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Liquidity, interbank network topology and bank capital

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Abstract

Purpose – While previous literature has emphasized the causal relationship from liquidity to capital, the impact of interbank network characteristics on this relationship remains unclear. By applying the interbank network simulation, this paper aims to examine whether the causal relationship between capital and liquidity is influenced by bank positions in the interbank network.

Design/methodology/approach – Using the sample of 506 commercial banks established in 28 European countries from 2001 to 2013, the author adopts the generalized method of moments simultaneous equations approach to investigate whether interbank network characteristics influence the causal relationship between bank capital and liquidity.

Findings – Drawing on a sample of commercial banks from 28 European countries, this study suggests that the interconnectedness of banks within interbank loan and deposit networks shapes their decisions to establish higher or lower regulatory capital ratios in the face of increased illiquidity. These findings support the implementation of minimum liquidity ratios alongside capital ratios, as advocated by the Basel Committee on Banking Regulation and Supervision. In addition, the paper underscores the importance of regulatory authorities considering the network characteristics of banks in their oversight and decision-making processes.

Originality/value – This paper makes a valuable contribution to the current body of research by examining the influence of interbank network characteristics on the relationship between a bank's capital and liquidity. The findings provide insights that add to the ongoing discourse on regulatory frameworks and emphasize the necessity of customized approaches that consider the varied interbank network positions of banks.

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

Paper type Research paper

1. Introduction

Financial regulators have made significant efforts to monitor banks' capital and liquidity after recent financial crises, aiming to strengthen financial market stability. The Basel Committee on Banking Regulation and Supervision introduced the Basel III guideline, which

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includes comprehensive capital and liquidity requirements (BCBS, 2010a, 2010b). The effectiveness of Basel III has been extensively debated (Allahrakha *et al.*, 2018; Le *et al.*, 2020; Merkl and Stolz, 2009; Petersen *et al.*, 2013). Recent studies have highlighted interrelationships between bank capital and liquidity (Berger and Bouwman, 2009; Bhattacharya and Thakor, 1993; Diamond and Rajan, 2001; Gorton and Winton, 2017; von Thadden, 2004). However, these studies have overlooked the significance of banks' interconnectedness in the interbank market regarding the capital–liquidity relationship.

Banks play a vital role in creating liquidity by using short-term liquid liabilities to finance long-term illiquid assets. This enables banks to hold illiquid assets and stimulate the economy through liquidity provision. However, it exposes banks to the risk of unexpected withdrawals from short-term liabilities invested in illiquid assets, increasing the likelihood of bank failures. The interbank market facilitates liquidity transformation by enabling the flow of short-term liquid funds between banks with surpluses and deficits. It acts as a connection among banks and aligns liquidity needs through bilateral interactions. Although the interbank market mitigates liquidity shocks, access is not uniform among banks, particularly during financial turmoil.

The Basel Committee's regulations aim to enhance banks' solvency and liquidity (BCBS, 2010a, 2010b). The Basel III capital and liquidity requirements are, however, independent of the banks' network topology or the quality of banks' interconnectedness in the interbank network.

Ardekani *et al.* (2020) provide evidence that banks' decisions regarding liquidity ratios are contingent upon their interbank network characteristics. Moreover, Distinguin *et al.* (2013), Fu *et al.* (2016) and Horváth *et al.* (2014) emphasize the existence of a causal relationship that flows from liquidity to capital. Consequently, a bank's position within the interbank network may also exert influence on the relationship between bank capital and liquidity.

The literature on the capital-liquidity relationship presents conflicting findings. Distinguin *et al.* (2013) suggest complementarity between liquidity and capital for large banks, while substitutionary effects are observed for small banks. Fu *et al.* (2016) find a negative interrelationship between capital and liquidity regardless of bank size in the Asia-Pacific region. Horváth *et al.* (2014) propose substitutionary impacts of liquidity on Czech banks' capital, indicating increased capital ratios during higher illiquidity. However, due to the lack of consistent empirical evidence on the causal relationship from liquidity to capital, the underlying reasons for these findings remain an open question. One possible explanation for these findings could be the banks' positions in the interbank network. Matz and Neu (2007) argue that increased liquidity creation exposes banks to higher liquidity risk, prompting solvency strengthening through increased capital. However, if banks are well positioned within the interbank network, they may have broader access to wholesale liquid funds, which reduces their need for higher capital.

This study is also related to literature on bank network topology, highlighting the role of interbank network connectedness in bank liquidity risk, systemic risk and the contagion of financial shocks (Ardekani *et al.*, 2020; Borges *et al.*, 2020; Capponi and Chen, 2015; Glasserman and Young, 2015; Huang *et al.*, 2016; Paltalidis *et al.*, 2015; Souza *et al.*, 2015). To assess banks' interconnectedness and access to wholesale liquid funds, this study uses network topology statistics. It distinguishes between system-wide and local network positions in the interbank market, where local topology measures immediate interbank fund access, and system-wide topology quantifies the crucial role of each bank in the interbank network.

I conduct research on a selection of 506 banks hailing from 28 European countries. These banks function within an integrated area overseen by a singular monetary authority, namely, the European Central Bank (ECB). This particular setup aims to promote smooth transactions between participating countries. However, it also has the potential to amplify global instability, particularly during periods of severe financial turmoil. European banks have previously encountered significant challenges such as the global financial crisis of 2007–2009 and the sovereign debt crisis of 2010–2012. These events offer an intriguing opportunity to examine the impact of interbank network characteristics on the connection between bank liquidity and capital ratios during both normal and crisis periods.

