads banks to store less liquidity. Finally, banks connected to centrally positioned banks (banks that are critical hubs or intermediaries within the market) in the interbank network (*PageRank*) also exhibit lower NSFR ratios, possibly because of strong links to highly connected counterparties.

[8] Table B3 in the Appendix presents a correlation matrix of the independent variables used in this study. As the network variables are highly correlated, we introduce them in the equation one by one.

[9] We consider the assets of the three largest commercial banks as a share of total commercial banking assets.

[10] Degree corresponds to the total number of links between nodes regardless of their direction. It is the total number of counterparties.

Table 4
Baseline instrumental variable model of network effects on banks' structural liquidity (NSFR).

	(1) NSFR	(2) NSFR	(3) NSFR	(4) NSFR	(5) NSFR	(6) NSFR	(7) NSFR	(8) NSFR
In-degree	−0.0144**							
	(0.00672)							
Out-degree		0.00253						
		(0.00749)						
ClusteringCo			0.461					
			(0.309)					
Hub				−1.507***				
				(0.430)				
Authority					−1.375***			
					(0.389)			
Betweenness						−0.837***		
						(0.280)		
Closeness							−0.419***	
							(0.118)	
PageRank								−1.023***
								(0.288)
L.Bank-size	−0.0491**	−0.0542**	−0.0412*	−0.0502**	−0.0495**	−0.0577**	−0.0503**	−0.0505**
	(0.0240)	(0.0239)	(0.0247)	(0.0239)	(0.0240)	(0.0240)	(0.0241)	(0.0239)
L.Z-score	−0.0000621	−0.0000706	−0.0000295	−0.0000688	−0.0000666	−0.0000560	−0.0000602	−0.0000653
	(0.0000642)	(0.0000644)	(0.0000718)	(0.0000643)	(0.0000644)	(0.0000673)	(0.0000652)	(0.0000644)
L.NIM	−0.00900	−0.00856	−0.00929	−0.0103	−0.00976	−0.0123	−0.0118	−0.0109
	(0.00923)	(0.00924)	(0.00950)	(0.00927)	(0.00925)	(0.00946)	(0.00934)	(0.00929)
L.ROA	0.0181*	0.0181*	0.0158	0.0192*	0.0193**	0.0192*	0.0208**	0.0197**
	(0.00985)	(0.00986)	(0.0102)	(0.00982)	(0.00982)	(0.00992)	(0.00991)	(0.00983)
L.Cost_inc	−0.000709	−0.000650	−0.000560	−0.000664	−0.000675	−0.000672	−0.000639	−0.000660
	(0.000549)	(0.000548)	(0.000574)	(0.000548)	(0.000547)	(0.000558)	(0.000552)	(0.000547)
L.Eq_TA	0.00373*	0.00364	0.00386*	0.00378*	0.00379*	0.00351	0.00372	0.00375*
	(0.00226)	(0.00225)	(0.00233)	(0.00225)	(0.00225)	(0.00227)	(0.00226)	(0.00225)
CB_policyrate	0.0160***	0.0151**	0.0133**	0.0151**	0.0152**	0.0162***	0.0150**	0.0154***
	(0.00593)	(0.00593)	(0.00654)	(0.00591)	(0.00591)	(0.00598)	(0.00593)	(0.00590)
L-GDPperCa	0.0633	0.0832	0.0518	0.00213	0.00325	0.0544	−0.0144	0.0159
	(0.147)	(0.147)	(0.147)	(0.147)	(0.146)	(0.152)	(0.149)	(0.146)
Inflation	−0.00408	−0.00431	−0.00461	−0.00317	−0.00325	−0.00252	−0.00456	−0.00349
	(0.00384)	(0.00390)	(0.00418)	(0.00381)	(0.00378)	(0.00415)	(0.00381)	(0.00379)
Sector-size	0.0437***	0.0445***	0.0440***	0.0435***	0.0435***	0.0358***	0.0430***	0.0434***
	(0.0101)	(0.0101)	(0.0102)	(0.0101)	(0.0101)	(0.0107)	(0.0101)	(0.0101)
HHI_TA	−0.285	−0.291	−0.326	−0.188	−0.192	−0.0699	−0.259	−0.210
	(0.216)	(0.217)	(0.213)	(0.224)	(0.223)	(0.242)	(0.217)	(0.221)
Investment	0.296**	0.298**	0.359**	0.325***	0.334***	0.302**	0.310***	0.323***
	(0.118)	(0.125)	(0.145)	(0.0577)	(0.0513)	(0.122)	(0.0894)	(0.0684)
Realestate	−0.259***	−0.256***	−0.185***	−0.258***	−0.257***	−0.291***	−0.259***	−0.257***
	(0.0150)	(0.0151)	(0.0480)	(0.0149)	(0.0149)	(0.0193)	(0.0150)	(0.0149)
Crisis_subprime	−0.0547***	−0.0522***	−0.0449***	−0.0500***	−0.0505***	−0.0551***	−0.0488***	−0.0512***
	(0.0149)	(0.0149)	(0.0166)	(0.0149)	(0.0148)	(0.0153)	(0.0149)	(0.0148)
Crisis_sovereign	−0.0561***	−0.0550***	−0.0480***	−0.0545***	−0.0542***	−0.0681***	−0.0526***	−0.0542***
	(0.0103)	(0.0103)	(0.0122)	(0.0102)	(0.0102)	(0.0115)	(0.0103)	(0.0102)
Number of obs	10,253	10,253	10,253	10,262	10,262	10,262	10,262	10,249
Number of banks	1178	1178	1178	1178	1178	1178	1178	1178
r^2	0.0223	0.0220	−0.136	0.0228	0.0242	−0.0405	0.00961	0.0235
Hansen J. test	0.414	0.296	7.460	1.134	1.227	4.781	0.958	1.230
Hansen J. *P*-value	0.813	0.862	0.0240	0.567	0.541	0.0916	0.620	0.541
Under-ident stat	23.55	35.79	51.27	40.80	38.39	39.18	46.44	40.62
Under-ident *p*-val	0.0000310	8.29e−08	4.28e−11	7.19e−09	2.33e−08	1.59e−08	4.58e−10	7.87e−09
Weak-id stat	68.37	24.68	23.09	195.6	141.0	40.08	131.8	154.4
Weak-id critical-value 5%	13.91	13.91	13.91	13.91	13.91	13.91	13.91	13.91

