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Bank stability in the uncollateralised overnight interbank market: A topological analysis☆

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A B S T R A C T

We study the topology characteristics of the Kenyan overnight interbank market and their impacts on bank stability. Our intraday transaction dataset covers 2003 to 2012, including six major liquidity shocks. We uncover new results that the Kenyan interbank network is an incomplete network with higher interconnectedness and exposure during liquidity shocks, such that the shocks tend to spread quickly throughout the network. The main implication of our finding is that in such tiered networks, core banks could pose risks to the whole system. Consistently, our further empirical results suggest that the high interbank network interconnectedness can smoothen liquidity flow during quiet times, but may lead to over-exposure to borrowing banks directly or indirectly, especially during disturbances.

1. Introduction

The interbank network serves like an insurance mechanism against liquidity shocks in normal situations by redistributing liquidity from surplus banks to deficit ones, which is essential for maintaining financial stability. However, a sudden strong demand for liquidity caused by unexpected shocks could also spread across the banking system via such intertwined linkages (see Green et al. (2016) for a detailed survey). When such financial networks become more complex and interconnected, the uncertainty during disturbances could be intensified, especially where, as is typical in the overnight interbank market, there is absence of collateral (Caballero & Simsek, 2009). It would appear, therefore, that the degree of the impact depends upon the net risk exposures of banks as well as their distribution within the network (Bougheas & Kirman, 2015). Indeed, recent theoretical work suggests a strong connection between financial networks and systemic risk; it is argued that a more densely connected financial network enhances financial stability, but

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beyond a certain point, dense interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015).

Nevertheless, the existing empirical evidence is limited and draws mixed conclusions, in either country-specific or cross-country settings, about the exact role played by interbank networks in creating systemic risk. One of the main challenges is access to high quality data; for example, because the availability of interbank direct bilateral exposures data is highly restricted, extant research seems to rely on aggregate interbank exposures data, or tends to use data from simulations based on restrictive assumptions such as maximum entropy method[1] (e.g. Chen, Li, Peng, & Anwar, 2020; Chen, Li, Peng, & Salim, 2020; Paltalidis, Gounopoulos, Kizys, & Koutelidakis, 2015; Upper & Worms, 2004), minimum entropy methods (e.g. Degryse & Nguyen, 2007; Elsinger, Lehar, & Summer, 2006; Upper, 2011), or relative entropy (e.g. Van Lelyveld & Liedorp, 2006). Some studies cast doubts on the relevancy of the results generated with simulations. For instance, adopting data from the Italian interbank market, Mistrulli (2011) finds that the simulation method overestimates the contagion risk compared to results using the actual bilateral exposure data. This paper complements the empirical literature on the relationship between the structure of the financial network and bank risk by conducting a comprehensive investigation on the topology characteristics of the interbank network and their dynamic impacts on bank stability. Our first contribution is that, in a country-specific setting, we use a unique dataset consisting of Kenyan overnight bilateral transaction information from 2003 to 2012. The real transaction data allows this study to model the relationship without making strong assumptions as those adopting simulation methods.

In addition, there are some methodological challenges due mainly to data unavailability; specifically, while the analysis of network dynamics requires essential information for a better understanding of financial stability, most analyses only provide static understanding of the network. The current simulation models assume the interbank market has a certain static network structure, such as a small-world network, a random network or a tiered network without accounting for the bank's own behavioural characteristics (such as balance sheet information) (Xu, He, & Li, 2016). Upper (2011) evaluates various studies in terms of the simulation method and finds that these models may have the power to correctly predict if contagion could be a concern and even potentially identify the banks triggering contagion. However, Upper (2011) suggests that these models may not be fit for stress testing or providing policy recommendations during crises, mainly due to their lack of behavioural basis. Xu et al. (2016) build a dynamic bank balance sheet model, in which the evolution of interbank network structure is analysed theoretically. They find that with the increase of bank lending preference, stability of the network structure is improved reflected in the increases in network clustering coefficient and decreases in the average shortest path length. Our second contribution to the literature is to provide better understanding of the dynamic nature of the network structure and its implication to bank stability empirically. The daily frequency ten-year sample adopted in our study covers six major liquidity shocks, not only enabling us to examine the time-varying properties of the interbank network but also, allowing us to study the dynamic relationship between network characteristics and bank stability with a clear distinction between tranquil and turbulent regimes. Furthermore, with the detailed transaction level information, the moderation effect of bank specific characteristics and behaviour change in the network are modelled explicitly in the empirical models. The empirical evidence bears important implications for policy makers and practitioners; for example, the evidence identifies the characteristics of those systematically important banks in the network in different regimes which policy makers need to take into account so to avoid a one-size-fits-all policy stance. The evidence thus extends the frontiers of existing knowledge; for example, while Martinez-Jaramillo, Alexandrova-Kabadjova, Bravo-Benitez, and Solórzano-Margain (2014) link connectedness with bank asset size, our study provides direct evidence on the moderation effects of bank size, ownership and headquarter location.

Few studies of the impact of network structure on financial stability that do use real transaction data are based on topological theories alone[2] drawing conclusions on bank stability with reference to individual topology measures in isolation. Hence, to the best of our knowledge, empirical results on the implications of interbank networks for financial stability are limited and inconclusive. The third contribution of our study is not only to study the relevant topology measures and their evolutions but also to examine them systematically in econometric models directly testing the relationship between various topology measures and bank stability controlling for bank-specific variables. Although the empirical evidence is based on one country data, they bear important implications for policy makers and practitioners in other interbank markets. For example, the evidence shows that bank stability could benefit from the private information acquired through direct lending relationships allowing bank lenders to better assess the credit risk of their counterparties. At the same time, banks can also be exposed to more risk via indirect links rising from their intermediation activities due to more information asymmetry and weaker peer monitoring power.

Last but not least, we contribute to the literature by extending interbank market research to an important emerging market, Kenya. While overnight interbank markets are well-established in the major industrial economies, where they buttress the financial system and act as the first link in the chain of financial markets' response to monetary policy, the markets are less well-established and correspondingly much less researched in developing countries like Kenya.[3] Few emerging markets experienced the same financial

[1] This approach assumes an even distribution of risk spreads across relevant institutions, which in turn contaminate the maximum possible number (Espinosa-Vega & Solé, 2011).

[2] For example, Iori, De Masi, Precup, Gabbi, & Caldarelli, 2008 on Italian overnight money market; Bech & Atalay, 2010 on Federal funds market; Martinez-Jaramillo et al., 2014 on Mexico.

[3] Chen, Li, Peng, and Salim (2020) simulate the effects of credit and liquidity shocks on China's banking network using maximum entropy method. Sun (2020) investigates the contagion effects in Chinese interbank market simulated based on the balance sheet data. Hausenblas, Kubicova and Lešanovska (2015) adopt a computational model to evaluate the resilience of the Czech banking system to interbank contagion. Their simulated network has taken into account the size and structure of interbank exposures and individual bank balance sheet and regulatory properties. Lublóy (2005) studies Hungary and Martinez-Jaramillo et al. (2014) on Mexico. So far, there are only very few working papers on Africa interbank markets, for example, Chipili et al. (2019) on Zambia; Kanyumbu (2019) on Malawi; Oduor et al. (2014) on Kenya.

trauma of 2007/08 as the industrial west, and their overnight markets have mostly not gone into reverse. Research on industrial countries shows that the overnight interbank topological characteristics are linked closely to institution-specific conditions in each market. Evidently, it is important to extend research on overnight markets to a wider range of countries to better understand the variety of experience and the lessons to be learnt for the banking system (Green et al., 2016).

The remainder of this paper is structured as follows. We review the relevant literature in Section 2, followed by discussions of data and the representation of the Kenyan interbank market network during quiet times and the six shocks in Section 3. Section 4 discusses different topological characteristics. Section 5 presents and discusses the relationship between different topological characteristics and banking stability. Section 6 concludes.

2. Literature review

Risk can spread among banks in turbulent times via direct or indirect interbank network channels. The direct channel refers to the financial exposures of one bank to another including outright loans (Blavarg & Nimander, 2002).[4] Risk spreading can arise due to unexpected liquidity shocks. When a sudden strong demand for liquidity cannot be met by a banks' own deposits at other banks or even proceeds from liquidating their long-term assets, the deterioration of their asset value further weakens their ability to repay their interbank loans (Brunnermeier, 2009; Geanakoplos, 2009). Consequently, financial stress in one bank or one region can spread to other banks or other regions (Allen & Gale, 2000). Freixas, Parigi, and Rochet (2000) discuss three scenarios of interbank exposures through credit lines: a credit chain, diversified lending (credit lines between any two banks exist) and a money centre case (one bank is central, the others only have interbank lending with it and not directly with one another). In their model, contagious failures are more likely to happen in the credit chain case than in the diversified lending case. In the money centre case, contagious failures can happen depending on the parameters of the model. However, indirect contagion can arise without explicit links. Studies suggest that in the absence of collateral, asymmetric information about the quality of counterparties may lead to adverse selection and moral hazard problems (Acharya & Merrouche, 2013; Allen & Gale, 2000). These problems can impede the basic interbank networks' functionality, especially when involving monopoly power in periods of distress. A bank facing difficulties may be perceived by prospective lenders as a signal of a potential systematic failure (Freixas et al., 2000). Such market expectations can become self-fulfilling, creating unexpected liquidity outflows.

Some literature focuses specifically on how a particular type of interbank network structure and distribution affect the spreading of risks within the system. For instance, banks with very similar portfolios tend to have a high clustering coefficient.[5] According to Allen and Babus (2009) and Allen, Babus, and Carletti (2010), the likelihood of early liquidation and thus contagion is higher in the clustered network structures but if the proceeds from early liquidation are sufficiently large, the depositors can still be better off under the clustered structure than the unclustered network structure.[6] Another commonly identified network property is the core-periphery (tiered) structure[7] where few heavily interconnected money centre banks are in the core and many small banks in the periphery with few connections to the core only. Core banks tend to be larger and active at the national or international level providing a wider range of financial services (Craig & Von Peter, 2014; Imakubo & Soejima, 2010). The important feature of the overnight interbank market is that in most countries the lending is all non-collateralised. Inevitably, relationship banking and network effects are important in these markets where less reputable institutions tend to transact consistently with relatively limited number of counterparties based on their established relationship (Green et al., 2016).[8] Normally fat-tailed, core-periphery networks exhibit strong clustering (Pröpper, van Lelyveld, & Heijmans, 2008). This mitigates asymmetric information (Furfine, 1999, 2000) but also means limited access to liquidity for some participants depending on the level of counterparty risk (Castiglionesi & Navarro, 2020). Money centre banks possess a comparative advantage due to long-standing business ties with smaller institutions. Meanwhile, domestic banks which lack market access tend to borrow from foreign banks (Cocco, Gomes, & Martins, 2009).

The literature is still inconclusive whether an incomplete network or a complete network is more vulnerable to disturbances. Allen and Gale (2000) and Babus (2006) show when an incomplete interbank market structure (e.g., core-periphery structure) is coupled with a high degree of interconnectedness, a liquidity shock can spread to other regions. When there is no aggregate uncertainty, more complete claims structures enable the optimal allocation of risk-sharing via the insurance mechanism of interbank agreements.

[4] see Allen, Babus, and Carletti (2009) for a survey on such domino effects.

[5] The clustering coefficient measures the probability that the two nearest neighbours of a node are connected (i.e., two banks A and B have transactions with the same bank C, A and B are likely to have transactions between themselves).