This paper contributes to existing literature by investigating how the interbank network characteristics influence the relationship between a bank's capital and liquidity. The findings suggest that weak interbank interconnectedness strengthens the substitutive effect of liquidity on capital. However, broader interbank market access acts as liquidity insurance and weakens this relationship under normal conditions. In times of economic distress, strongly locally interconnected banks do not substitute capital for liquidity, likely due to their wider access to interbank funds and reducing pressure from depositors. Interestingly, the findings reveal that strongly system-wide interconnected banks tend to maintain lower capital ratios when facing higher levels of illiquidity.

The remaining content of this article is organized as follows: Section 2 elaborates on the development of hypotheses. Section 3 introduces the data and variables used in the study. Section 4 outlines the methodology used. Section 5 offers a summary of the results. Robustness checks are discussed in Section 6. Finally, Section 7 presents the conclusion.

2. Hypotheses development

Recent literature has indicated a causal link between the liquidity creation and capital, presenting two divergent hypotheses. Horváth *et al.* (2014) extensively explore this relationship by examining empirical research on the impact of risk on banks' capital buffers. The first hypothesis, referred to as the "liquidity risk" hypothesis, posits that an increase in liquidity creation raises the risk of illiquidity for banks, compelling them to strengthen their solvency. Capital acts as a protective buffer against unexpected customer withdrawals, establishing a positive connection between liquidity creation and bank capital. Conversely, the "liquidity substitution" hypothesis, put forward by Distinguin *et al.* (2013), suggests a negative relationship between liquidity creation and bank capital. When faced with heightened illiquidity, banks may view certain liquid liabilities as stable sources of funding, leading banks to replace capital with these perceived "stable" liabilities. Consequently, banks may refrain from reinforcing their capital when confronted with illiquidity, as defined in the new Basel regulations. In addition, by holding a favorable position within the interbank network, banks may enjoy broader access to wholesale liquid funds. Consequently, aligning with the liquidity substitution hypothesis and as a response to heightened illiquidity, banks could replace capital with interbank fund, thereby reducing their need for higher capital levels.

Building upon the existing literature, this study examines how interbank market access affects the interrelationship between banks' capital and liquidity. Based on the aforementioned rationale, the following hypotheses are proposed:

H1. Banks with strong local network positions do not substitute capital for liquidity.

H2. Banks with weak local network positions substitute capital for liquidity.

This study distinguishes between system-wide and local network positions in the interbank market. Local network topology measures a bank's immediate access to interbank funds, while system-wide network topology quantifies the crucial role played by each bank in the entire interbank network. Banks with strong local positions in the interbank network specialize in diversifying their interbank borrowing or lending, enabling them to maintain their connections even during economic distress. According to the substitutionary effect of liquidity on capital, banks set higher capital ratios to strengthen their solvency and enhance their fundraising capabilities when faced with increased illiquidity. It is assumed that the fundraising capability of illiquid banks is less affected by their solvency if banks have greater diversification in lending and borrowing within the interbank market. Similarly, it is expected that a strong local position in the interbank network weakens this substitutionary effect when banks face higher levels of illiquidity. In addition, banks with limited local interconnectedness opt to substitute capital with liquidity. Due to their limited access to interbank funds, these banks focus on reinforcing their solvency to enhance their fundraising capabilities:

H3. Banks with strong system-wide network positions substitute less capital for liquidity.

H4. Banks with weak system-wide network positions substitute capital for liquidity.

A bank's strong system-wide position in the interbank network enhances their access to interbank funds but also poses a potential source of contagion and systemic risk. Consequently, the impact of system-wide network variables on the relationship between capital and liquidity depends on the economic situation (crisis vs normal). Overall, it is anticipated that banks with strong system-wide interconnectedness substitute less capital for liquidity. It is also assumed that widespread accessibility to interbank funds enhances banks' fundraising capabilities and alleviates the pressure to further strengthen their solvency. Furthermore, banks with weak system-wide positions in the interbank network may have less confidence in their ability to secure liquidity funding from highly connected counterparties. As a result, banks prioritize strengthening their solvency to enhance their external fundraising capabilities.

By empirically testing these hypotheses, this study aims to provide a deeper understanding of the interrelationship between capital and liquidity in the context of banks' interbank market access and network positions.

3. Sample and variables

3.1 Sample

The sample for this study comprises 506 commercial banks operating in 28 European countries [1]. To construct the interbank networks, I include all available commercial, investment and real estate banks from the Bankscope database in each country [2]. Therefore, the network statistics in this study capture the connections of commercial banks in the sample with all possible banks in their respective countries.

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

3.2 Definition of variables

This section introduces the dependent variables, various independent variables representing interbank network characteristics and control variables used in the estimations. Table 2

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

Source: By author

provides descriptive statistics and definitions of these variables. To mitigate the effect of outliers, the extreme observations for the dependent variables and bank-level control variables are winsorized, with the 1% lowest and highest values adjusted.