This table presents the baseline regression results using instrumental variables for an unbalanced panel of European commercial, investment, and real estate banks over the 2001–2013 period. We employ IV estimator with bank-specific fixed effect to estimate the following equation:

$$NSFR_{i,t} = \alpha_0 + \alpha_1 Netw(x)_{i,t} + \alpha_2 B_{i,t-1} + \alpha_3 C_{j,t} + \alpha_4 Crisis\_subprime_t + \alpha_5 Crisis\_sovereign_t + \alpha_6 Investment_i + \alpha_7 Realestate_i + \mu_i + \varepsilon_{i,t}$$

Dependent variable is *NSFR*. Network statistics are our main independent variables, including *In-degree*, *Out-degree*, *ClusteringCo*, *Hub*, *Authority*, *Betweenness*, *Closeness*, and *PageRank*. Because of high correlation among our network variables, we estimate them by separate equations. $B_{i,t-1}$ is a vector of the one-year lagged value of bank-level control variables, including *Bank-size*, *Z-score*, *NIM*, *ROA*, *Cost_inc*, and *Eq_TA*. C_j is a vector of country-level control variables that includes *CB_policyrate*, log *GDPperCa*, *Inflation*, *Sector-size*, and *HHI_TA*. *Crisis_subprime* and *Crisis_sovereign* are dummy variables for the subprime crisis and sovereign crisis, respectively. *Investment* and *Realestate* are bank specialization dummy variables. Hansen J Test is an overidentification test to reject the null hypothesis that the equation is overidentified. We provide the critical values for the Under-Identification test (Kleibergen-Paap rk LM), Weak-Identification test (Kleibergen-Paap rk Wald F statistic), and Stock-Yogo weak ID test. All dependent and bank-level control variables are winsorized at 5% - 95%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

As a whole, our results show that banks with broader access to interbank liquidity have lower NSFR ratios, presumably to reduce the cost of holding liquid assets on their balance sheets. Setting lower liquidity ratios might be optimal for banks with strong local interconnectedness because of their ability to diversify their borrowing on the interbank market. By contrast, it could expose systemwide interconnected banks to higher liquidity risk as they might lose their network advantages during crisis times because of higher probability of contagion and systemic risk.

Concerning bank-level liquidity determinants, bank size has a negative and significant effect on NSFR. Large banks have more options to access liquidity through other channels than small banks do. They thereby set lower NSFRs to decrease the cost of holding large amounts of liquid assets. *ROA* has a positive and significant impact on NSFR, in line with Chen et al. (2015). Banks that are more profitable hold more liquid assets, possibly to prevent fire sales of illiquid assets. At 10%, the positive coefficient of the equity-to-total-assets ratio is in accordance with Dietrich et al. (2014), illustrating that well-capitalized banks set higher NSFR ratios.

Concerning country-level liquidity determinants, the central bank's policy rate and the banking sector size to GDP ratio have positive influences on the NSFR ratio. It shows that banks in countries with larger banking sectors or higher central bank rates have higher NSFR ratios. Our results also show a negative and positive relationship between real estate specialization and investment specialization with the NSFR ratio, respectively. In addition, our baseline results point out that both the sovereign and subprime crises have a negative and statistically significant effect on the NSFR ratios of European banks.

3.2. Western and Eastern European banking sectors

Countries with relatively large banking sectors are more exposed to contagion risk than countries with less developed banking sectors (BIS, 2001). In the European Union, monitoring individual banks' liquidity management is a critical issue for regulators because of the spillover effects from one Euro country to another. Also, banks operating in relatively large or small banking sectors might behave differently in terms of liquidity management because of higher or lower contagion risk in differently scaled networks.