[6] Kanyumbu (2019) finds that the network for Malawi's interbank market is fairly dense with a significantly high clustering and a small average path length. The average clustering coefficient (0.581) for Malawi's interbank market is far lower compared to German credit network, which has the clustering coefficient decreasing from 0.87 in 2002 to 0.80 in 2012 (Roukny, Georg, & Battiston, 2014). While Malawi network is a lot denser compared with Russian interbank network (0.198) in Vandermarliere, Karas, Ryckebusch, and Schoors (2015) and the US Federal funds market (in-clustering-coefficients: 0.2–0.4; out-clustering-coefficient: 0.1–0.2) in Bech and Atalay (2010).

[7] Boss et al. (2004) find that the Austrian interbank network structure is characterised by a small clustering coefficient and a short average path length, consistent with the characteristics of a highly tiered system. Similar conclusions are found in overnight federal funds network (Bech & Atalay, 2010); Canada (Embree & Roberts, 2009); Australia (Sokolov, Webster, Melatos, & Kieu, 2012); Germany (Craig & Von Peter, 2014) and Hungary (Lublóy, 2005). Similar structure is also identified in some African markets: Zambia (Chipili et al., 2019) and Kenya (Oduor et al., 2014).

[8] Cocco et al. (2009) find that Portuguese banks with a higher proportion of non-performing loans rely more heavily on banks with which they have established long-term relationship for liquidity. Kobayashi and Takaguchi (2018) suggest that Italian banks reply on relationship banking as the "lender of last resort" for liquidity needs during financial crisis even at high interest cost.

However, when there is a global liquidity shortage, a more complete banking network could facilitate the spreading of the decreasing bank asset value (Acemoglu et al., 2015) as well. Teteryatnikova (2014) argues that in core-periphery networks, the banking system's resilience to shocks increases with the level of tiering. However, Lenzu and Tedeschi (2012) suggest that the isolated clusters in a tiered network could lead to the sub-optimal liquidity reallocation and hence higher credit risk. Furthermore, such network may be more vulnerable to attacks due to heterogeneous distributions through the interaction of noise and feedback effects. Consistent with the too-big-to-fail phenomenon, if a large institution in the core is removed (due to say, bank failure), the network structure can be destabilised dramatically (Boss, Elsinger, Summer, & Thurner, 2004).

3. Kenyan interbank network data and visualisation

One of the few African countries which has a well-established and relatively liquid interbank market is Kenya. Interbank transactions in Kenya are uncollateralised and limited to an overnight basis (see Green et al., 2018 for a comprehensive overview). This study utilises a dataset provided by the Central Bank of Kenya on daily individual bank transactions in the Kenyan interbank market from 16th June 2003 to 4th April 2012. The dataset identifies the date, interest rate, amount and identities of the lender and borrower for each transaction. These wire transfers among 42[9] domestic and foreign commercial banks include 214,928 overnight loans worth over Ksh22 trillion (around USD220 billion).[10] The dataset also details bank attributes including size (large, medium and small),[11] ownership (private vs. listed) and location of their headquarters (local vs. foreign).

We discuss and analyse various topological properties of the Kenyan interbank network. The topological concepts we use are summarised in Table 1, together with our hypotheses concerning the impact of topology on bank stability. We explain these concepts more fully as we proceed. The directed interbank network consists of nodes (i.e., banks) linked by edges (i.e., transactions). Each edge is weighted with the transaction value.[12] The direct visualisation of the network graphs (Fig. 1) could reveal the holistic picture of the interconnectedness of the banks. For instance, Fig. 1.1 shows that on 16 June 2003, a total of 18 banks conducted 21 transactions. The Kenyan interbank market exhibits the typical core-periphery network structure discussed in section 2. The three most interconnected banks are pure borrowers.[13] Two of them are private banks (35 and 39) that only borrowed from other private banks, while the listed bank, (15), borrowed most heavily from other listed banks. However, banks connected to these three banks had very little or no connections among themselves. Consistent with discussion in Section 2, those less reputable institutions rely on established relationship with relatively small number of counterparties to reduce information asymmetry. If heavily interconnected nodes, e.g., node 15 are removed due to bank failure, the structure of the network and liquidity flow among individual nodes can change dramatically.

The Kenyan interbank market experienced six major liquidity shocks during the sample period (Table 2). Accordingly, we divide the sample into three sub-periods, i.e., pre-shock (16/06/2003–30/04/2006), shock (01/05/2006–30/11/2009), and past-shock (01/12/2009–04/04/2012). Networks during the liquidity shocks exhibits the same segmented-market characteristics.

The direct visualisation of the network graphs reveals not only network structure but also the dynamics of the connectivity depth and width. Building upon the same algorithm, the direct comparison across the eight figures (Fig. 1) shows contrasting network connectivity during this tranquil time and turbulent times, during which significantly more banks participate the market with some large transactions. The single largest transaction during the six liquidity shocks happened on the first trading day of the Safaricom IPO[14] (Fig. 1.3). Contrary to what one may expect, the largest transactions that took place during the 2007/08 financial crisis (Fig. 1.4 and 1.5) were much lower than during this domestic liquidity shock.[15]

[9] Another eight banks have disappeared from the sample at different time mainly due to bank merge and acquisition.

[10] In 2003, the total transaction volume of these large and uncollateralised overnight loans amount to Ksh173 billion. They increase to Ksh5.7 trillion in 2008 before decreasing between 2009 and 2010 due to several liquidity shocks including the global financial crisis.

[11] The CBK defines large banks as those with a market share of more than 5% (in terms of gross assets and deposits); medium banks are those with a market share of more than 1% but less than 5% and small banks are those with a market share of less than 1%. Public banks refer to those listed in the stock market contrasting to the private ones. Local banks refer to those banks' headquarters locate in Kenya contrasting to the foreign counterparties.

[12] If bank j borrow more than once from bank i on the same day, we aggregate all the loan amount between the pair (i,j) so that $w(i,j)$ measures the total interbank exposures of the lender bank i overnight to bank j.

[13] The arrow of the edge following the direction of fund flows originates from a lender and points at a borrower.

[14] As most profitable company in Sub-Saharan Africa, Safaricom IPO was the largest one ever in the region. During the three-week IPO, foreign and local investors over-subscribed 360% for Ksh231m worth of shares. Many investors took loans from commercial banks including almost all local banks to finance their investment. The vast liquidity demand could be seen in interbank market. (https://www.networkworld.com/article/2280772/kenya-s-safaricom-ipo-disappoints-small-investors.html; https://biznakenya.com/how-safaricom-has-rewarded-ipo-investors-8-years-after-turbulent-ipo/).

[15] When Lehman Brothers went bankrupt on 15th September 2019, a private large bank lent the largest volume to a listed large bank. Two days later, investors withdrew $144 billion from U.S. money market funds, causing the short-term lending market to freeze. On that day, the highest bilateral transaction increased, but was still less than half the highest bilateral transaction volume in the Safaricom IPO.

Table 1
Topology measurements and hypotheses.

Variables	Definition	Explanation	Hypo.	Relationship with bank risk
Node measures				
In_deg (In-stren)	the number of borrowings (loan value-weighted number of borrowing)	Measures the importance of a bank as a borrower.	+/−	Sharing risk but overborrowing could lead to higher risk
Out_deg (Out-stren)	number of lending (loan value-weighted number of lending)	Measures the importance of a bank as a lender.	+/−	Diversify loan portfolio but overexposure can lead to higher credit risk
net_strength	Difference between (out-stren) and (in-stren)	Measures the net position of a bank. The negative entries signify that the bank is borrowing more than it is lending in value.	+/−	Diversify loan portfolio but overexposure can lead to higher credit risk
in_centr	In-degree centrality	Measures the total number of in-degrees of a node relative to the possible number of in-degrees. The higher the number, the more prominent the bank is as a borrower.	+/−	Sharing risk but overborrowing could lead to higher risk
out_centr	Out-degree centrality	Measures the total number of out-degrees of a node relative to the possible number of out-degrees. The higher the number, the more prominent the bank is as a lender.	+/−	Diversify loan portfolio but overexposure can lead to higher credit risk
betweeness	Betweeness centrality = the fraction of shortest paths between all nodes that go through this node.	Measures the importance of the bank as an “intermediary”, for both lending and borrowing.	+/−	Better access to information via relationship banking but may be exposed to risk spillover during liquidity shocks
out-cluster	Clustering-out coefficient: the probability that two nodes that are the neighbours of the same node themselves share a link	Measures how many lending relationships there are among the banks that bank lends to relative to all possible lending relationships among them.	–	the likelihood of early liquidation and thus contagion risk is higher in the clustered structure
per_core	The percentage of core banks	The number of nodes as cores divided by the total number of nodes participating the network	+	money centre banks possess a comparative advantage, the core consisting of safe banks that are fully connected
c2p	The number of nodes in the core that have links to the periphery divided by the total number of nodes participating the network	Indication of market tiered structure and segmentation	+/−	Core connecting to peripheries, depending on the level of counterparty risk
p2c	The number of nodes in the periphery that have links to the core divided by the total number of nodes participating the network	Indication of market tiered structure and segmentation	+	Peripheries connecting to well-reputable core banks can enhance the bank’s stability
Network measures				
nodes	number of nodes	Network size measure	+/−	Diversify risk or risk spillover in particular during liquidity shocks
edge	number of directed edges	Measure the extent of liquidity flows in a network	+/−	Diversify risk or risk spillover in particular during liquidity shocks
completeness	the number of edges relative to the number of possible edges	allows direct comparison between networks with different sizes	+/−	Diversify risk or risk spillover in particular during liquidity shocks
diameter	the longest among the shortest paths between any two nodes	Measure of small-world property. It is best-case scenario of contagion.	+/−	the longer the path, the longer the chain of liquidity flow/risk spreading.
path	the longest path length with edges weighted by loan values	the longest path among all multiple paths between two nodes considering indirect relationship. It measures the worst-case scenario of contagion.	+/−	the longer the path, the longer the chain of liquidity flow/risk spreading.
avrate	The average interest rate in the network		+/−	The change of financing cost has opposite implications to net lenders and net borrowers.

Notes: Hypo denotes hypothesis, where the predicted effects are presented as + (for positive effects), - (for negative effects) and +/− (the effects are indeterminate).