3.2.1 Total capital ratio. The Basel Committee on Banking Regulation and Supervision has implemented capital ratio requirements for banks to control excessive leverage. These requirements mandate banks to maintain a specified amount of Tiers 1 and 2 capital against all on- and off-balance sheet exposures (BCBS, 2010a, 2010b). The total capital ratio (TCR), as defined by Basel III guidelines, is calculated by dividing the sum of Tiers 1 and 2 capital by risk-weighted assets (RWA):

$$TCR = \frac{Tier\ 1 + Tier\ 2}{RWA} \tag{1}$$

Tier 1 capital encompasses a bank's core capital, including shareholder equity and noncumulative preferred shares. Tier 2 capital, on the other hand, is additional capital that includes hybrid instruments and subordinated debts [3].

3.2.2 Inverse of structural liquidity indicator (I. NSFR). Apart from the *TCR*, the Basel Committee introduced a framework called the "net stable funding ratio" (NSFR) to assess

Table 2. Descriptive statistics and definitions of my variables

Variables	Definition	Mean	SD	Min	Median	Max
Capital measure						
TCR	Total capital ratio	15.02	6.06	9.00	13.40	40.23
Liquidity measure						
I.NSFR	Inverse of net stable funding ratio	2.61	4.56	0.15	1.19	43.72
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	0.36	0.48	0.00	0.00	1.00
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	0.35	0.47	0.00	0.00	1.00
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	0.42	0.49	0.00	0.00	1.00
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	0.70	0.45	0.00	1.00	1.00
Controls						
Bank Size	Logarithm of total assets	15.39	1.97	10.64	15.42	18.20
Z-Score	Indicator of bank distance to bankruptcy	60.23	70.05	3.28	34.35	311.58
ROE	Return on equity	7.39	10.54	−19.13	7.92	28.44
LLP_NIR	Loans loss provisions to net interest revenue	23.69	27.14	−13.68	15.63	100.56
MKT_POW	Market power measured by bank total assets divided by country total assets	0.07	0.12	0.00	0.01	0.87
NIM	Net interest margin	2.62	1.52	0.13	2.38	7.02
GDPperCa	Natural logarithm of GDP per capita	27.13	1.59	22.23	27.96	30.79
CB_Policy	ECB policy rates	1.91	1.31	0.00	2.00	7.75
Crises	Dummy variable for crisis times. Takes a value of one for the periods of 2007–2009 (Global Financial Crisis) and 2010–2012 (European Sovereign Debt Crisis)	0.54	0.49	0.00	1.00	1.00

Source: By author

banks' liquidity. The NSFR, with longer-term liquidity requirements, aims to address liquidity mismatch by encouraging banks to finance their illiquid assets with more stable and less risky funds. It serves as a structural tool for effective liquidity measurement, examining both sides of the balance sheet and categorizing assets and liabilities as illiquid, semi-liquid and liquid, assigning weights accordingly. To measure illiquidity, this study follows the approach of Distinguin *et al.* (2013) and uses the inverse of the liquidity regulatory ratio [4]. This ratio is defined as:

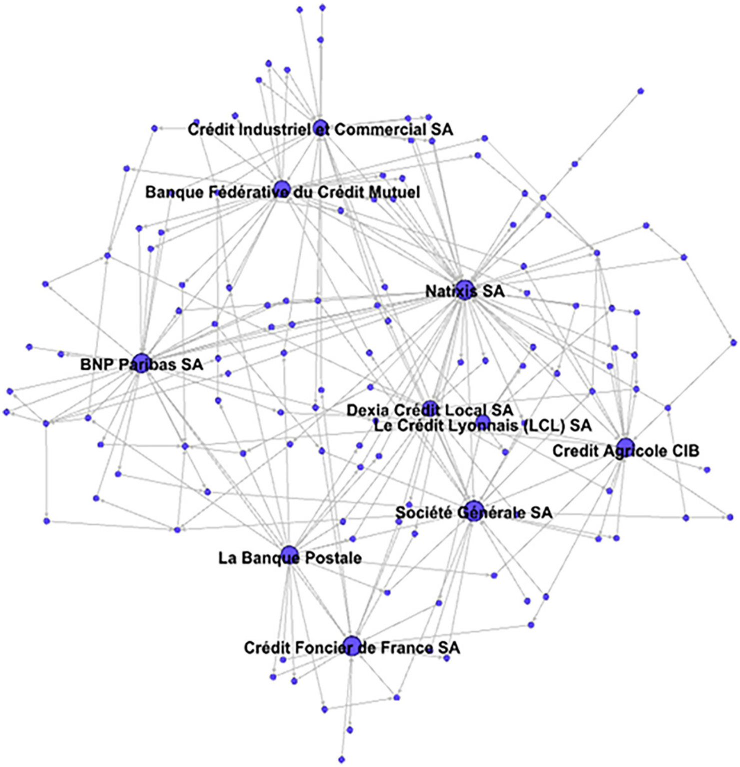
$$I.NSFR = \frac{Required\ amount\ of\ stable\ funds}{Available\ amount\ of\ stable\ funds} \tag{2}$$

The stable funds available to banks include their total capital, the portion of time deposits and stable demand deposits (with a maturity of less than one year) that are expected to remain within the bank, and liabilities with a maturity equal to or greater than one year. On the other hand, the required amount of stable funding comprises assets that serve as collateral for borrowing during periods of liquidity stress or assets that are not easily convertible into cash. Basel III mandates banks to maintain an NSFR ratio above 1 (100%). Estimating NSFR according to the guidelines of the Basel Committee on Banking Supervision (BCBS; 2010a, 2010b) is challenging due to the lack of detailed balance sheet data. Therefore, in this study, I approximate the NSFR using Bankscope data and the weights defined by Vazquez and Federico (2015) [5].