To examine the impact of interbank network topology on banks' liquidity ratios in different environments, we distinguish banks operating in Western Europe from those operating in Eastern Europe. Indeed, most large European banks are in Western Europe, and as a whole the relative size of the banking industry itself is larger in the West than in the East. To determine whether network characteristics have a different impact on liquidity for Western versus Eastern European networks, we run our regressions on these two subsamples.[11]

The results presented in Table 5 show that apart from *In-degree*, only systemwide network characteristics are significant for banks operating in Western Europe. Conversely, systemwide measures are never significant for banks in Eastern Europe, but all the local network statistics are highly significant, suggesting that local network positions play an important role. *In-degree* is significant as in Table 4. The significance of *Out-degree* shows that banks appear to be more conservative regarding the level of liquid assets they hold or with regard to maturity transformation, when they have more direct borrowers, possibly because they are more exposed to default. *ClusteringCo* is also significant, with the expected sign showing that banks that lend to other banks that are themselves connected are more cautious and store more liquidity. In fact, the default of each borrowing bank has a direct and indirect consequence on the bank located in the vertices of a triangular relationship. Thus, in this case, because of higher uncertainty, banks appear to be more cautious and tend to store more liquidity.

Such results are consistent with the less important role that systemwide positions play in less developed financial systems. Banks in Eastern Europe might be less confident in targeting their liquidity ratios based on more complex links requiring more sophisticated operations. Also, presumably because banks are smaller in Eastern Europe, they might rely more on less sophisticated and hence less costly local positions. This is in line with previous findings that smaller banks rely on stable borrowing and lending relationships and are less likely to act as intermediaries (Bräuning & Fecht, 2017; Cocco et al., 2009).

3.3. Effect of interbank network topology on bank liquidity ratio: the role of bank size

On the interbank market, the network characteristics of large and small banks are not similar. Small banks are more inclined to connect with large banks and form core-periphery network structures (Cocco et al., 2009). Because they are more subject to asymmetric information (Furfine, 2001), they also have fewer counterparties than large banks in the interbank market. As a whole, because they are less financially constrained, large banks are more reliant on interbank funding than small banks (George, 2014).

To examine the impact of interbank network topology on the liquidity ratios of banks of different sizes, we introduce two dummy variables: *G-SIFIs* and *Small-size*. We consider three different groups of banks: small banks, medium and large banks, and G-SIFIs (globally systemically important financial institutions). Among the largest banks, global systemically important financial institutions (G-SIFIs) should behave differently in terms of liquidity holdings. G-SIFIs are large, complex, and highly systemically interconnected entities. Under Basel III they are required to hold more capital than other financial institutions to provide an extra cushion against insolvency and contagion. They are also prone to moral-hazard behavior because of the role they play in the financial system ("too big to fail"/"too interconnected to fail"). In our sample, a bank is small if its total assets are below 1 billion euros. G-SIFIs are defined in line with lists published by the FSB.[12] Because we exclude cooperative and savings bank from our sample, our final subsample of European G-SIFIs consists of 13 banks.

Table 6 illustrates the results of our liquidity model for small banks, medium and large banks, and G-SIFIs. Considering the local network measurements, *Out-degree* is statistically significant for small banks, but large and medium banks set their liquidity ratios based on *In-degree*. When they have more interbank lenders, large banks set a weaker NSFR. Note that larger banks tend to use the interbank market more extensively to borrow than to lend (George, 2014). We refer to Cocco et al. (2009) and Craig and Von Peter (2014) to explain the unexpected negative sign for the *ClusteringCo*, although at the 10% significance level, for small banks. They argue that the probability of an interbank relationship forming between a large bank and a small bank is significantly higher than the probability of forming an interbank relationship between banks of the same size. Therefore, increasing the connection density of small banks' direct neighbors (mostly large banks) boosts the confidence small banks have in their peers, leading them to set weaker liquidity ratios. Systemwide network statistics are statistically significant, with the expected sign mostly for large and medium banks.

Overall, our results suggest that to set higher or lower liquidity ratios, small banks mostly consider their local network positions but medium and large banks mostly consider their systemwide network positions. G-SIFIs only consider the number of direct borrowers (*Out-degree*) or connections with centrally positioned peers (*PageRank*) to set their liquidity ratios. They increase their liquidity when they have a large number of borrowers and decrease it when they are connected to centrally positioned banks. Our results are in line with the findings of DeYoung, Distinguin and Tarazi (2018) and Distinguin et al. (2013) that show that liquidity behavior of large banks differs from that of small banks justifying the need of a differentiated liquidity regulation.

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

[12] Table B4 in the appendix presents this list. We consider the 2012 list for the 2003–2012 period, and we consider the 2013 list for the last year.

Table 5
Instrumental variable model of network effects on structural liquidity for subsamples of banks in Western and Eastern European countries.