4. Kenyan interbank topological characteristics

4.1. Overall network measures

Fig. 2 presents several topological measures at the network level with the shock period indicated by red boxes. The network size, defined as the number of banks participating the network, is on average 35 with substantial daily variation. Unsurprisingly, all 42 banks participated on several days in June and July 2008, during which the market is exposed to the Safaricom IPO and the 2007/08 financial crisis simultaneously. The extent of liquidity flows in a network can be quantified as the total number of edges, which ranges from one to 543 edges, with an average of 99 in our sample. Third, completeness as the number of edges relative to the possible number

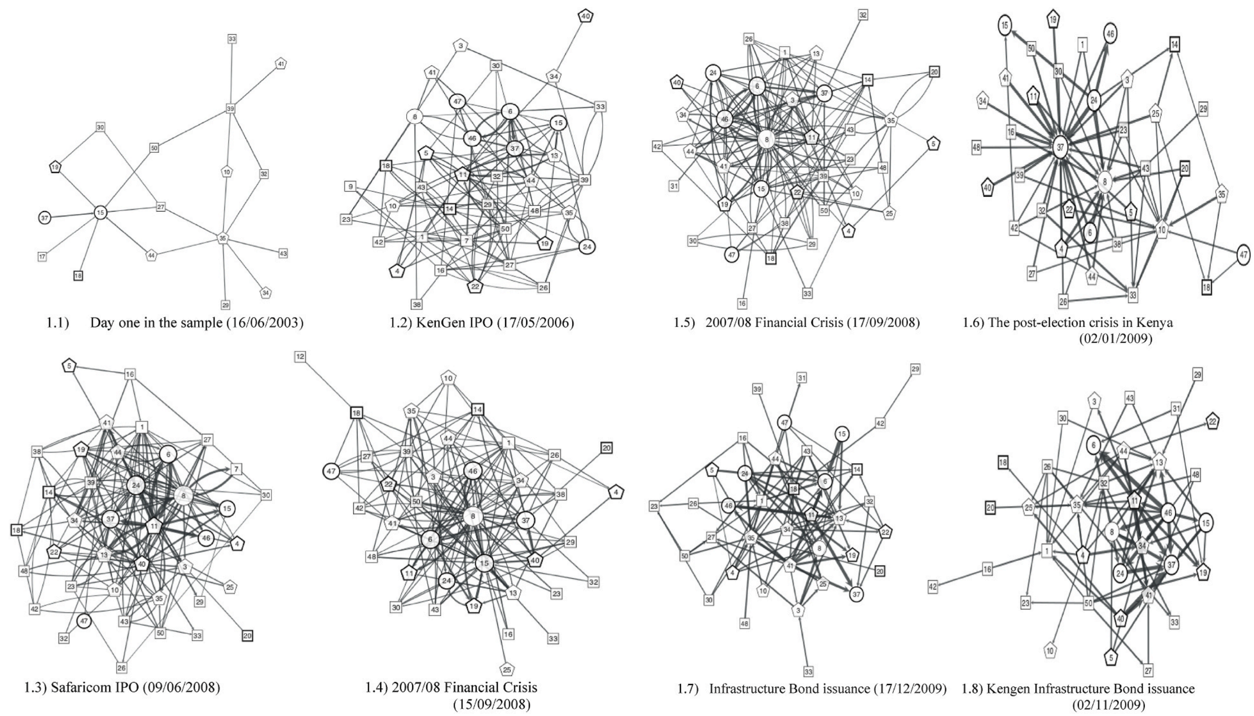

Fig. 1. Interbank network on eight days during the tranquil period and six liquidity shock events
Note: Node shapes distinguish small (square) from medium-sized (pentagon) and large (circle) banks, while the thickness of the node border indicates if a bank is listed (thick) or private (thin). The node size increases with the number of transactions the bank has (node degree). The edge thickness increases with the aggregate transaction value between the two banks. The arrow of the edge originates from a lender and points at a borrower.

Table 2
Six major liquidity shocks in Kenya interbank market during the sample period.

	Event_dummy	Event	Event date
1	kgipo	KenGen IPO (1st, 2nd quarters 2006)	first trading on 17/05/2006
2	saipo	Safaricom IPO (2nd quarter 2008)	first trading on 9/6/2008
3	elec	The post-election crisis in Kenya[b] (1st quarter 2008)	2/1/2008 for January start of crisis
4	gfc	2007/08 Financial Crisis (2nd, 3rd quarters 2008)	15/09/2008; 17/09/2008[a]
5	kgb	Kengen Infrastructure Bond issuance (3rd, 4th quarters 2009)	issued on 2/11/2009
6	inf	Infrastructure Bond issuance (1st quarter 2010, 4th quarter 2009)	period of sale: 12/02/2010 to 24/02/2010, issued on 7/12/2009

Note.
[a] Some key developments during the 2007/08 crisis: Lehman Brothers bankruptcy triggered global panic (15/09/2008) and due to the losses from Lehman's bankruptcy, investors fled money market mutual funds (17/09/2008). (https://www.thebalance.com/2008-financial-crisis-timeline-3305540).
[b] Sources: https://www.csis.org/blogs/smart-global-health/background-post-election-crisis-kenya

of edges allows direct comparison between networks with different sizes. Completeness is normalised between zero (disconnected nodes) and one (completely connected network). The Kenyan interbank network is relatively dense with an average degree of completeness of 7.76% compared to the highly sparse fed funds network (Bech & Atalay, 2010) and the network of Fedwire payments (Soramäki, Bech, Arnold, Glass, & Beyeler, 2007), both with a degree of completeness of less than 1%. Fourth, the number of edges considers only direct lending relationships while a path[16] captures the indirect links through intermediaries and reflects the course that liquidity and risk follow in the banking sector. The so-called small-world property in the banking sector means that the degree of intermediation between (initial) lender and (final) borrower is low (Bech & Atalay, 2010) so that the extent of contagion may be limited. Consider the solid edges in the stylised network of 5 banks in Fig. 3, banks 5 and 3 are indirectly connected through the

[16] Path helps to measure how close nodes are to one another at any given time. A path is a sequence of nodes and links beginning and ending with nodes, where any link or node is not included more than once. The length of a path is measured by its number of links.

intermediary bank 2. Hence if bank 3 fail to repay bank 2, bank 2 might be unable to meet its obligations to bank 5. Such small-world property can be measured as network diameter capturing the longest among the shortest possible paths between any two nodes (Brandes & Erlebach, 2005) (in Fig. 3 the network diameter is 2). The average diameter in pre-shock period in Kenya is 2.83 suggesting that if the bank at one end of this path fails, it could induce three other banks to fail accordingly. However, only focusing on diameter may underestimate the scale of contagion when pair of nodes are connected with multiple paths. For example, if bank 5 were also connected to bank 3 via banks 1 (hence the dashed edge for the imagined connection) and 2 (Fig. 3), the diameter of Fig. 3 would be still 2 (shortest possible paths) but the longest path length would be 3 instead. As the diameter measures the best-case scenario, the longest path length between any two nodes could indicate the worst-case scenario of contagion. In Kenya, there is little noticeable difference between the diameter and the longest path length during the tranquil periods (Fig. 2). However, during the shocks, the longest path length (12.94) is on average more than double the diameter (5.43), showing that more than twice as many banks could be at risk when a bank fails due to the long borrowing chains.

4.2. Node-specific and edge-specific topological measures

This section discusses topological measures that characterise the structure and distribution of the network over time. Node measures (degree, strength and degree centrality) focus on the relative importance of a bank in the network while edge measures focus on the connectivity of the bank to others in the network (betweenness centrality, clustering coefficient).

4.2.1. Degree, strength and degree centrality

Net degree measures the net exposure of the bank in the overnight market as the difference between the in-degree (the number of borrowings of a bank) and out-degree (the number of loans of a bank) (Bech & Atalay, 2010). The transaction values are as important to network stability as the number of transactions. A diversified loan portfolio with small amounts exposes the lender to smaller risk relative to concentrated large-volume lending to a single borrower. Hence edges in a network are weighted by loan value to differentiate the importance of each transaction. Net strength is the net degree weighted by transaction value. A negative value signifies that the bank is a net borrower. Net degree and net strength do not need to have the same sign depending on the transaction volumes. Table 3 presents the summary statistics of the average daily degree and strength in the sub-periods and across bank groups. During pre-shock period, medium-sized (large) banks are the most active borrowers (lender) on average. While during the shock, large banks dominate the interbank transactions on both borrowing and lending sides.[17] Local banks have consistently been the most active borrowers and lenders in terms of number of transactions. However, according to the summary of strength, foreign banks have smaller number of borrowings at larger value during the shocks. They have smaller number of lending at larger value than local banks throughout the sample. Private banks have been the main borrowers before the shocks. Since then, listed banks have taken over but they are the most prominent lenders throughout the sample period. The summary statistics of net strength shows that only medium-sized banks are net borrowers before the shock period and large banks become the only net borrower during and after the shocks. This finding contrasts with those observed in Zambia, where most small banks are net borrowers, and big banks are primarily net lenders. Foreign banks are net lenders while local banks are consistently net borrowers. This is consistent with the literature (e.g., Cihák & Podpiera, 2005) on Eastern Africa including Zambia. Listed (private) banks have been net borrowers (lenders) during and after the shocks. Among all bank types, large banks contribute significantly to the overall liquidity flow in the network experiencing the largest exposure during the shocks. This is consistent with the 'too-big-to-fail' notion. Fig. 4 plots the time series of net strength during the sample. The large peaks unsurprisingly happened during the overlap of three shocks, the Safaricom IPO, the post-election crisis in Kenya and the 2007/08 financial crisis during the first half of 2008.

When comparing networks of different sizes, the degree centrality[18] of a node is a better indicator of the systematic importance of the bank in the system. It is defined as the number of banks to which a bank is connected divided by the total number of banks to which it could be connected. *Degree centrality* is normalised between zero (unconnected bank) to one (connected to every other bank). The most central bank is the one with the most direct relationships. The higher the in-degree/out-degree centrality, the more prominent the bank is as a borrower/lender. The relative importance of different types of banks based on degree centrality are consistent with those based on in-/out-degree (Table 3). Allen and Gale (2000) show when an incomplete interbank market structure is coupled with a high degree of interconnectedness, a crisis caused by a liquidity shock can spread from one to other regions. We have observed these characteristics in the Kenyan overnight interbank market, especially during the shock period.

4.2.2. Betweenness centrality

Degree centrality focusses solely on direct links; betweenness centrality considers both direct and indirect relationships. The betweenness of bank *i* is the fraction of shortest paths between all banks that go through bank *i*. Hence it indicates how likely a bank is used as an intermediary on the shortest path between any two other nodes (e.g., Bank 2 in Fig. 3). The larger the betweenness, the more paths bank *i* handles, the more important it is as an intermediary in the network for facilitating the liquidity flow and/or spreading risk. The summary statistics (Table 4) shows that during shocks there are significant surges in betweenness score with large, local and listed

[17] They on average borrow from seven other banks and lend to six other banks with the most volatile borrowing activities (standard deviation nearly reaches 5).

[18] Degree centrality was first proposed by Bonacich (1987). Bech and Atalay (2010) has applied it to the federal funds network. The literature suggests several centrality measures (refer to Borgatti and Everett (1999) for a comprehensive review).

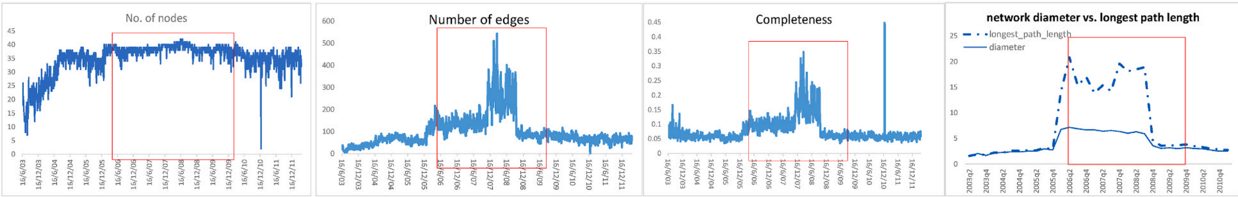

Fig. 2. Overall topological network measures for the Kenyan interbank market between 2003 and 2012.

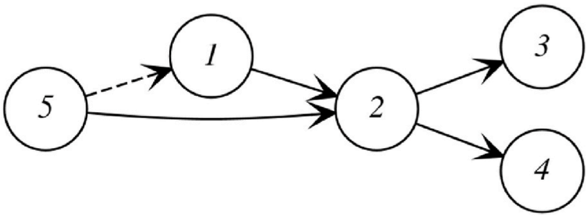

Fig. 3. Diameter vs. longest path for a network.

banks being the key intermediary. Fig. 5 presents the trend of betweenness centrality across bank groups, which is consistent with the summary statistics. It is particularly noticeable that the probability that the node is used as an intermediary on the shortest path between any two other nodes is particularly high for the first four shocks till the end of 2008 for all bank groups, which has dwarfed the other betweenness levels in the rest of turbulent time in the graphs.