3.2.3 Interbank network. Network variables are derived from interbank lending and borrowing relationships. However, the lack of bilateral transaction data poses a significant challenge in studying interbank exposure, as most European countries do not require banks to report such information. Instead, only aggregate interbank loans and deposits data are available. To address this limitation, the minimum density (MD) algorithm, proposed by Anand *et al.* (2015), is commonly used to construct the interbank network based on aggregate transaction data. The MD algorithm is economically rational, as it minimizes the costly creation and maintenance of additional network linkages in the interbank market. It incorporates known characteristics of the interbank network, such as the high cost of connections with all possible banks and the hierarchical nature of the interbank loan and deposit market highlighted by Anand *et al.* (2015). Moreover, it aligns with previous research that emphasizes the importance of minimum correlated liquidity shocks and long-term lending relationships in shaping the interbank connections, as suggested by Cocco *et al.* (2009), Chiu *et al.* (2019) and Craig and Von Peter (2014) in their exploration of the core-periphery structure and tiering properties of the interbank network.

Ardekani *et al.* (2020) use the MD algorithm to construct their interbank exposure network and investigate the connection between interbank network characteristics and liquidity ratios of European banks. In line with their methodology, I adopt the MD algorithm proposed by Anand *et al.* (2015) to simulate the bilateral exposure network. Subsequently, I compute network centrality measurements [6].

Centrality is a crucial concept in social network analysis, used to determine the importance, influence and power of entities within a network. It has also been extensively applied in the field of financial economics to evaluate the risk, vulnerability and performance of financial networks (Boss *et al.*, 2004; Langfield *et al.*, 2014; Minoiu and Reyes, 2013; Rørdam and Bech, 2009). This study uses centrality measures to assess the accessibility of interbank market funds for each bank by examining the interconnectedness among banks in the interbank network. Figure 1 depicts the configuration of the simulated interbank network in France, representing a selected European country in 2013. Each node



Note: Highlighted nodes represent banks with extreme number of direct linkages
Source: By author

Figure 1. Interbank network configurations of selected European country (France–2013)

represents a bank, and the links indicate the interbank lending and borrowing relationships. Highlighted banks exhibit significant interconnectedness compared to others. To capture the interconnectedness of banks, the network variables are categorized into two subgroups: local and system-wide network variables.

3.2.3.1 Local network variables. Local network variables assess the direct connections between banks within the interbank network. Local network variables consist of two measures: In-Degree and Out-Degree. In-Degree quantifies the number of immediate incoming links, representing direct lenders, while Out-Degree measures the number of immediate outgoing links, representing direct borrowers:

$$D_j^{in} = \sum_j L_{ji}, \tag{3}$$

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

$$D_j^{out} = \sum_j L_{ij}, \tag{4}$$

where L_{ij} takes a value of one if there is interbank deposit from $bank_i$ to $bank_j$, and zero otherwise.

Hence, In-Degree and Out-Degree serve as indicators of the bank's capacity to broaden its borrowing and lending across the interbank market, ensuring greater diversification.

Network dummy variables are introduced in this research to differentiate between strong and weak local interconnectedness. Specifically, *HIn-Degree* and *HOut-Degree* dummy variables are assigned a value of one if their respective values are equal to or exceed the median value.

3.2.3.2 System-wide network variables. System-wide network variables assess a bank's ability to access interbank funds within the entire network. These variables quantify the network attributes of each bank in relation to all other banks in the interbank market, thus, offering a broader perspective on a bank's interconnectedness compared to local measurements.

Betweenness centrality quantifies the systemic position of each bank within the entire network:

$$Betweenness_i = \sum\nolimits_{j<k} \frac{g_{jik}}{g_{jk}} \tag{5}$$

Where g_{jik} represents the count of geodesic paths between bank j and bank k that pass through bank i. Increasing bank i's Betweenness demonstrates its growing intermediary role in the network, as all connections between j and k must traverse through i. This grants bank i the ability to influence and shape relationships. Banks with higher Betweenness ratios act as dominant intermediaries in the system.

Ultimately, PageRank evaluates the significance of each bank's counterparties in determining the crucial role of a bank within the interbank network:

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

Where for bank i, TL represents the total number of links originating from its out degree, while d is a factor recommended by Winograd (1999) and typically set to 0.85. Thus, PageRank considers both the quantity of liquidity-providing banks and the relative importance of lenders. Greater lender importance corresponds to a higher PageRank. To distinguish between strong and weak access of banks to interbank funds across the entire network, I introduce system-wide network dummy variables. The *HBetweenness* and *HPageRank* dummy variables take a value of one if their respective values are greater than or equal to the median value [7].

3.2.4 Control variables. The study includes control variables affecting bank capital and liquidity. In the capital equation, bank size is controlled using the logarithm of total assets (*Size*), return on equity (*ROE*) proxies bank profitability and loan loss provision to net interest income (*LLP_NIR*) proxies asset riskiness. The *Z-Score*, indicating a bank's proximity to bankruptcy, is also included in the regressions:

$$Zscore = \frac{ROAmma3 + \left(\frac{Equity}{TA}\right)mma3}{ROAsdma3} \tag{7}$$

where ROAmma3 is the three-year rolling average return on assets, (Equity/TA)mma3 represents the three-year rolling average of equity to total assets and ROAsdma3 represents the three-year rolling standard deviation of return on assets.