	(1) NSFR In-degree	(2) NSFR Out-degree	(3) NSFR ClusteringCo	(4) NSFR Hub	(5) NSFR Authority	(6) NSFR Betweenness	(7) NSFR Closeness	(8) NSFR PageRank
Western Europe								
Network	−0.0141**	−0.00623	0.468	−1.986***	−1.804***	−1.331***	−0.561***	−1.373***
	(0.00666)	(0.00773)	(0.307)	(0.564)	(0.515)	(0.416)	(0.151)	(0.382)
Number of obs	8634	8634	8634	8621	8621	8621	8621	8608
Number of banks	968	968	968	968	968	968	968	968
r2	0.0227	0.0214	−0.135	0.0236	0.0249	−0.0783	0.00508	0.0237
Hansen J. test	7.397	7.205	15.88	0.758	0.722	0.727	0.566	0.694
Hansen J. P-value	0.0248	0.0273	0.000357	0.685	0.697	0.695	0.754	0.707
Under-ident stat	20.11	22.83	40.91	25.93	27.35	25.16	28.29	26.72
Under-ident p-val	0.000161	0.0000438	6.83e−09	0.00000988	0.00000498	0.0000143	0.00000316	0.00000674
Weak-id stat	61.86	14.47	19.11	159.9	198.4	29.09	64.27	151.4
Weak-id critical-value 5%	13.91	13.91	13.91	13.91	13.91	13.91	13.91	13.91
Eastern Europe								
Network	−0.0525***	0.0414***	0.668***	−0.588	−0.456	−0.441	−0.204	−0.412
	(0.0120)	(0.0160)	(0.211)	(0.562)	(0.516)	(0.297)	(0.159)	(0.369)
Number of obs	1619	1619	1619	1641	1641	1641	1641	1641
Number of banks	210	210	210	210	210	210	210	210
r2	0.0461	0.0574	−0.391	0.0750	0.0765	−0.0170	0.0598	0.0789
Hansen J. test	22.49	15.97	7.936	6.562	6.563	6.393	5.690	6.245
Hansen J. P-value	0.0000131	0.000340	0.0189	0.0376	0.0376	0.0409	0.0581	0.0441
Under-ident stat	19.42	23.49	35.68	21.63	21.64	30.99	29.99	21.77
Under-ident p-val	0.000224	0.0000319	8.76e−08	0.0000780	0.0000776	0.000000852	0.00000139	0.0000730
Weak-id stat	10.12	38.51	21.44	54.28	32.23	21.33	72.41	39.01
Weak-id critical-value 5%	13.91	13.91	13.91	13.91	13.91	13.91	13.91	13.91
Bank-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank specialization Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crises dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the baseline regression results using instrumental variables for an unbalanced panel of European commercial, investment, and real estate banks over the 2001–2013 period. We employ IV estimator with bank-specific fixed effect to estimate the following equation on the subsamples of Western and Eastern European countries: $NSFR_{i,t} = \alpha_0 + \alpha_1 Netw(x)_{i,t} + \alpha_2 B_{i,t-1} + \alpha_3 C_{j,t} + \alpha_4 Crisis\_subprime_t + \alpha_5 Crisis\_sovereign_t + \alpha_6 Investment_i + \alpha_7 Realestate_i + \mu_i + \varepsilon_{i,t}$
Dependent variable is *NSFR*. Network statistics are our main independent variables, including *In-degree*, *Out-degree*, *ClusteringCo*, *Hub*, *Authority*, *Betweenness*, *Closeness*, and *PageRank*. Because of high correlation among our network variables, we estimate them by separate equations. $B_{i,t-1}$ is a vector of one-year lagged value of bank-level control variables including *Bank-size*, *Z-score*, *NIM*, *ROA*, *Cost_inc*, and *Eq_TA*. C_j is a vector of country-level control variables that includes *CB_policyrate*, log *GDPperCa*, *Inflation*, *Sector-size*, and *HHI_TA*. *Crisis_subprime* and *Crisis_sovereign* are dummy variables for the subprime crisis and sovereign crisis, respectively. *Investment* and *Realestate* are bank specialization dummy variables. Hansen J test is an overidentification test to reject the null hypothesis that the equation is overidentified. We provide the critical values for the Under-Identification test (Kleibergen-Paap rk LM), Weak-Identification test (Kleibergen-Paap rk Wald F statistic), and Stock-Yogo weak ID test. All dependent and bank-level control variables are winsorized at 5% - 95%. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

3.4. Effect of interbank network topology on bank liquidity ratio during crises

We consider how network topology affects banks' structural liquidity during crisis periods by looking at both the global financial crisis of 2007–2008 and the European sovereign debt crisis of 2010–2011. Both crises are meaningfully important in the euro area of interbank markets because during these events banks were reluctant to deal with one another in unsecured interbank markets and preferred to interact through the Eurosystem. Under such circumstances, network roles should dramatically change. In addition, during crisis periods, banks are more likely to hoard liquidity and cut their lending, leading to frozen liquidity markets.

To determine whether network characteristics have a different impact on liquidity during crises for small banks, medium and large banks, and G-SIFIs, we interact the network variables with the size dummy variables and the crisis dummies.