4.2.3. Clustering coefficient

As discussed in section 2, relationship banking is particularly crucial for non-collateralised overnight market. The clustering coefficient denotes the probability that two nodes that are the neighbours of the same node themselves share a link (i.e., you are more likely to be friends if both of you share some mutual friends). The out-clustering coefficient measures how many lending relationships there are among the banks that bank *i* lends to relative to all possible lending relationships among them. The out-clustering coefficient is zero (one) if none (all) of the banks that bank *i* lends to also lends to each other. The summary statistics (Table 4) shows that during shocks there are significant increases in the density of connections in the immediate neighbourhood of banks, especially large, foreign and listed ones. For instance, the probability that two nearest neighbours of large banks lend to each other is 0.105 during the shock relative to 0.01 in tranquil time. Fig. 6 shows consistent results.

4.3. Core-periphery network structure

The direct visualisation of the Kenyan interbank network in Section 3 has shown characteristics of core-periphery structure on different sample days. To investigate further, we identify the periphery by successively removing the nodes with the highest degree (i.e., total number of borrowing and lending transactions) (including their links) to the core list until the remaining nodes are unconnected. Hence each bank in the core is connected to at least another two banks in the core and may/may not have links with the periphery banks while periphery banks only have connections with some core banks and not with each other. We further construct two variables $c2p$ (=1, if a core bank had a transaction with a periphery bank, 0 otherwise) and conversely for $p2c$. By examining the proportion of such connections against the number of banks participating in the interbank market daily, we can see how the extent of the market segmentation evolves over time (Table 5). On average, 20%–50% of active banks are in the core independent of a bank's characteristics and the sub-period. The only exceptions are the much higher proportion of large (77%),[19] local (58%) and listed (65%) banks in the core during the shock period. This is consistent with findings in the literature that relatively safer and more reputable banks tend to form the core (Chiu & Monnet, 2016). It is noticeable that there are more local banks in the core than foreign banks independent of the sub-periods. Those core local banks have only slightly more transactions with periphery foreign banks than with other local ones in the periphery. Hence, the foreign banks (dominant net lenders) predominantly lend to local banks in the core. This also indicates that local banks have transactions among themselves in the core besides their transaction with local peers in the periphery. Overall, it suggests that Kenyan local banks do not lack market access. Unlike Oduor, Sichei, Tiriongo, and Shimba (2014), our evidence suggests that small banks are mainly in the periphery. Therefore, they mainly interact with the core banks, i.e., medium-sized and large banks, rather than with their peers. On the other hand, listed banks have transactions among themselves in the core and peers in the periphery. The time-series plots in Fig. 7 show consistent picture of the segmented structure.

[19] This result is similar to Zambia, where all large banks trade with each other by utilizing all available credit lines (see Chipili et al., 2019).

Table 3
Summary statistics of group average daily node distribution during the sub-sample period.

node measure	16/6/2003–30/04/2006 (obs: 701)				01/05/2006–28/2/2010 (obs: 956)				01/3/2010–04/04/2012 (obs: 523)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
in_deg_l	1.33	1.13	0.00	8.13	**5.91**	4.62	0.00	30.00	1.52	0.82	0.00	4.13
in_deg_m	**1.63**	0.83	0.00	6.00	3.27	1.93	0.53	16.07	**2.12**	0.55	0.00	3.93
in_deg_s	0.88	0.49	0.04	2.44	1.28	0.60	0.15	3.26	0.85	0.29	0.00	1.85
in_stren_l	**116.21**	114.85	0.00	1049.50	**1123.64**	1509.71	0.00	21301.38	**658.89**	351.56	0.00	2226.63
in_stren_m	94.49	57.44	0.00	403.73	273.08	276.92	22.40	2713.60	292.86	113.74	0.00	647.47
in_stren_s	36.51	22.34	0.19	109.07	63.08	66.55	6.81	1265.33	51.21	21.18	0.00	115.19
in_centr_l	0.027	0.023	0.000	0.17	**0.14**	0.09	0.01	0.61	0.03	0.018	0.00	0.0842
in_centr_m	**0.033**	0.017	0.000	0.12	0.07	0.04	0.01	0.33	**0.04**	0.011	0.00	0.0803
in_centr_s	0.018	0.010	0.001	0.05	0.03	0.01	0.00	0.07	0.02	0.006	0.00	0.0378
in_deg_for	0.94	0.64	0.00	4.17	2.63	1.57	0.28	11.28	1.00	0.43	0.00	2.67
in_deg_loc	**1.31**	0.63	0.03	4.44	**3.05**	1.56	0.50	10.63	**1.53**	0.39	0.03	2.69
in_stren_for	65.54	54.71	0.00	373.72	**433.60**	492.30	21.67	5193.72	180.12	101.16	0.00	530.50
in_stren_loc	**67.29**	35.52	1.41	364.56	303.38	302.19	49.44	3939.81	**243.89**	95.76	9.38	645.34
in_centr_for	0.019	0.013	0.000	0.085	0.05	0.03	0.006	0.23	0.02	0.009	0.000	0.054
in_centr_loc	**0.027**	0.013	0.001	0.091	**0.06**	0.03	0.010	0.22	**0.03**	0.008	0.001	0.055
in_deg_prv	**1.29**	0.62	0.06	3.62	2.25	1.08	0.32	7.74	1.26	0.32	0.00	2.35
in_deg_lst	0.95	0.76	0.00	5.88	**4.28**	2.63	0.94	17.50	**1.51**	0.56	0.06	3.50
in_stren_prv	60.97	32.84	1.91	229.76	171.33	165.30	22.56	2830.47	126.72	52.05	0.00	343.38
in_stren_lst	**78.74**	68.03	0.00	611.56	**730.46**	812.24	69.81	10957.88	**421.14**	200.70	18.75	1303.38
in_centr_prv	**0.026**	0.013	0.001	0.074	0.05	0.02	0.01	0.16	0.026	0.007	0.000	0.048
in_centr_lst	0.019	0.016	0.000	0.120	**0.09**	0.05	0.02	0.36	**0.031**	0.011	0.001	0.071
out_deg_l	**1.44**	1.36	0.00	12.50	**4.99**	4.70	0.13	31.38	1.07	0.59	0.00	4.00
out_deg_m	0.91	0.66	0.00	4.93	2.77	1.66	0.13	12.93	**1.72**	0.56	0.00	3.67
out_deg_s	1.26	0.46	0.11	2.63	1.83	0.68	0.48	5.26	1.21	0.25	0.00	2.19
out_stren_l	**131.25**	128.70	0.00	1269.00	**681.96**	769.42	2.50	5911.25	**381.68**	247.42	0.00	1183.75
out_stren_m	53.50	44.61	0.00	348.40	448.78	741.74	5.20	11718.07	391.18	163.46	20.00	1334.73
out_stren_s	54.83	20.28	3.52	106.52	96.34	50.53	10.85	952.74	78.72	22.54	0.00	146.11
out_centr_l	**0.029**	0.028	0.000	0.255	**0.12**	0.10	0.003	0.64	0.022	0.012	0.000	0.082
out_centr_m	0.019	0.014	0.000	0.101	0.06	0.03	0.014	0.26	**0.035**	0.012	0.001	0.075
out_centr_s	0.026	0.009	0.002	0.054	0.04	0.01	0.015	0.11	0.025	0.005	0.000	0.045
out_deg_for	1.07	0.73	0.00	5.39	2.84	1.75	0.33	13.06	1.22	0.40	0.06	2.50
out_deg_loc	**1.25**	0.55	0.19	3.75	**2.93**	1.50	0.91	9.97	**1.41**	0.35	0.00	2.59
out_stren_for	**67.02**	49.13	0.00	464.72	**460.95**	685.71	27.89	10068.28	**246.25**	126.37	14.17	1129.06
out_stren_loc	66.46	35.55	4.53	285.03	287.99	200.87	41.28	1988.09	206.69	74.99	0.00	438.19
out_centr_for	0.022	0.015	0.000	0.110	0.058	0.04	0.01	0.27	0.025	0.008	0.001	0.051
out_centr_loc	**0.025**	0.011	0.004	0.077	**0.060**	0.03	0.02	0.20	**0.029**	0.007	0.000	0.053

(*continued on next page*)

Table 3 (*continued*)

node measure	16/6/2003–30/04/2006 (obs: 701)				01/05/2006–28/2/2010 (obs: 956)				01/3/2010–04/04/2012 (obs: 523)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
out_deg_prv	1.17	0.46	0.15	3.35	2.49	1.14	0.97	7.32	1.26	0.29	0.00	2.41
out_deg_lst	**1.20**	0.93	0.00	6.44	**3.76**	2.57	0.44	18.63	**1.51**	0.45	0.06	3.44
out_stren_prv	53.53	25.37	3.38	228.41	201.55	149.91	32.79	1631.27	136.02	52.85	0.00	309.94
out_stren_lst	**94.56**	71.97	0.00	649.13	**666.26**	854.08	55.13	11560.75	**401.38**	171.04	18.75	1245.50
out_centr_prv	0.0240	0.009	0.003	0.068	0.05	0.02	0.02	0.15	0.026	0.006	0.000	0.049
out_centr_lst	**0.0244**	0.019	0.000	0.131	**0.08**	0.05	0.01	0.38	**0.031**	0.009	0.001	0.070
Net-strength_l	15.04	91.40	−383.75	332.13	**−557.24**	1169.79	−18638.13	2069.25	**−277.21**	311.48	−1518.88	965.88
Net-strength_m	**−40.99**	44.73	−178.53	177.20	231.63	618.86	−1149.93	9783.20	98.32	158.22	−496.80	699.40
Net-strength_s	18.32	18.26	−38.93	75.04	36.42	69.06	−886.78	849.22	27.51	25.37	−65.00	101.67
Net-strength_for	1.48	40.34	−184.56	182.00	27.35	308.81	−1304.56	4874.56	66.14	151.17	−373.06	867.33
Net-strength_loc	**−0.83**	22.69	−102.38	103.81	**−15.38**	173.71	−2741.94	733.81	**−37.20**	85.04	−487.88	209.84
Net-strength_prv	**−20.02**	22.08	−88.41	35.24	7.37	103.54	−1420.56	485.06	−13.96	75.76	−244.74	218.53
Net-strength_lst	15.83	43.57	−107.06	157.50	**−64.20**	223.96	−1100.44	2944.75	**−19.76**	151.38	−482.06	450.38

Note: Variable details refer to Table 1. Table 3 presents summary statistics for degree and centrality measures focusing on direct links cross different bank groups. The bold font indicates the larger value or the net-borrowers (net-strength). The relative importance of different types of banks based on degree centrality are consistent with those based on degree. Allen and Gale (2000) show when an incomplete interbank market structure is coupled with a high degree of interconnectedness, a crisis caused by a liquidity shock can spread from one to other regions. We have observed these characteristics in the Kenyan overnight interbank market, especially during the shock period.

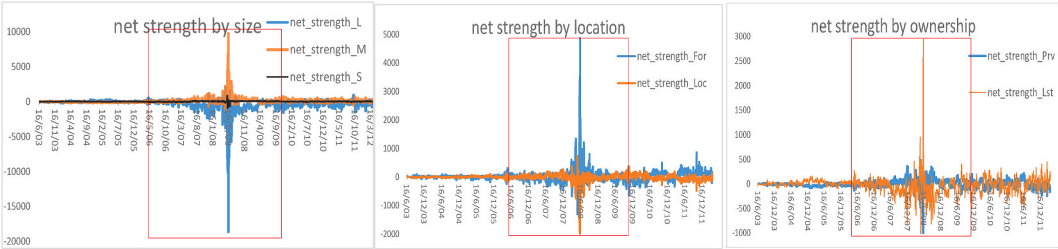

Fig. 4. Bank net position across bank groups.