In addition, the natural logarithm of GDP per capita (*GDPperCa*) serve as country-level control variables. *GDPperCa* represents a country's gross domestic product per capita. A dummy variable captures the effects of the global financial crisis of 2007–2009 and the European sovereign debt crisis of 2010–2012, taking the value of one during those crisis years and zero otherwise.

In the liquidity equation, bank network characteristics are controlled using the network dummy (*HNetwork*). Other variables considered include the net interest margin (*NIM*) as a proxy for 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. A dummy variable for crises is also included.

The correlation matrix shows low correlation coefficients between independent variables, except for bank size (*Size*) and some network measures.[8] To test the impact of this correlation, a robustness test is performed by replacing bank size with an uncorrelated size dummy variable. The results remain qualitatively similar across all specifications [8]. Therefore, the reported results are obtained with Size and network variables introduced simultaneously [9].

4. Methodology

This paper examines the potential influence of bank network topology on the interrelationship between bank liquidity and capital. However, the existing literature on the causal relationship between capital and liquidity raises concerns regarding serial correlation and endogeneity. To address these issues, I adopt the generalized method of moments (GMM) simultaneous equations model, following the approach of Distinguin *et al.* (2013) and Sclip *et al.* (2019). GMM is preferred over 2SLS (two-stage least squares) regression as it considers error heteroskedasticity and is robust to error distribution (Distinguin *et al.*, 2013; Hall, 2005).

The capital equation is represented as follows:

$$TCR_{i,t} = \alpha_0 + \alpha_1 I.NSFR_{i,t} + \alpha_2 HNetw(x)_{i,j,t} + \alpha_3 HNetw(x)_{i,j,t} * I.NSFR_{i,t} + \alpha_4 B_{i,j,t-1} + \alpha_5 C_{j,t} + \alpha_6 Crises_t + \varepsilon_{i,t} \quad (8)$$

In this equation, $TCR_{i,t}$ denotes the TCR, α_0 represents the constant term, $I.NSFR_{i,t}$ corresponds to the inverse of the net stable funding ratio, $HNetw(x)_{i,j,t}$ represents a network dummy variable (such as *HIn-degree*, *HOut-degree*, *HBetweenness* or *HPageRank*) that takes the value of one if the network measurement is greater than or equal to the median value. $B_{i,j,t-1}$ represents a vector of bank-level control variables including *Size*, *Z-score*, *LLP_NIR* and *ROE*. $C_{j,t}$ is a vector of country-level control variables that includes the natural logarithm of *GDPperCa*. The variable $Crises_t$ is a crisis dummy variable that takes the value of one during the 2007–2012 period (global financial crisis and sovereign debt crisis) and $\varepsilon_{i,t}$ denotes the error term.

The liquidity equation is represented as follows:

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

In this equation, $I.NSFR_{i,t}$ represents the illiquidity ratio, $TCR_{i,t}$ denotes the TCR and the other variables have the same meanings as in the capital equation. $B_{i,j,t-1}$ represents a vector of bank-level control variables including *NIM* and *MKT_POW*, while $C_{j,t}$ represents the vector of country-level control variable comprising the *CB_Policy*. The standard errors are clustered at the bank level. To address potential endogeneity, I replace all bank-level controls with their one-year lagged values in both equations. After testing for cross-section and time random versus fixed effects, random effect estimations using the Huber-White estimator are applied in both equations. The Huber–White estimator provides standard errors robust to panel correlation and cross-sectional heteroscedasticity. Finally, time and cross-section fixed effects are included in the regressions.

5. Results

5.1 Impact of network topology on causal relationships between bank liquidity and capital

The first part of the analysis focuses on examining the relationship between illiquidity and capital of European banks with different positions in the interbank network. In addition, it investigates how this relationship is influenced by network topology under normal and crisis conditions.

Initially, without considering interbank network interactions (column 1 of Table 3), the findings reveal that higher illiquidity prompts banks to increase their capital ratios. Banks facing higher illiquidity are more inclined to strengthen their solvency standards, thereby enhancing their ability to raise funds. Similarly, in the liquidity equation, a higher regulatory capital ratio is associated with higher illiquidity, consistent with the "Risk Absorption" theory (Bhattacharya and Thakor, 1993; von Thadden, 2004). This theory suggests that higher capital enables banks to absorb greater risks, resulting in increased liquidity creation. These results indicate that banks perceive capital as a substitute for liquidity when confronted with higher illiquidity.

Columns 2 to 5 of Table 3 present the results of the impact of bank network topology on the liquidity-capital relationship. Banks with a limited number of immediate interbank borrowers (Out-Degree) or lenders (In-Degree) substitute capital for liquidity due to their restricted access to interbank funds. Banks strengthen their solvency to improve their fundraising abilities. On the other hand, no significant evidence is found regarding the impact of illiquidity on capital for banks with strong local positions in the network. This suggests that these banks do not substitute capital for liquidity. Their broader local access to the interbank market and strong diversification in interbank lending and borrowing serve as liquidity insurance, mitigating the need for capital substitution. Such banks can easily raise funds without compromising their solvency.