Table 7 shows that crises do not significantly change the relationship between network positions and liquidity ratios for small, medium, and large banks: small banks still consider their local positions, and medium and large banks consider their local and systemwide positions. However, the relationship changes for G-SIFIs. G-SIFIs become sensitive to their systemwide connections during crisis times, especially during the global crisis. This corresponds to the findings of Angelini, Nobili and Picillo (2011) that indicate that during the global financial crisis the "too-big-to-fail" subsidy provided to some banks has increased with the value of the safety net support enabling them to have better lending conditions.

All in all, our results show that crises do not significantly change how sensitive liquidity ratios are to the network characteristics of small, medium, and large banks. However, G-SIFIs take advantage of their network positions during crises, possibly because of their too-big-to fail or too-complex-to-fail status, which enables them to benefit from lower fluctuations in interbank borrowing rates.

4. Robustness checks and further issues

To check the robustness of our results and to go deeper in our empirical investigation, we conduct several sensitivity analyses.

4.1. Estimation of NSFR with different weights

To check the robustness of the NSFR ratio estimation, according to the Basel accords, we apply minimum, maximum, and extreme case weights (0.5, 0.85 or 1) for demand and savings deposits. Our conclusions remain the same.[13]

[13] The results are available upon request.

Table 6
Instrumental variable model of network effects on structural liquidity for small banks, medium and large banks, and G-SIFIs.

	(1) NSFR In-Degree	(2) NSFR Out-Degree	(3) NSFR ClusteringCo	(4) NSFR Hub	(5) NSFR Authority	(6) NSFR Betweenness	(7) NSFR Closeness	(8) NSFR PageRank
Network (A)	−0.0195**	−0.00360	0.896*	−1.570***	−1.417***	−0.519***	−1.128***	−1.047***
(M&L)	(0.00826)	(0.0104)	(0.539)	(0.475)	(0.431)	(0.135)	(0.349)	(0.322)
NETWORK*SIFI (B)	0.0167*	0.0179	−0.795	0.683	0.583	0.678	1.519*	0.272
	(0.00956)	(0.0115)	(0.526)	(0.695)	(0.617)	(0.449)	(0.907)	(0.476)
NETWORK*Small-size	0.00811	0.0511**	−0.934*	0.918	1.063	0.709***	1.126***	0.905*
(C)	(0.0241)	(0.0212)	(0.536)	(0.745)	(0.763)	(0.154)	(0.342)	(0.527)
Wald test								
$A+B$ (SIFI)	−0.002	.0142**	.1003	−0.886	−0.8343	.159	.391	−0.774**
$A+C$ (Small)	−0.0113	.0475**	−0.0388*	−0.6521	−0.3545	.189**	−0.774	−0.141
Number of obs	10,253	10,253	10,253	10,262	10,262	10,262	10,262	10,249
Number of banks	1178	1178	1178	1178	1178	1178	1178	1178
r2	0.0221	0.0240	−0.255	0.0236	0.0251	0.0141	−0.0408	0.0246
Hansen J. test	0.498	0.354	5.610	1.085	1.173	1.056	3.216	1.166
Hansen J. P-value	0.780	0.838	0.0605	0.581	0.556	0.590	0.200	0.558
Under-ident stat	28.61	51.53	38.48	44.72	44.19	55.90	44.82	47.07
Under-ident p-val	0.00000270	3.76e−11	2.24e−08	1.06e−09	1.37e−09	4.41e−12	1.01e−09	3.35e−10
Weak-id stat	26.38	19.74	10.93	161.1	109.2	104.4	30.35	115.0
Weak-id critical-value 5%	13.91	13.91	13.91	13.91	13.91	13.91	13.91	13.91
Bank-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank specialization Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crises dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents regression results using instrumental variables for an unbalanced panel of European commercial, investment and real estate banks over the 2001–2013 period by introducing the interaction between the bank-size dummy variables and the network variable. We employ IV estimator with bank-specific fixed effect to estimate the following equation:

$NSFR_{i,t} = \alpha_0 + \alpha_1 Netw(x)_{i,t} + \alpha_2 B_{i,t-1} + \alpha_3 C_{j,t} + \alpha_4 Crisis\_Subprime_t + \alpha_5 Crisis\_Sovereign_t + \alpha_6 Investment_i + \alpha_7 Realestate_i + \alpha_8 GSIFIs_{i,t} + \alpha_9 Small\_Size_{i,t} + \alpha_{10} GSIFIs_{i,t} * Netw(x)_{i,t} + \alpha_{11} Small\_Size_{i,t} + Netw(x)_{i,t} + \mu_i + \varepsilon_{i,t}$