Table 4
Summary statistics of group average daily node connectivity measures during the sub-sample period.

node measure	16/6/2003–30/04/2006 (obs: 701)				01/05/2006–28/2/2010 (obs: 956)				01/3/2010–04/04/2012 (obs: 523)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
betwness_l	**0.00188**	0.006	0.000	0.041	**0.02**	0.02	0.00	0.09	0.0002	0.0005	0.00	0.0052
betwness_m	0.00181	0.005	0.000	0.031	0.01	0.01	0.00	0.04	**0.0003**	0.0005	0.00	0.0067
betwness_s	0.001	0.003	0.000	0.018	0.0047	0.004	0.00	0.02	0.0001	0.0001	0.00	0.0012
betwness_for	0.0014	0.004	0.000	0.026	0.007	0.01	0.00	0.03	**0.00021**	0.0003	0.00	0.0031
betwness_loc	**0.0015**	0.004	0.000	0.023	**0.010**	0.01	0.00	0.03	0.00015	0.0002	0.00	0.0025
betwness_prv	0.001	0.004	0.000	0.021	0.008	0.01	0.00	0.02	0.0001	0.0002	0.00	0.0023
betwness_lst	**0.002**	0.005	0.000	0.029	**0.011**	0.01	0.00	0.04	0.0002	0.0004	0.00	0.0040
out_cluster_l	**0.014**	0.030	0.000	0.205	**0.10**	0.09	0.00	0.48	0.009	0.0175	0.00	0.1250
out_cluster_m	0.008	0.014	0.000	0.161	0.07	0.06	0.00	0.38	**0.011**	0.0154	0.00	0.1089
out_cluster_s	0.013	0.014	0.000	0.095	0.04	0.03	0.00	0.19	0.007	0.0097	0.00	0.0623
out_cluster_for	0.011	0.019	0.000	0.129	**0.062**	0.05	0.00	0.25	0.0083	0.0118	0.00	0.0741
out_cluster_loc	**0.012**	0.013	0.000	0.099	0.056	0.05	0.00	0.25	**0.0087**	0.0104	0.00	0.0646
out_cluster_prv	**0.012**	0.014	0.000	0.094	**0.08**	0.07	0.00	0.34	**0.010**	0.0145	0.00	0.0997
out_cluster_lst	0.010	0.019	0.000	0.118	0.05	0.04	0.00	0.21	0.008	0.0091	0.00	0.0608

Note: Variable details refer to Table 1. Table 4 presents the banking relationship also considering indirect links as well as bank intermediary role. The bold font indicates the larger value. During shocks there are significant surges in the betweenness score with large, local and listed banks being the key intermediary and increases in the density of connections in the immediate neighbourhood of banks, especially large, foreign and listed ones.

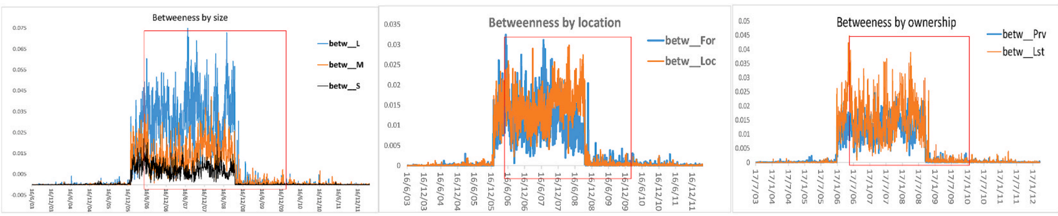

Fig. 5. Bank betweenness centrality scores across bank groups.

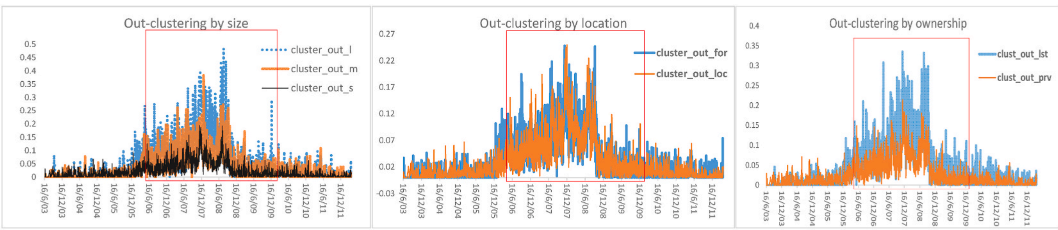

Fig. 6. Bank out clustering coefficients across bank groups.

Table 5
Summary statistics of group average daily node core-periphery measures during the sub-sample period.

Variable	16/6/2003–30/04/2006 (obs: 701)				01/05/2006–28/2/2010 (obs: 956)				01/3/2010–04/04/2012 (obs: 523)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
per_core_l	**0.27**	0.28	0.00	0.88	**0.75**	0.18	0.00	0.88	0.34	0.23	0.00	0.75
per_core_m	0.25	0.23	0.00	0.80	0.66	0.16	0.00	0.93	**0.49**	0.21	0.00	0.93
per_core_s	0.22	0.20	0.00	0.67	0.40	0.13	0.00	0.70	0.27	0.14	0.00	0.56
per_core_for	0.19	0.19	0.00	0.67	0.46	0.13	0.00	0.72	0.27	0.14	0.00	0.61
per_core_loc	**0.27**	0.23	0.00	0.72	**0.57**	0.14	0.00	0.81	**0.39**	0.17	0.00	0.72
per_core_lst	0.19	0.20	0.00	0.75	**0.64**	0.17	0.00	0.94	**0.37**	0.19	0.00	0.75
per_core_prv	**0.26**	0.22	0.00	0.68	0.48	0.11	0.00	0.71	0.34	0.15	0.00	0.65
p2c_l	**0.133**	0.16	0.00	0.75	0.09	0.13	0.00	0.75	0.22	0.17	0.00	0.75
p2c_m	0.126	0.12	0.00	0.47	0.18	0.11	0.00	0.67	0.238	0.14	0.00	0.67
p2c_s	0.18	0.15	0.00	0.52	**0.25**	0.09	0.00	0.48	**0.239**	0.11	0.00	0.52
p2c_for	**0.19**	0.16	0.00	0.56	**0.22**	0.10	0.00	0.50	**0.25**	0.12	0.00	0.56
p2c_loc	0.14	0.12	0.00	0.44	0.20	0.09	0.00	0.50	0.23	0.11	0.00	0.53
p2c_lst	**0.17**	0.15	0.00	0.56	**0.22**	0.12	0.00	0.69	**0.30**	0.14	0.00	0.69
p2c_prv	0.15	0.13	0.00	0.47	0.20	0.08	0.00	0.44	0.21	0.10	0.00	0.44
c2p_l	0.143	0.16	0.00	0.63	**0.34**	0.17	0.00	0.88	0.17	0.13	0.00	0.63
c2p_m	**0.144**	0.13	0.00	0.47	0.23	0.11	0.00	0.67	**0.29**	0.13	0.00	0.60
c2p_s	0.10	0.09	0.00	0.37	0.11	0.05	0.00	0.30	0.12	0.07	0.00	0.30
c2p_for	0.09	0.09	0.00	0.39	0.16	0.08	0.00	0.44	0.15	0.08	0.00	0.39
c2p_loc	**0.14**	0.11	0.00	0.38	**0.20**	0.06	0.00	0.41	**0.20**	0.09	0.00	0.38
c2p_lst	0.10	0.10	0.00	0.38	**0.25**	0.10	0.00	0.50	**0.20**	0.11	0.00	0.56
c2p_prv	**0.13**	0.11	0.00	0.38	0.15	0.06	0.00	0.32	0.17	0.08	0.00	0.32

Note: Variable details refer to Table 1. Table 5 present core-periphery relationship summary statistics. The bold font indicates the larger value. Kenyan local banks do not lack market access. Unlike Oduor et al. (2014), our evidence suggests that small banks are mainly in the periphery. Therefore, they mainly interact with the core banks, i.e., medium-sized and large banks, rather than with their peers. On the other hand, listed banks have transactions among themselves in the core and peers in the periphery.

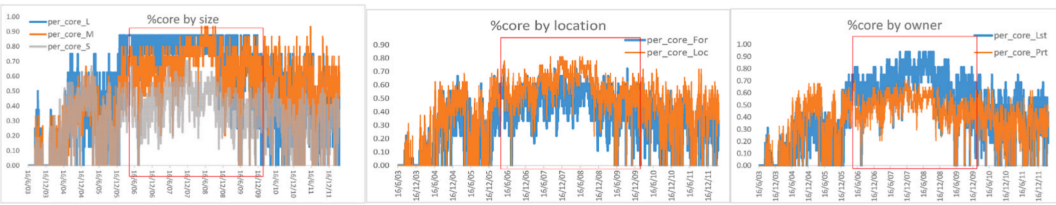

Fig. 7. Core bank distribution across bank groups.

Based on the literature and our summary statistics of the interbank network, we now build hypotheses of the potential relationship between topology measures and bank stability which are summarised in Table 1.

5. The relationship between bank stability and network properties

5.1. A two-stage model

We now consider how the Kenyan interbank network properties could affect bank risk and bank stability given the bank characteristics. Following de Bandt, Camara, Maitre, and Pessarossi (2018) and Jin, Kanagaretnam, and Liu (2018), we use quarterly data and adopt a two-stage model. First, we regress our bank risk measure (the Z-score) on a set of control variables including macroeconomic conditions and bank-specific characteristics for each individual bank t:

$$Z_{i,t} = \alpha + \beta MAC_t + \gamma BNK_{i,t} + \varepsilon_{i,t} \ldots \tag{1}$$

where MAC_t and $BNK_{i,t}$ are the vectors of macroeconomic and bank-specific controls, respectively.[20] Z-score is an accounting-based measure of risk,[21] and is calculated at the bank level as:

[20] The detailed explanations of the control variables are including in Table A1 note.

[21] This is particularly suitable for our sample. Other typical measure of banks risks especially contagion risk measures involve the use of market data. Since listed banks in Kenya are only a small proportion, by using the market data, we would lose more than half of the sample.

$$Z_{i,t} \equiv \left(RoA_{i,t}\alpha + k_{i,t}\right) \Big/ \sigma_{i,t}^{RoA} \ \ldots \tag{2}$$

$Z_{i,t} = (RoA_{i,t} + k_{i,t})/\sigma_{i,t}^{RoA}$, Where $Z_{i,t}$ is the z-score, $RoA_{i,t}$ is the return on assets for bank i at time t, $k_{i,t}$ is the capital (equity to assets) ratio and $\sigma_{i,t}^{RoA}$ is the standard deviation of the return on assets (See for example Cummins, Rubio-Misas, & Vencappa, 2017.). We use a one-year (four-quarter) rolling window returns to calculate $\sigma_{i,t}^{RoA}$, which allows for sufficient variation in the denominator and avoids the Z-score being driven primarily by the fluctuations in the level of the return on assets and the capital ratio. Z-score is interpreted as a 'distance to default' measuring the number of standard deviations a bank's return on assets has to decrease to drain its equity (de-Ramon, Francis, & Straughan, 2018). A lower Z-score indicates a higher probability of default and hence greater instability. Following the literature, we use the logarithm of the Z-score to deal with outliers and large skewness in the Z-scores in the sample.