Regarding system-wide network measures, similar to the findings for local network variables, banks facing higher illiquidity strengthen their solvency when characterized by weak PageRank. Due to weak linkages with highly connected counterparties, banks may have less confidence in their liquidity funding capabilities in the interbank network. Consequently, these banks reinforce their solvency to enhance their external fundraising capabilities. However, the liquidity-capital relationship does not significantly influence banks with weak Betweenness. Surprisingly, banks with a strong intermediation role in the interbank market (Betweenness) or those strongly interconnected with centrally positioned peers (PageRank) set lower capital ratios when facing higher illiquidity. The increasing global accessibility to wholesale liquid funds might strengthen their fundraising abilities, explaining the negative relationship observed.

In terms of control variables, bank *Size* emerges as the most influential factor explaining regulatory capital, with larger banks setting lower capital ratios. Regarding liquidity determinants, *NIM*, *CB_Policy* and *Crises_Dummy* play significant roles. The results indicate that more profitable banks tend to maintain lower liquidity ratios. Furthermore,

Table 3. Baseline GMM model of interaction between network topology and liquidity on bank capital ratio

VARIABLES	1	2 *HIn-Degree*	3 *HOut-Degree*	4 *HBetweenness*	5 *HPageRank*
Capital equation					
I.NSFR (A; weak network)	2.55*** (0.96)	2.84*** (0.62)	2.60*** (0.55)	0.61 (0.77)	2.51** (1.09)
HNetw		6.36*** (1.70)	7.30*** (1.70)	6.15*** (1.82)	4.78*** (1.80)
*HNetw * I.NSFR (B)*		−2.88*** (0.63)	−2.60*** (0.55)	−0.85 (0.77)	−2.63** (1.10)
Bank size	−1.10*** (0.36)	−0.59** (0.26)	−0.91*** (0.28)	−1.19*** (0.20)	−0.58*** (0.21)
Z-score	−0.00 (0.00)	−0.01* (0.00)	−0.00 (0.00)	−0.00 (0.00)	−0.00 (0.00)
LLP_NIR	−0.02 (0.02)	−0.03** (0.01)	−0.01 (0.01)	−0.01 (0.01)	−0.01 (0.01)
ROE	−0.07 (0.06)	−0.06* (0.03)	−0.04 (0.03)	−0.06** (0.03)	−0.02 (0.03)
GDPperCa	−2.14 (1.38)	−1.11** (0.53)	−0.86* (0.52)	0.56 (0.72)	−1.50 (1.22)
Crises	0.17 (0.64)	0.28 (0.40)	0.45 (0.40)	0.85* (0.45)	−0.38 (0.75)
Constant	84.51** (40.39)	48.76*** (16.14)	45.86*** (15.95)	15.10 (19.50)	59.69* (32.74)
Liquidity equation					
TCR	0.53* (0.28)	0.28** (0.11)	0.21** (0.10)	0.22 (0.29)	0.31*** (0.11)
HNetw		0.51* (0.30)	−0.47* (0.24)	−0.93 (2.92)	−0.052 (0.30)
NIM	−0.40** (0.16)	−0.20*** (0.07)	−0.24*** (0.07)	−0.34*** (0.10)	−0.33*** (0.10)
MKT_POW	0.69 (1.55)	−0.33 (1.19)	1.08 (1.12)	1.82 (4.72)	0.50 (1.28)
CB_Policy	−0.02 (0.19)	−0.17** (0.07)	−0.20*** (0.06)	−0.14 (0.17)	−0.10 (0.09)
Crises	−0.41** (0.21)	−0.35** (0.16)	−0.33** (0.16)	−0.33 (0.20)	−0.36** (0.17)
Constant	−4.04 (4.19)	−0.91 (1.72)	0.71 (1.48)	0.82 (5.44)	−0.91 (1.54)

(*continued*)

Table 3.

	1	2	3	4	5
VARIABLES		*HIn-Degree*	*HOut-Degree*	*HBetweenness*	*HPageRank*
Wald test					
A + B (strong network)		−0.04	0.00	−0.24***	−0.11**
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*	0.6	4.29	4.20	2.91	2.57
Hansen's *J* *p*-value	0.72	0.37	0.38	0.23	0.46

Notes: This table presents the outcomes of a regression analysis conducted on an unbalanced panel of European commercial banks from 2001 to 2013. The analysis used the GMM simultaneous equations model and introduced the interaction between the network dummy and I.NSFR variables. The estimation process used a two-step GMM estimator with robust standard errors:

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

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

TCR represents the capital ratio, while I.NSFR serves as my measurement of illiquidity. The network statistics dummies (HNetw) encompass HIn-degree, HOut-degree, HBetweenness and HPageRank. $Bi_{,t-1}$ is a vector comprising bank-level control variables. In the capital equation, $Bi_{,t-1}$ incorporates Bank size, *Z*-score, loans loss provisions to net interest revenue (LLP_NIR) and return on equity (ROE). In the liquidity equation, it includes net interest margin (NIM) and market power (MKT_POW). *Cj* represents a vector of country-level control variables. For the capital equation, *Cj* includes GDP per capita (GDPperCa), while in the liquidity equation, it incorporates ECB policy rates (CB_Policy). The variable Crises serves as a dummy variable indicating financial crises from 2007 to 2012. The regressions include fixed effects for both time and cross-section, using the Huber–White estimator. The Hansen test is used, and the VIF test examines multicollinearity among all variables. In the test section, we report the Wald test for total effects. We test the impact of the illiquidity variable for strongly interconnected banks with ($\alpha 1 + \alpha 3$). All dependent and bank-level control variables are winsorized at the 1st and 99th percentiles. Standard errors are displayed in parentheses. The notation *, ** and ***denote statistical significance at the 10, 5 and 1% levels, respectively
Source: By author

raising central bank policy rates or experiencing financial crises leads banks to adopt lower liquidity ratios.