Dependent variable is NSFR. Network statistics are our main independent variables including *In-degree, Out-degree*, *ClusteringCo*, *Hub*, *Authority*, *Betweenness*, *Closeness*, and *PageRank*. Because of high correlation among our network variables, we estimate them by separate equations. $B_{i,t}$ is a vector of bank-level control variables including one-year lagged value of *Bank-size*, *Z-score*, *NIM*, *ROA*, *Cost_inc*, and *Eq_TA*. C_j is a vector of country-level control variables that includes *CB_policyrate*, log *GDPperCa*, *Inflation*, *Sector-size,* and *HHI_TA*. *Crisis_subprime* and *Crisis_sovereign* are dummy variables for the subprime crisis and sovereign crisis, respectively. *Investment* and *Realestate* are bank specialization dummy variables. Hansen J Test is an overidentification test to reject the null hypothesis that the equation is overidentified. The results for Under-Identification test (Kleibergen-Paap rk LM), Weak-Identification test (Kleibergen-Paap rk Wald F statistic), and Stock-Yogo weak ID test critical values are provided. All dependent and bank-level control variables are winsorized at 5% - 95%. *G-SIFIS* and *Small-size* are equal 1 for G-SIFIs and small banks, respectively. *Investment* and *Realestate* are bank specialization dummy variables. We test the impact of the network variables for G-SIFIs with $(\alpha_1 + \alpha_{10})$ and for small banks with $(\alpha_1 + \alpha_{11})$. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

4.2. Estimation with year dummy variables

We add year dummy variables and drop the two crisis dummies from the model. Our main findings remain unchanged. The results are in Table C1 in the Appendix.

4.3. Estimation with bootstrap

As our networks are estimated, we perform a robustness check by considering a bootstrapping procedure to obtain standard errors. As shown in Table C2 in the Appendix, our conclusions remain unchanged.

4.4. Estimation on the subsample of commercial banks

As discussed by Venkat and Baird (2016), the NSFR has a limited capability to deal with diverse banking business models. For instance, investment banks have easier access to financial markets and stronger capability of liquidating their investments compared to retail banks. Also, real estate and mortgage banks are more specialized in securitizing their assets during stress times. Hence, in both cases, this could warrant lower required stable funding factors (RSF) for marketable assets of these banks. Therefore, to check for robustness, we perform an analysis on the subsample of commercial banks only. As shown in Table C3, the results remain unchanged.

4.5. Fixed-effect panel regression model and additional explanatory power of network variables

We perform a robustness check by estimating a panel data fixed-effect model. We use lagged values of our network variables and the same control variables as in the baseline model. The standard errors are robust and clustered at the bank level. As illustrated in Table C4, the results are close to those of the instrumental variables model, except for *Betweenness* and *Closeness*, which are no longer significant, and two local network variables (*Out-degree* and *ClusteringCo*) that are significant. Furthermore, to determine the additional explanatory power of our network topology statistics to previous liquidity models in the literature, we perform a Wald test. The results indicate that, with the exception of *Betweenness* and *Closeness*, all other network variables significantly add value to explain liquidity ratios.

4.6. Dynamic system GMM (Generalized Method of Moments)

To check for robustness, we employ the dynamic system GMM procedure of Arellano and Bond (1991). We use robust standard errors in our model, and we cluster standard errors at the bank level. Our findings remain unchanged (see Table C5 in Appendix).

4.7. Network constructed with all types of banks

We conduct our estimations by excluding savings, cooperatives, and mutual banks from our sample to construct our banking ex-

Table 7
Instrumental variable model of network effects on structural liquidity among banks of different sizes during crisis and normal times.