All the controls at the first stage are variables suggested by the literature affecting bank stability without considering any network effect. The (robust) Z-score residuals from Eq. (1) are that part of the overall variance that the controls cannot explain. On the other hand, at the second stage, the baseline model regresses the Z-score residuals ($Residual_{Z_{i,t}}$) on topological network measures using random effect panel regression with time effect and robust error clustered at bank level:[22]

Baseline model:

$$Residual_{Z_{i,t}} = \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \mu_{i,t} \ldots \tag{3}$$

Model 2: The moderation effect of liquidity shocks on topology measures

$$Residual_{Z_{i,t}} = \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \alpha_7 Event_t \times Network_t + \alpha_8 Event_t \times Node_t + \mu_{i,t} \ldots \tag{4}$$

Model 3: Nonlinearity in topological impact

$$Residual_{Z_{i,t}} = \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \alpha_7 Network_t^2 + \alpha_8 Node_t^2 + \mu_{i,t} \ldots \tag{5}$$

Model 4: The moderation effect of bank attributes on topology measures:

$$\begin{aligned} Residual_{Z_{i,t}} = {} & \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \alpha_7 Event_t \times Network_t + \alpha_8 Event_t \times Node_t \\ & + \alpha_9 Network_t^2 + \alpha_{10} Node_t^2 + \alpha_{11} Size_i + \alpha_{12} Size_i \times Node_{i,t} + \alpha_{13} Size_i \times Network_t + \mu_{i,t} \ldots \end{aligned} \tag{6a}$$

$$\begin{aligned} Residual_{Z_{i,t}} = {} & \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \alpha_7 Event_t \times Network_t + \alpha_8 Event_t \times Node_t \\ & + \alpha_9 Network_t^2 + \alpha_{10} Node_t^2 + \alpha_{11} location_i + \alpha_{12} location_i \times Node_{i,t} + \alpha_{13} location_i \times Network_t + \mu_{i,t} \ldots \end{aligned} \tag{6b}$$

$$\begin{aligned} Residual_{Z_{i,t}} = {} & \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Network_{t-1} + \alpha_5 Node_{i,t-1} + \alpha_6 Event_t + \alpha_7 Event_t \times Network_t + \alpha_8 Event_t \times Node_t \\ & + \alpha_9 Network_t^2 + \alpha_{10} Node_t^2 + \alpha_{11} ownership_i + \alpha_{12} ownership_i \times Node_{i,t} + \alpha_{13} ownership_i \times Network_t + \mu_{i,t} \ldots \end{aligned} \tag{6c}$$

where we distinguish measures characterising the entire network ($Network_t$) and node-specific network measures at time t ($Node_{i,t}$) as well as their counterparties in the previous quarter ($Network_{t-1}$) and ($Node_{i,t-1}$).[23] $Event_t$ is the liquidity shock vector including six shock event dummies. Liquidity shocks arise for different reasons and will have different mechanisms through which they affect bank stability which is captured by the interaction terms between event dummies and topological measures ($Event_t \times Network_t$) and ($Event_t \times Node_{i,t}$), respectively in Model 2. To capture any non-linear relationship, in model 4, we add the square term of the topological measures ($Network_t^2$ and $Node_{i,t}^2$) in the baseline model. The summary statistics given in section 4 (Tables 3–5) show that topological properties vary cross different bank groups. Hence, we study the moderation effect of bank attributes on topology measures by including the vector of attribute dummies, (*attribute*: size,[24] location and ownership) for bank size, headquarter location and ownership. We then add interaction terms of the attribute dummies and the topological properties ($attribute \times Network_t$ and $attribute_t \times Node_{i,t}$) to differentiate the relationship by bank groups on top of models 3 and 4 in model 6a, 6b and 6c respectively.

The first stage regression adopts quarterly bank balance sheet data on the 43 banks which participated in interbank transactions during the whole sample period. In the second stage regression, we aggregate the daily topologic measures to quarterly by taking the

[22] The panel diagnostic test results are presented in Table A2 in the Appendix.

[23] We thank the anonymous referees and Editor for their useful suggestions on this.

[24] Size = 1, small banks; = 2, medium banks and = 3, large banks. Location = 0, local banks; = 1, foreign banks. Ownership = 0, private banks; = 1, listed banks.

quarterly average so as to match the quarterly frequency of the first stage residuals. Appendix TableA1 presents the summary statistics of the quarterly network, control variables and Z-score residuals used in the second stage regression.[25]

5.2. Potential endogeneity issue

Some may have concern with potential endogeneity issue here. We conduct the following strict exogeneity test (Wooldridge, 2002) on the baseline model.

$$Residual_{Z_{i,t}} = \alpha_1 + \alpha_2 Network_t + \alpha_3 Node_{i,t} + \alpha_4 Event_t + \rho_1 Network_{t+1} + \rho_2 Node_{i,t+1} + \mu_{i,t}, t = 1, 2, \ldots, T-1 \ldots \quad (7)$$

Under the strict exogeneity, $H_{0:}\rho_1 = \rho_2 = 0$ (excluding the event dummies). We have the last quarter missing by leading node and network measures.

The results are presented in the Appendix Table A3. The F-test on the leading network and node variables are insignificant hence we cannot reject the null. Therefore, the strict exogeneity test does not support endogeneity.

5.3. Empirical results

5.3.1. Baseline model results

In general, the independent variables are highly significant in the first stage regression results which have high adjusted R-squares.[26] Table 6 presents the second-stage baseline model results.[27] The three network-level topological measures and liquidity event dummies have highly significant impact on the bank stability. The same network variables from the previous quarter have the opposite effects on bank stability in the current quarter relative to their current counterparts. Consistent with the hypotheses in Table 1, first, increases in the average network interest rate tend to increase bank stability in the same quarter. In general, higher interest rate implies higher earning potential for lending banks, hence enhancing their stability. While if facing liquidity shocks in the financial system, consistent with interbank market adverse selection model in Flannery (1996), lending banks raise interest rates across the board. This is because their fear of more uncertainty and information asymmetry about the borrowing banks credit quality. In the similar vein, the average interest rate in the last quarter is negatively related to z-score. When the average financing cost is higher in the previous quarter, market expects higher difficulty for banks to borrow based on such signal which reduces the bank stability. Second, the positive coefficient of the number of edges in the network indicates that with one additional direct transaction (borrowing or lending) increasing bank stability by 7.68% on average. This is in line with the literature (Brunnermeier, 2009; Geanakoplos, 2009) that in the normal situation, regardless of the particular bank lending structure, the overall interbank connection has the advantage of insurance mechanism sharing risk. However, the expected risk sharing insurance function of interbank seems to be dominated by the potential concerns of increasing uncertainty during liquidity shocks, especially where there is an absence of collateral (Caballero & Simsek, 2009). The negative coefficient of the number of edges in the network in the last quarter indicates that with one additional direct transaction in the last quarter reducing bank stability in the current quarter by 0.6% on average. On the other hand, the weighted longest path length which captures the indirect links through intermediaries, is positively related to bank stability. Consistent with Acemoglu et al. (2015), better connected (i.e., more completed) networks are more robust since the liquidity demand to one bank's portfolio can be shared with more banks via interbank agreements. Hence the initial impact of a liquidity shock may be better contained in the system hence bank stability increases with the weighted path length. Similar to the direct transaction measure (number of edges), such risk sharing expectation is also dominated by the potential concerns of more connected interbank network indirectly in the last quarter and hence risk could spread more easily in the current quarter.

As to node-level measures, the net-strength coefficient suggests that every unit (thousand Kshs) of additional net lending (borrowing) reduces (increases) the bank stability by 0.007%. The increased net borrowing allows banks to meet their liquidity needs hence enhancing their stability however, the increasing lending also exposes lending banks to more potential credit risk and contagion risk in a cascade event. On the other hand, additional net lending (borrowing) from the last quarter increases (reduces) the current bank stability. It seems that the existing increased bank lending are expected to enhance bank stability possibly due to enhanced loan portfolio while at the same time, increased existing loan burden is viewed as a potential risk. The increasing of betweenness centrality means that banks are increasingly exposed not only to their borrowers but also to the counterparties of their immediate counterparties. Such increasing direct and indirect connectivity exposes intermediate banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power hence bank stabilities decreases (Craig, Fecht, & Tümer-Alkan, 2015). Furthermore, the positive impact of out-degree centrality on bank stability means when the bank is a more prominent lender via the direct link, the private information acquired through current direct lending relationships allows bank lender to better assess the credit risk of its counterparty, hence enhancing its stability. However, the impacts of these two variables from last quarter are the opposite. It seems that existing direct and indirect links in the last quarter are expected to provide better protections to banks in this quarter since asymmetric information problem could be diminishing over the past three months instead banks are better protected to be involved in a more connected network. While as a more prominent lender via the direct link from the last quarter seems to be expected to become potential risk reducing bank stability in this quarter. All the liquidity event dummies are negatively related to bank stability.

[25] Interestingly, all network measures have larger mean with a higher standard deviation during the turbulent period than tranquil times.
[26] To economise the space, the first stage regression results for 43 individual banks are available upon request.
[27] Due to multicollinearity, some of the topology variables are omitted in the baseline model.

Table 6
The relationship between bank stability and topology measures baseline model results.

	Coeff	Z stats	
Network measures			
avrate	0.876	[40.94]	***
edges	0.074	[63.85]	***
path *1000	0.030	[7.19]	***
P2c	0.123	[1.85]	*
avrate (t−1)	−0.969	[−44.17]	***
edges (t−1)	−0.006	[−50.57]	***
path *1000 (t−1)	−0.723	[−28.31]	***
p2c (t−1)	−0.050	[−0.74]	
Node measures			
Net-strength* 1000	−0.132	[−4.51]	***
betweenness	−4.271	[−3.78]	***
out_centr	1.250	[4.05]	***
Net-strength* 1000 (t−1)	0.113	[4.05]	***
betweenness (t−1)	2.304	[2.11]	**
out_centr (t−1)	−0.895	[−3.49]	***
Liquidity shock dummies			
kgipo	−4.841	[−60.55]	***
saipo	−0.722	[−21.8]	***
elec	−14.176	[−66.05]	***
gfc	−10.315	[−82.88]	***
inf	−0.818	[−42.83]	***
kgb	−0.397	[−101.74]	***
constant	−3.218	[−75.28]	***
overall R^2	0.099		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 6 presents the second-stage random effect regression results of the baseline model (Eq. (3)), which contains only topological measures and the liquidity shock dummies. Some of the time dummies are omitted due to multi-collinearity with the shock event dummies. The three network-level topological measures and liquidity event dummies have highly significant impact on the bank stability. The same network variables from the previous quarter have the opposite effects on bank stability in the current quarter relative to their current counterparts. For instance, consistent with the hypotheses in Table 1, higher interest rate implies higher earning potential for lending banks, hence enhancing their stability. When the average financing cost is higher in the previous quarter, market expects higher difficulty for banks to borrow based on such signal which reduces the bank stability. While the positive coefficient of the number of edges in the network indicates that with one additional direct transaction (borrowing or lending) increasing bank stability by 7.68% on average. Both of the number of edges and the weighted longest path length suggest better connected networks are more robust since the liquidity demand to one bank's portfolio can be shared with more banks via interbank agreements. However, such expectation is dominated by the potential concerns of more connected interbank network in the last quarter and hence risk could spread more easily in the current quarter. The net-strength coefficient suggests that every unit (thousand Kshs) of additional net lending (borrowing) reduces (increases) the bank stability by 0.007%. The increased net borrowing allows banks to meet their liquidity needs hence enhancing their stability however, the increasing lending also exposes lending banks to more potential credit risk and contagion risk in a cascade event. All the liquidity event dummies are negatively and highly significantly related to bank stability.