In summary, the findings suggest that a strong system-wide network position leads banks to set lower capital ratios when confronted with higher illiquidity. Conversely, banks with weak local network positions or limited connections to centrally positioned peers reinforce their solvency standards. Lastly, banks with strong local positions or weak intermediation role in the interbank network do not substitute capital for liquidity.

5.2 Impact of network topology on causal relationships between bank liquidity and capital during normal and crisis times

This section investigates the influence of interbank network topology on the relationship between bank liquidity and capital ratios during normal periods and crisis periods, specifically examining the global financial crisis of 2007–2009 and the European sovereign debt crisis of 2010–2012. These crises had a significant impact on the interconnectedness of European banks, as these banks exhibited reluctance to engage in unsecured interbank transactions and preferred interactions through the Eurosystem. Consequently, the role of network interconnectedness was expected to undergo substantial changes.

Furthermore, the financial crises had a profound effect on banks' fundraising capabilities, resulting in increased funding costs and liquidity risks. Schanz (2011) argues that depositors tend to be more risk-averse during crisis periods, pressuring banks to strengthen their solvency and offer higher deposit rates to encourage deposit rollovers. These requirements imposed by depositors may potentially amplify the liquidity-capital substitution. This section aims to examine how the ease of a bank's access to the interbank market might affect the substitutionary effects of liquidity on capital during both normal and crisis times.

The findings presented in Table 4 indicate that banks with strong local interconnectedness do not substitute capital for liquidity during normal or crisis periods. In contrast, banks with weak local positions set higher capital ratios when faced with higher illiquidity in both periods.

During normal times, banks with limited system-wide access to the interbank market tend to substitute capital for liquidity. However, the broader system-wide position acts as liquidity insurance, weakening these substitutionary effects. Crises further weaken the substitutionary effects of liquidity on capital for banks with a weak system-wide position. Although a weak system-wide position suggests reduced access to interbank liquid funds, it can also be interpreted as indicating fewer counterparty and systemic risks during crisis times. However, banks with strong system-wide access to the interbank market begin targeting lower capital ratios when confronted with higher illiquidity. Due to their "too-interconnected-to-fail" status, these highly interconnected intermediaries are expected to have higher bailout expectations during crises. Such expectations enhance the confidence their interbank peers have in these banks, enabling banks to leverage their system-wide network positions during crises and benefit from lower fluctuations in interbank borrowing rates. Consequently, bank managers might perceive interbank funds as stable and substitute them for capital when faced with higher illiquidity. Therefore, by targeting a lower capital ratio, banks could potentially achieve higher profits.

6. Robustness checks

To assess the robustness of the findings, several sensitivity analyses are conducted, as described in the following sections.

Table 4. GMM model of interaction between network topology and liquidity on bank capital ratio during normal times and crisis times

VARIABLES	1	2 *HIn-Degree*	3 *HOut-Degree*	4 *HBetweenness*	5 *HPageRank*
Capital equation					
I.NSFR (A; weak network–normal time)	4.25*** (1.63)	6.76*** (2.56)	5.40*** (1.64)	6.75*** (1.97)	4.85*** (1.28)
HNetw		9.25 (6.71)	9.04** (4.37)	7.59*** (2.50)	4.98*** (1.10)
*HNetw * I.NSFR (B)*		−7.36 (5.05)	−5.73* (3.20)	−6.21*** (1.83)	−4.60*** (1.21)
*Crises * I.NSFR (C)*	−4.21** (1.64)	−6.30*** (2.35)	−5.08*** (1.53)	−6.41*** (1.90)	−4.62*** (1.24)
*HNetw * I.NSFR * crises (D)*		6.37 (4.41)	4.88* (2.78)	5.19*** (1.51)	3.47*** (0.99)
Liquidity equation					
TCR	0.53* (0.28)	0.19 (0.31)	0.23 (0.26)	0.16 (0.25)	0.36*** (0.10)
Wald test					
A + B (strong network–normal time)	0.04	−0.60	−0.33	0.54***	0.25**
A + C (weak network–crisis time)		0.46*	0.32**	0.34***	0.23***
A + B+C + D (strong network–crisis time)		−0.53	−0.53	−0.68*	−0.89***
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	1.17	2.67	1.97	2.95	3.09
Hansen's J *p*-value	0.56	2.67	0.16	0.40	0.54
Bank-level controls	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the regression results for both crisis times and normal times using the GMM simultaneous equations model. The analysis was conducted on an unbalanced panel of European commercial banks from 2001 to 2013. In this analysis, the interaction between the network dummy, crises dummy and I.NSFR variables was introduced. The estimation process used a two-step GMM estimator with robust standard errors:

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

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

TCR represents the capital ratio, while I.NSFR serves as the measure of illiquidity. The network statistics dummies (HNetw) encompass HIn-degree, HOut-degree, HBetweenness and HPageRank. $Bi_{,t-1}$ is a vector consisting of bank-level control variables. In the capital equation, $Bi_{,t-1}$ includes Bank size, Z-score, Loans loss provisions to net interest revenue (LLP_NIR) and return on equity (ROE). In the liquidity equation, it includes net interest margin (NIM) and market power (MKT_POW). *Cj* represents a vector of country-level control variables. For the capital equation, *Cj* includes GDP per capita (GDPperCa), while in the liquidity equation, it incorporates ECB policy rates (CB_Policy). Crises is a dummy variable indicating financial crises from 2007 to 2012. The regressions include time and cross-section fixed effects and use the Huber–White estimator. The Hansen test is used, and the VIF test examines multicollinearity among all variables. In the test section, we report the Wald test for total effects. I test the impact of the illiquidity variable for strongly interconnected banks during the normal time with ($\alpha 1 + \alpha 3$) and during the crisis time with ($\alpha 1 + \alpha 3 + \alpha 4 + \alpha 5$). I also test the impact of the illiquidity variable for weakly interconnected banks during the crisis time with ($\alpha 1 + \alpha 4$). All dependent and bank-level control variables are winsorized between the 1st and 99th percentiles. Standard errors are reported in parentheses. The notation *, ** and ***indicate statistical significance at the 10, 5 and 1% levels, respectively

Source: By author

6.1 Alternative capital ratio

To verify the robustness of the results, a regression analysis is performed by substituting the *TCR* with the Tier-1 capital ratio, which is defined as the ratio of Tier-1 capital to *RWA*. The results are consistent with the baseline model [10].

6.2 Alternative measure of strong network interconnectedness

Furthermore, the impact of liquidity on capital is examined with regard to exceptionally strong interconnectedness within the interbank network. For this purpose, the network dummy variable is replaced with the extreme network dummy, which takes a value of one if the network variable exceeds or equals the 90th percentile. The results remain unchanged.

6.3 Size dummy variable

Given the correlation between the logarithm of bank total assets (*Size*) and the network dummy variables (ranging from 47% to 56%), except for *HPageRank*, a robustness test is conducted to ensure that this correlation does not affect the results. This is achieved by replacing *bank Size* with a dummy variable (*Size_Dummy*), which takes a value of one for small banks (those with total assets less than one billion euro) and zero otherwise. The main results remain unaffected.[11]

6.4 Additional controls

To validate the simultaneous equations and align with existing literature, additional controls for *Size* and *GDPperCapita* are included in the liquidity equation. The results remain consistent.[11]

6.5 Estimation of net stable funding ratio with different weights

To examine the robustness of the *NSFR* estimation, different weights are used for demand and savings deposits, using minimum, maximum and extreme case weights (0.5, 0.85 or 1), as specified by the Basel accords. The conclusion remains unchanged.[11]

7. Conclusion

Existing literature has overlooked the influence of network characteristics on the causal relationship between bank liquidity and capital. This study addresses this gap by incorporating network statistics into traditional capital–liquidity relationship models, investigating how this relationship is contingent upon a bank's local and system-wide network characteristics in the interbank market. By using a GMM simultaneous equations approach on a data set comprising listed and unlisted banks from 28 European countries, the findings of this study reveal that the bank's capital ratio is not solely determined by the macro environment and individual bank characteristics outlined in existing literature, but also by the interplay between liquidity and interbank network topology.

The results indicate that banks with weak local or system-wide interbank positions enhance their solvency standards when confronted with higher illiquidity, opting to strengthen their capital. Conversely, banks with strong local interconnectedness do not substitute capital for liquidity. Similarly, banks with strong system-wide interconnectedness set lower capital ratios when facing heightened illiquidity.

Moreover, the study highlights that during financial crises, banks with a strong system-wide position in the interbank network experience a decline in solvency as these banks encounter higher levels of illiquidity. This outcome is likely due to the elevated expectations of receiving bailouts. As heightened system-wide interconnectedness prompts banks to adopt lower liquidity ratios during crisis periods (Ardekani *et al.*, 2020), these banks become more susceptible to insolvency and liquidity risks compared to their counterparts. Consequently, these findings support the implementation of minimum liquidity ratios alongside capital ratios, as advocated by the Basel Committee on Banking Regulation and Supervision.

However, the findings also raise doubts about the uniform liquidity and capital requirements currently imposed on banks with varying interbank network topology. It is suggested that incorporating liquidity ratios into capital requirements may hold greater relevance for institutions with strong system-wide positions, as these banks might underestimate liquidity and insolvency risks due to their "too-interconnected-to-fail" status.

Overall, this study emphasizes the significance of considering network characteristics when analyzing the relationship between bank liquidity and capital. The findings contribute to the ongoing discussions surrounding regulatory frameworks and highlight the need for tailored approaches that account for the diverse interbank network positions of banks.

Notes

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 and Elsinger, 2004; Worms, 2001).
3. For robustness, Tier 1 ratio has been replaced with TCR (see 6.1).
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.
5. Vazquez and 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.
6. A detailed description of the minimum-density algorithm applied for construction of the interbank network is provided in Ardekani *et al.* (2020) Appendix A.
7. The centrality measurements are calculated based on the methods of Bastian and Heymann (2009).
8. The results are available upon the request.
9. I also perform multicollinearity checks among all variables by running a VIF test. The results of the VIF test in Tables 3 and 4 indicate low multicollinearity.
10. The results are available upon request.

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