	(1) NSFR In-Degree	(2) NSFR Out-Degree	(3) NSFR ClusteringCo	(4) NSFR Hub	(5) NSFR Authority	(6) NSFR Betweenness	(7) NSFR Closeness	(8) NSFR PageRank
Netw (A)	−0.0214***	−0.00404	2.006***	−1.595***	−1.440***	−0.523***	−1.137***	−1.062***
(M&L Normal-times)	(0.00778)	(0.0107)	(0.720)	(0.488)	(0.443)	(0.136)	(0.352)	(0.329)
Netw*SIFI (B)	0.0214**	0.0201*	−1.807***	0.667	0.590	0.677	1.472	0.210
	(0.00933)	(0.0122)	(0.682)	(0.783)	(0.694)	(0.488)	(0.902)	(0.535)
Netw*Small-size (C)	0.0123	0.0537**	−1.932***	0.949	1.050	0.699***	1.122***	0.874
	(0.0231)	(0.0211)	(0.682)	(0.767)	(0.787)	(0.153)	(0.340)	(0.534)
Netw*Subprime (D)	−0.00623*	−0.00193	−1.691***	−0.0476	−0.0826	0.00175	0.0532*	0.0136
	(0.00338)	(0.00379)	(0.617)	(0.257)	(0.230)	(0.00110)	(0.0285)	(0.183)
Netw*SIFI*Subprime (E)	−0.000864	−0.00542	0.973**	−1.226	−1.110	−0.316	−0.211	−1.096
	(0.00434)	(0.00504)	(0.494)	(0.862)	(0.807)	(0.231)	(0.132)	(0.677)
Netw*Small*Subprime	0.00177	0.00665	1.320***	−0.641	−0.429	−0.223	0.0260	−0.957
(F)	(0.0222)	(0.0212)	(0.501)	(0.689)	(0.706)	(0.225)	(0.0741)	(0.874)
Netw*Sovereign (G)	−0.00228	−0.00361	−1.651***	0.0184	−0.00753	−0.000753	0.0303	0.00558
	(0.00279)	(0.00344)	(0.618)	(0.272)	(0.241)	(0.000558)	(0.0440)	(0.00703)
Netw*SIFI*Sovereign (H)	−0.00559	−0.00501	0.567	−1.331	−1.185	−0.281	−0.103	−1.334
	(0.00344)	(0.00437)	(1.381)	(1.207)	(0.988)	(0.177)	(0.161)	(0.869)
Netw*Small-size	−0.0189	−0.0397	1.237**	0.668	1.038	0.386	−0.0245	1.116
*Sovereign (I)	(0.0273)	(0.0247)	(0.495)	(0.816)	(0.861)	(0.644)	(0.0915)	(1.041)
Wald Test								
$A+B$ (SIFI –Normal-times)	.00005	.0161**	.199	−0.928	−0.8499	.1534	.3348	−0.8524*
$A+C$ (Small–Normal-times)	−0.009	.0496**	.0743	−0.646	−0.3902	.175**	−0.0151	−0.1885
$A+D$ (M&L-Subprime)	−0.0276***	−0.0059	.3151***	−1.642***	−1.522***	−0.5214***	−1.083***	−1.048***
$A+B+D+E$ (SIFI-Subprime)	−0.007	.0087*	−0.5186*	−2.201***	−2.042***	−0.1610	.1768	−1.934***
$A+C+D+F$ (Small-Subprime)	−0.0135	.0543**	−0.296***	−1.335*	−0.9014	−0.0464	.0641	−1.132
$A+G$ (M&L-Sovereign)	−0.0236***	−0.0076	.3545***	−1.576***	−1.447***	−0.523***	−1.106***	−1.056***
$A+B+G+H$ (SIFI-Sovereign)	−0.0078	.0074	−0.885	−2.241*	−2.042**	−0.1285	.2616	−2.1807**
$A+C+G+I$ (Small-Sovereign)	−0.0302	.0063	−0.339***	.0402	.640	.5603	−0.0093	.9326
Number of obs	10,253	10,253	10,253	10,262	10,262	10,262	10,262	10,249
Number of banks	1178	1178	1178	1178	1178	1178	1178	1178
r2	0.0224	0.0249	−1.016	0.0240	0.0256	0.0145	−0.0411	0.0253
Hansen J. test	0.535	0.371	0.759	0.702	0.773	1.011	3.268	0.854
Hansen J. P-value	0.765	0.831	0.684	0.704	0.680	0.603	0.195	0.652
Under-ident stat	28.19	47.22	32.84	45.19	44.57	55.74	44.89	46.76
Under-ident p-val	0.00000332	3.12e-10	0.000000348	8.43e-10	1.14e-09	4.78e-12	9.74e-10	3.92e-10
Weak-id stat	29.43	19.62	13.05	163.1	116.1	106.6	30.84	112.7
Weak-id critical-value 5%	13.91	13.91	13.91	13.91	13.91	13.91	13.91	13.91
Bank-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank specialization Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crises dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents regression results for crisis times and normal times using instrumental variables for an unbalanced panel of European commercial, investment, and real estate banks over the 2001–2013 period by introducing the interaction between *Bank-size*, the network variable, and crisis dummy variables. We employ IV estimator with bank-specific fixed effect to estimate the following equation:

$$NSFR_{i,t} = \alpha_0 + \alpha_1 Netw(x)_{i,t} + \alpha_2 B_{i,t-1} + \alpha_3 C_{j,t} + \alpha_4 Crisis\_Subprime_t + \alpha_5 Crisis\_Sovereign_t + \alpha_6 Investment_i + \alpha_7 Realestate_i + \alpha_8 GSIFIs_{i,t} + \alpha_9 Small\_Size_{i,t} + \alpha_{10} GSIFIs_{i,t} * Netw(x)_{i,t} + \alpha_{11} Small\_Size_{i,t} * Netw(x)_{i,t} + \alpha_{12} Crisis\_Subprime_t * Netw(x)_{i,t} + \alpha_{13} Crisis\_Subprime_t * GSIFIs_{i,t} * Netw(x)_{i,t} + \alpha_{14} Crisis\_Subprime_t * Small\_Size_{i,t} * Netw(x)_{i,t} + \alpha_{15} Crisis\_Sovereign_t * Netw(x)_{i,t} + \alpha_{16} Crisis\_Sovereign_t * GSIFIs_{i,t} * Netw(x)_{i,t} + \alpha_{17} Crisis\_Sovereign_t * Small\_Size_{i,t} * Netw(x)_{i,t} + \mu_i + \varepsilon_{i,t}$$