5.3.2. The liquidity shock moderation effect on the relationship between bank stability and topology measures

Table 7 presents the liquidity shock moderation effect results based on model 2 (Eq. (4)). The liquidity shock moderation effect is captured by the interaction terms between network and node topological measures and the liquidity dummies. Some of the interaction terms have been omitted in the regression due to multi-collinearity. The interactions between the network average interest rate and KenGen IPO (*kgipo*) and Infrastructure Bond issuance (*inf*) liquidity shocks are highly significant. The positive impact of average rate has been enhanced during the KenGen IPO. Kengen IPO has attracted over KSh26 billion investment capital from an estimated 280,000 investors. The figure suggests roughly an oversubscription of KSh18.2 billion.[28] Such a larger than expected liquidity demand was met during the issuance which may have had some impact on the liquidity buffer of the lending banks. Acharya and Merrouche (2013) find that a lender who has a higher liquidity buffer charges a higher price to release it during the crisis. While during 2009 Infrastructure Bond issuance, a total of $145 million infrastructure bond was issued by the Central Bank of Kenya, the positive impact of average rate is a bit smaller.

[28] https://allafrica.com/stories/200604280762.html.

Table 7
The relationship between bank stability and topology measures considering liquidity shock moderation effect.

	Coeff	Z stats	
Network measures			
avrate	0.967	[37.95]	***
edges	0.073	[54.69]	***
path *1000	0.127	[56.9]	***
avrate (t−1)	−1.081	[−40.29]	***
edges (t−1)	0.003	[9.68]	***
path *1000 (t−1)	−0.691	[−27.45]	***
Node measures			
Net-strength* 1000	−0.115	[−2.73]	***
betweenness	−2.805	[−1.12]	
out_centr	0.818	[0.89]	
P2c	0.168	[2.19]	**
Net-strength* 1000 (t−1)	0.099	[2.9]	***
betweenness (t−1)	1.822	[1.02]	
out_centr (t−1)	−0.762	[−1.68]	*
P2c(t−1)	−0.061	[−0.84]	
Liquidity shock dummies			
kgipo	−42.992	[−63.18]	***
saipo	−1.713	[−24.16]	***
elec	−15.437	[−53.12]	***
gfc	−11.498	[−56.68]	***
inf	5.951	[17.83]	***
kgb	0.059	[0.7]	
shock dummy interactions with topology measures			
kgipo_avrate	5.249	[63.56]	***
inf_avrate	−2.536	[−18.55]	***
kgipo_net_strength	0.164	[1.02]	
saipo_net_strength	−0.178	[−9.63]	***
ele_net_strength	−0.032	[−0.9]	
gfc_net_strength	0.115	[3.17]	***
inf_net_strength	0.084	[0.68]	
kgb_net_strength	−0.011	[−0.11]	
saipo_betwee	−0.491	[−0.41]	
kgipo_betwee	−4.017	[−1.96]	**
ele_betweenness	−5.316	[−2.48]	**
gfc_betweenness	0.782	[0.38]	
inf_betweenness	297.808	[11.23]	***
kgb_betweenness	−216.358	[−8.07]	***
kgipo_out_centr	2.457	[3.23]	***
saipo_out_centr	1.507	[4.98]	***
ele_out_centr	0.912	[1.1]	
gfc_out_centr	−0.989	[−1.24]	
inf_out_centr	−0.432	[−0.38]	
kgb_out_centr	0.790	[0.82]	
kgipo_p2c	0.006	[0.08]	
saipo_p2c	0.822	[28.27]	***
ele_p2c	0.195	[2.78]	***
gfc_p2c	−0.817	[−12.09]	***
inf_p2c	0.344	[3.25]	***
kgb_p2c	−0.481	[−5.04]	***
constant	−3.910	[−56.63]	***
overall R squ	0.121		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 7 presents the results of the liquidity shock moderation effect (eq. (4)), which is captured by the interaction terms between network and node topological measures and the liquidity dummies. The results for instance show that during the liquidity shocks (KenGen IPO and Kengen Infrastructure Bond issuance) and political uncertainty (Kenya election crisis), the increasing negative impact of betweenness centrality means that banks are increasingly exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes intermediate banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015), which further reduces bank stability.

The results show that the positive impact of the fraction of connections that a periphery bank connecting to a core bank (*p2c*) is further enhanced during Safaricom IPO, Kenya election crisis and 2009 Infrastructure Bond issuance. Consistent with the literature that when there is no aggregate uncertainty, the proportion of the losses in one bank's portfolio can be shared in the network, especially, by connecting to the more reputable core banks, periphery banks have better chance to access liquidity and diversify risks, hence enhancing their stability. While during the 2007/08 financial crisis and Kengen Infrastructure Bond issuance, the positive impact is weakened to different extents. This may suggest that during these particular liquidity shocks, over exposure to core banks among which the dominant ones are also the net borrowers (large, local and listed banks), could increase periphery banks' counterparty risk and uncertainties.

In terms of the liquidity event moderation effects on node measures, the results show that the negative impact of net-strength is enhanced during the Safaricom IPO. During the global financial crisis, the negative impact is almost offset. Consistent with the understanding that few emerging markets experienced the same financial trauma of 2007/08 as the industrial west, and the emerging overnight markets have mostly not gone into reverse.

Furthermore, during the liquidity shocks (KenGen IPO and Kengen Infrastructure Bond issuance[29]) and political uncertainty (Kenya election crisis), the increasing negative impact of betweenness centrality means that banks are increasingly exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes intermediate banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015), which further reduces bank stability. On the other hand, during 2009 Infrastructure Bond issuance, the impact is positive. Large, local and listed banks are net borrowers and also the dominant intermediate banks. One possible explanation is that the increasing connectivity for those net borrowing banks can better smooth the impact of a very large, unexpected liquidity shock, hence increasing their stability.

The positive impact of out-degree centrality on bank stability is further enhanced during the Safaricom and KenGen IPOs. The higher the out-degree centrality, the more prominent the bank is as a lender via the direct link. The private information acquired through direct lending relationships allows bank lender to better assess the credit risk of its counterparty, hence enhancing its stability during these liquidity shocks.

5.3.3. The nonlinear topological impact on bank stability

Table 8 present the results of model 3 (Eq. (5)). The robust-yet-fragile network property of the network raises the question of whether the topological impact on bank stability could change at certain thresholds. The non-linear effect is captured by the highly significant square term of network measures. The negative coefficient of the square of average rate suggests initially when lending banks raise interest rates across the board to reflect the increasing uncertainty and information asymmetry about the borrowing banks credit quality hence to reduce their exposure to credit risk increasing lending bank stability. However, when the bank increases the lending charge to borrowing banks to the extent that the normal insurance functionality of the interbank market is jeopardised especially when involving monopoly power in periods of distress. A bank facing difficulties may be overly generalised as a signal of a potential systematic failure. Such market expectations can become self-fulfilling creating unexpected liquidity outflows (Freixas et al., 2000) damaging bank stability.

The negative coefficient of the square of number of edges suggests that initially one additional direct transaction enhances bank stability, but such relation turns negative. Lenzu and Tedeschi (2012) suggest that the isolated clusters in a tiered network could lead to the sub-optimal liquidity reallocation and hence higher credit risk. Furthermore, such network may be more vulnerable to attacks due to heterogeneous distributions through the interaction of noise and feedback effects. With the increases in the financial connections, overexposure could reduce stability especially in shock periods.

As discussed in Section 4.1, the longest path among all multiple paths between two nodes considering indirect relationship. It measures the worst-case scenario of contagion. The positive coefficient of the square of the longest path suggests initial stability reducing effect can reverse to stability enhancing effect. It means that initially the concerns of risk spreading increase when the credit chain in the multiple paths increases. Being in the credit chain could exposes a bank to more asymmetric information. However, literature suggests that when there is no aggregate uncertainty, more complete claims structures enable the optimal allocation of risk-sharing via the insurance mechanism of interbank agreements. Teteryatnikova (2014) argues that in core-periphery networks, the banking system's resilience to shocks increases with the level of tiering. Therefore, once the increasing connections in the network are beyond the threshold, the risk sharing function of an interbank network takes over instead.

5.3.4. The moderation effect of bank attributes on topological impact

Table 9 shows the results of bank size moderation effect (Eq. (6a)). The interactions between the longest path and size shows that the positive effects of longest path on stability is stronger for large and medium-sized banks than for small banks. In particular, such effect is significant for large banks. Large banks are the dominant net borrower during the shock and post shock periods. The better connected they are along the credit chain, the more likely for them to meet their liquidity demand. While the negative impact of Betweenness centrality is further enhanced with medium-sized banks. Higher Betweenness indicates increasing direct and indirect connectivity exposes intermediate banks to more credit risk due to higher level of asymmetric information and lower peer monitoring

[29] The Kenya Electricity Generating investment plan was oversubscribed by 77%. Therefore, the company was able to take up an additional $133 million through a greenshoe option. A provision that allows an issuer to scale up an offer in the event of higher-than-expected demand (https://www.theeastafrican.co.ke/tea/business/kengen-s-200m-bond-to-power-extra-500mw-1296898).

Table 8
The relationship between bank stability and topology measures considering non-linearity.

	Coeff	Z stats	
Network measures			
avrate	0.213	[2.23]	**
edges	0.091	[3.39]	***
path *1000	−4.972	[−2.21]	**
p2c	0.129	[0.74]	
avrate (t−1)	−0.126	[−16.33]	***
edges (t−1)	−0.006	[−3.7]	***
path *1000 (t−1)	0.446	[5.34]	***
p2c (t−1)	−0.049	[−0.71]	
Node measures			
Net-strength* 1000	−0.144	[−4.65]	***
betweenness	−4.727	[−1.89]	*
out_centr	1.086	[2.23]	**
Net-strength* 1000 (t−1)	0.093	[2.81]	***
betweenness (t−1)	1.797	[1.43]	
out_centr (t−1)	−0.673	[−2.05]	**
Liquidity shock dummies			
kgipo	−1.976	[−2.27]	**
saipo	−13.667	[−2.3]	**
elec	9.445	[2.61]	***
gfc	−4.941	[−2.43]	**
inf	−0.235	[−27.33]	***
kgb	−0.373	[−69.81]	***
square of topology measures			
avrate_squ	−0.028	[−2.77]	***
edges_squ	−392.944	[−2.97]	***
path_squ	2.284	[2.3]	**
net_strength_sqr	−0.014	[−1.79]	*
betwee_squ	5.303	[0.43]	
outcentr_squ	0.276	[0.69]	
p2c_squ	−0.009	[−0.05]	
constant	−1.792	[−8.63]	***
overall R^2	0.110		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 8 presents the results of the nonlinear topological impact on bank stability (eq. (5)). The non-linear effect is captured by the highly significant square term of network and node measures. The results for instance show that the negative coefficient of the square of average rate suggests initially when lending banks raise interest rates across the board to reflect the increasing uncertainty and information asymmetry about the borrowing banks credit quality hence to reduce their exposure to credit risk increasing lending bank stability. However, when the bank increases the lending charge to borrowing banks to the extent that the normal insurance functionality of the interbank market is jeopardised especially when involving monopoly power in periods of distress. A bank facing difficulties may be overly generalised as a signal of a potential systematic failure. Such market expectations can become self-fulfilling creating unexpected liquidity outflows (Freixas et al., 2000) damaging bank stability.

power (Craig et al., 2015). As the dominant net lender during the shock period, such exposure unsurprisingly exposes medium-size banks to more uncertainties. Interestingly, out-degree centrality has positive impact for medium-size banks. Rochet and Tirole (1996) argue that private information and peer monitoring are essential in interbank markets. If private information acquired through direct lending relationships allows an interbank lender to assess its counterparty's credit risk more accurately hence reducing its credit risk exposure which seems to be the case for medium-size banks. Finally, the positive impact of the fraction of connections that a periphery bank connecting to a core bank is negative for large banks. The dominant core banks in Kenya are the large, local and listed banks who are also the net borrowers during the shock period. By increasing connections to these net borrowers especially during the shock period may lead to over exposure to credit risk and uncertainties hence damaging the stability of the large periphery banks.