Dependent variable is *NSFR*. Network statistics are our main independent variables, including *In-degree*, *Out-degree*, *ClusteringCo*, *Hub*, *Authority*, *Betweenness*, *Closeness*, and *PageRank*. Because of high correlation among our network variables, we estimate them by separate equations. $B_{i,t-1}$ is a vector of one-year lagged value of bank-level control variables, including *Bank-size*, *Z-score*, *NIM*, *ROA*, *Cost_inc*, and *Eq_TA*. C_j is a vector of country-level control variables that includes *CB_policyrate*, log *GDPperCa*, *Inflation*, *Sector-size*, and *HHI_TA*. *Crisis_subprime* and *Crisis_sovereign* are dummy variables for the subprime crisis and sovereign crisis, respectively. *Investment* and *Realestate* are bank specialization dummy variables. Hansen J test is an overidentification test to reject the null hypothesis that the equation is overidentified. We provide the critical values for the Under-Identification test (Kleibergen-Paap rk LM), Weak-Identification test (Kleibergen-Paap rk Wald F statistic), and Stock-Yogo weak ID test. All dependent and bank-level control variables are winsorized at 5% - 95%. *G-SIFIS* and *Small-size* are dummy variables that equal 1 for G-SIFIs and small banks, respectively. *Investment* and *Realestate* are bank specialization dummy variables. In the test section, we report the Wald test for total effects. Standard errors are shown in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

posure network more accurately, as those banks tend to interact with counterparties from the same group and are less likely to engage in lending-borrowing relationships with banks beyond their specialization. However, to check the robustness of our results we reconstruct our exposure network with the assumption that banks of all types tend toward building interbank relationships regardless of specialization. Hence, we add savings, cooperatives, and mutual banks to our sample, run the MD algorithm based on this extended sample, and estimate network topology parameters accordingly. Table C6 in the Appendix summarizes the regression results. Except *ClusteringCo*, which is significant at 10% with a negative sign, and *In-degree*, which is more highly significant, our results remain the same. The heterogenous interbank network structure of cooperative and savings banks compared to other types of banks could explain the deviation from our baseline results for these variables.

4.8. Network constructed with an alternative parametrization

In this study, we have constructed our network by applying the MD algorithm. This algorithm minimizes the number of linkages and consequently reduces the cost of building and maintaining such connections. According to Anand et al. (2015), we can obtain a less aggressive solution by allowing the algorithm to parametrically move from MD to Low-Density (LD). This solution results in higher density and lower concentration of the interbank link distribution compared with MD. Consequently, we reconstruct our interbank networks by applying the LD extension and re-estimate our liquidity model based on our new network configuration. As shown in Table C7 (Appendix), the main results remain unchanged.

5. Conclusion

The literature neglects the role interbank network characteristics play in explaining how banks set their liquidity ratios. In this paper, we show how simulated network statistics can improve the explanatory power of bank liquidity ratio models. Specifically, our results indicate that local network characteristics and systemwide characteristics play a very different role. Applied on data from 28 European countries, our findings highlight that higher numbers of direct lenders, more powerful strategic positions in interbank networks, higher direct dominant lending and borrowing positions, and eventually higher counterparty importance lead banks to set lower liquidity ratios, as they have easier access to short-term interbank funding. More specifically, our results show that local network positions are significant in explaining the liquidity ratios among small banks and that systemwide network positions matter more for large and medium-size banks. Similarly, presumably because of higher contagion risk during turmoil, systemwide positions matter more than local ones in countries with larger interbank networks, but only local positions influence bank liquidity ratios in countries with smaller networks. In times of crisis, G-SIFIs take advantage of their network positions, highlighting their too-big-to fail or too-complex-to-fail status.

Our results highlight that highly systemwide connected banks in the interbank market might underestimate liquidity risk because they believe they can easily access liquidity when needed and enjoy a too-connected-to-fail position. These banks should be watched more carefully as, in crisis time, the liquidity hoarding behavior of banks that are dominant lenders can lead to severe disruptions in the wholesale liquidity market (Berrospide, 2013) and jeopardize banks that are dominant interbank borrowers leading to panic and widespread contagion. Likewise, our findings suggest that regulators should impose higher liquidity requirements for banks with strong system-wide network positions. Our findings thus cast doubt on the Basel III uniform liquidity requirements for banks with different connectedness characteristics and support the need to implement minimum liquidity requirements by considering the interbank network characteristics of each banking industry and possibly of each systemically important bank. Imposing uniform liquidity requirements without considering network characteristics could weaken the intermediation role banks play and encourage institutions to invest less in long-term projects irrespective of their individual ability to access liquidity.

Our study has several caveats that provide avenues for future research. First, data on LCR is not currently available for the majority of European banks in our sample. Future research could examine the impact of interbank network characteristics on the LCR ratio. Second, our study only covers a period prior to the implementation of Basel III liquidity regulation; hence future studies could explore the impact of network topology on bank liquidity ratios on post implementation periods. Finally, as data on bilateral interbank exposure is not available for the majority of European countries, we have used simulation techniques to construct our interbank network. Future research could examine the impact of interbank networks on liquidity ratios by using actual bilateral interbank exposure data at least for one country, which would allow refined policy recommendations.

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Supplementary materials

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