Tables 10 and 11 shows the results of bank headquarter location and ownership moderation effects (Eqs. (6b) and (6c)) respectively. The results show that both foreign and listed bank attributes have the same moderation effects on two centrality measures: out-degree and betweenness as medium-size banks. The same explanations apply here as well.

To sum up, the results show that interbank topological measures affect bank stability significantly both contemporaneously and based on expectations. Many of such impacts contain nonlinearity. Different liquidity shocks and bank attributes have different moderation effects on the impacts. A certain level of interconnectedness among banks is vital for the stability of the whole system but such interconnections can overly expose banks to more uncertainties during the shocks whether due to direct exposure or market expectation. For an individual bank's stability, it is crucial in which capacity (lender, borrower, core or intermediary) the bank

Table 9
The relationship between bank stability and topology measures with bank size moderation effect.

	Coeff	Z stats	
Bank attribute dummies – Size (small bank is the base)			
Medium	0.064	[0.62]	
Large	0.096	[0.99]	
Size dummies interact with topology measures			
medium_avrate	−0.023	[−1.85]	*
large_avrate	0.006	[0.47]	
medium_edge	0.232	[0.31]	
large_edge	−2.035	[−1.44]	
medium_path	0.019	[0.35]	
large_path	0.156	[2.09]	**
medium_p2c	−0.107	[−0.91]	
large_p2c	−0.226	[−2]	**
medium_net_strength	0.089	[0.48]	
large_net_strength	0.144	[1.08]	
medium_betweeness	−7.936	[−2.08]	**
large_betweeness	−2.984	[−0.9]	
medium_outcentr	2.025	[2.06]	**
large_outcentr	−0.204	[−0.21]	
constant	−1.781	[−23.67]	***
overall R^2	0.126		
controlled for same variables in Table 7 and 8	Yes		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 9 shows the results of bank size moderation effect (eq. (6a)). The moderation effect is captured by the interactions between topological measures and bank size dummies. The results for instance show that the positive impact of the fraction of connections that a periphery bank connecting to a core bank is negative for large banks. The dominant core banks in Kenya a the large, local and listed banks who are also the net borrowers during the shock period. By increasing connections to these net borrowers especially during the shock period may lead to over exposure to credit risk and uncertainties hence damaging the stability of the large periphery banks.

Table 10
The relationship between bank stability and topology measures with bank headquarter location moderation effect.

	Coeff	Z stats	
Bank attribute dummies – headquarter (Local bank is the base)			
Foreign	0.029	[0.44]	
Location dummy interact with topology measures			
foreign_avrate	−0.012	[−1.35]	
foreign_edge	−0.828	[−1.64]	
foreign_path	0.077	[2.04]	**
foreign_p2c	−0.060	[−0.6]	
foreign_net_strength	−0.073	[−0.76]	
foreign_betweeness	−14.320	[−2.23]	**
foreign_out_centr	2.216	[2.27]	**
Constant	−1.772	[−24.43]	***
overall R^2	0.145		
controlled for same variables in Table 7 and 8	Yes		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 10 shows the results of bank headquarter location moderation effect (eq. (6b)). The moderation effect is captured by the interactions between topological measures and bank location dummy. The significant interplay between the two centrality measures out-degree centrality and betweenness centrality with bank location attributes show that private information acquired through direct lending relationships allows foreign bank lenders to better assess the credit risk of its counterparty, hence enhancing its stability. However, banks are also exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015).

Table 11
The relationship between bank stability and topology measures with bank ownership moderation effect.

	Coeff	Z stats	
Bank attribute dummies – Ownership (Private bank is the base)			
Listed	−0.004	[−0.06]	
Ownership dummy interact with topology measures			
listed_avrate	−0.009	[−0.98]	
listed_edge	−0.111	[−0.18]	
listed_path	0.047	[1.15]	
listed_p2c	−0.103	[−1.03]	
listed_net_strength	−0.075	[−0.7]	
listed_betweeness	−14.692	[−2.42]	**
listed_out_centr	2.342	[3.32]	***
constant	−1.752	[−28.65]	***
overall R^2	0.144		
controlled for same variables in Table 7 and 8	Yes		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table 11 shows the results of bank ownership moderation effect (eq. (6c)). The moderation effect is captured by the interactions between topological measures and bank ownership dummy. The significant interplay between the two centrality measures out-degree centrality and betweenness centrality with bank ownership attributes show that private information acquired through direct lending relationships allows bank lenders to better assess the credit risk of its counterparty, hence enhancing its stability. However, listed banks are also exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015).

participates. Having diverse lending relationships can improve bank stability especially during tranquil times while being in the credit chain could exposes a bank to more asymmetric information. The significant interplay between the two centrality measures out-degree centrality and betweenness centrality with bank attributes show that private information acquired through direct lending relationships allows bank lenders to better assess the credit risk of its counterparty, hence enhancing its stability. However, banks are also exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015).

6. Conclusion

Following the 2007/08 financial crisis, greater attention has been given to possible adverse implications of network interconnections among banks, particularly in the overnight interbank market, which has created new concerns for bank supervision. The interbank network structure affects the scale and speed at which risk spreads within the market. However, partly due to data unavailability, empirical studies in this area are limited and the results are inconclusive. This paper complements the existing empirical literature by providing an in-depth analysis of an overnight interbank market in a developing economy, Kenya. By using complete intraday transaction data from 2003 to 2012, we have been able to explore comprehensively the evolution of the network of Kenya's interbank market in different liquidity shock regimes. We also provide direct empirical evidence of the dynamic relationship between topological characteristics and bank stability.

Overall, the results show that the Kenyan overnight interbank market has some different network characteristics to those in industrial countries. The comparative analysis of different liquidity regimes shows hyper-connected networks during liquidity shocks with increasing number of banks participating in more and larger transactions. Local liquidity shocks such as the Safaricom IPO and the 2007/08 financial crisis have had a significant impact on the interbank market network structure and connectivity. The analysis also reveals the existence of a core-periphery structure, in which large, local and listed banks are overrepresented in the core. Small, foreign and private banks are predominantly in the periphery. The core banks are essential in facilitating liquidity flow to other core and periphery banks, especially during turbulent periods. The removal of a core bank, e.g., due to bankruptcy, would have far-reaching consequences on the stability of the interbank market. This is consistent with the notion of 'too-connected-to-fail'. The topological characteristics of the market suggest that the Kenyan interbank network is relatively dense compared to the extremely sparse fed funds network represented in Bech and Atalay (2010) and the network of Fedwire payments study by Soramäki et al. (2007). The identified systematically important banks may need different attention from the regulators and the market. In addition, the empirical results show that interbank topological measures affect bank stability significantly both contemporaneously and based on expectations. Many of such impacts contain nonlinearity. Different liquidity shocks and bank attributes have different moderation effects on the impacts. A certain level of interconnectedness among banks is vital for the stability of the whole system and for dominant net borrowers such as large banks during the shock period. However, such interconnections can overly expose banks to more uncertainties during the shocks whether due to direct exposure or market expectation. The interplay between the two centrality measures out-degree centrality and betweenness centrality with size, location and ownership attribute show that private information acquired through direct lending relationships allows medium-size, foreign and listed bank lenders to better assess the credit risk of their counterparties, hence enhancing their stability. However, as typical core banks, listed banks are also exposed not only to their immediate counterparties but also to the counterparties of their borrowers. Such increasing direct and indirect connectivity exposes listed banks to more credit risk due to higher level of asymmetric information and lower peer monitoring power (Craig et al., 2015).

Overall, the new evidence uncovered in this paper is very clear that the Kenya interbank network is an incomplete interbank network with a high degree of interconnectedness especially during shocks. Such networks exhibit a "robust-yet-fragile" property, which means that being a more connected network especially by connecting to the more reputable core banks, periphery banks have better chance to access liquidity and diversify risks, hence enhancing their stability in tranquil periods, but such interconnections can overly expose banks to more uncertainties during the shocks. Large transactions, especially those in long borrowing chains, pose a danger to bank stability as argued by Freixas et al. (2000). A fall in bank asset values in some regions can lead to spillover even in a more complete network (Allen & Gale, 2000; Babus, 2006). These results not only have important policy implications to financial regulators in Kenya, but also with great relevance to other developing economies which are now developing their interbank networks, especially so as to avoid one-size-fits-all financial regulatory policies.

Data availability

The data that has been used is confidential.

Appendix

Table A1
Summary Statistics of quarterly data during sub-periods

Variable	2003Q2-2006Q1 (obs: 516)				2006Q2-2010Q1 (obs: 688)				2010Q2-2011Q1 (obs: 172)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Edge	54.47	22.52	23.76	105.38	143.31	65.27	75.56	285.52	66.64	5.64	61.16	75.23
Avrate	4.42	3.26	0.50	8.41	5.98	1.58	2.80	7.41	1.42	0.33	1.10	1.95
Net-strength	1.41	149.79	−613.46	601.73	12.73	668.88	−5682.76	6123.14	4.46	553.93	−2613.20	2475.98
Path	362345.3	193604.1	216666.7	974930.9	1813394.0	903019.3	861160.6	4406266.0	1192046.0	132016.7	1020301.0	1341322.0
out_centr	0.02	0.03	0.00	0.16	0.07	0.10	0.00	0.93	0.03	0.03	0.00	0.12
betweenness	0.001	0.01	0.00	0.08	0.01	0.02	0.00	0.19	0.0002	0.0003	0.00	0.0015
p2c	0.15	0.17	0.00	0.85	0.23	0.22	0.00	0.90	0.26	0.16	0.00	0.75
Log of total assets	8.79	1.14	6.95	11.62	9.35	1.23	6.06	12.22	9.77	1.30	6.98	12.39
liquid liability ratio	0.47	0.27	−0.44	2.55	0.45	0.32	0.05	5.54	0.43	0.17	0.05	0.84
total loans/assets	0.54	0.23	0.01	1.24	0.53	0.18	0.00	1.05	0.49	0.16	0.00	0.96
non-interest revenue/total revenue	2.40	11.69	−9.75	195.29	1.65	5.63	−36.64	105.74	1.41	3.39	−14.65	31.18
tier one capital/total assets ratio	0.15	0.10	−0.17	0.60	0.14	0.09	0.01	0.77	0.13	0.08	0.01	0.66
the tier one capital/total capital ratio	0.91	0.30	−2.17	1.06	0.93	0.15	0.03	1.00	0.89	0.21	0.03	1.00
net charge-offs/equity	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
the log of a bank's market share	−4.37	1.13	−6.14	−1.56	−4.46	1.22	−8.14	−1.73	−4.56	1.30	−7.33	−2.02
GDP per capita	8251.14	375.43	7537.19	8917.27	9002.93	344.01	8289.94	9443.66	9399.23	400.91	8834.52	9688.49
Kenya$/US$ exchange rate	76.32	2.56	71.87	81.11	71.57	5.49	62.68	80.43	81.61	0.93	80.75	82.99
the Kenya stock index return	0.09	0.12	−0.11	0.24	0.00	0.11	−0.25	0.21	0.04	0.08	−0.06	0.15
Inflation	−0.01	0.14	−0.50	0.08	0.02	0.02	−0.01	0.07	0.02	0.02	0.01	0.05
Population	33.90	0.89	32.45	35.35	37.44	1.05	35.60	38.90	39.64	0.32	39.20	40.05
Z_score_residual	−0.02	0.38	−2.71	2.39	0.03	0.46	−3.59	4.51	−0.01	0.55	−2.89	3.42

Note: 1. Bank size (log of total assets) captures the possibility that, on the one hand, larger banks may be incentivised by the moral hazard of ''too-big-to fail' belief. On the other hand, larger banks could be better equipped with more diversified business portfolio and operational geographic regions. 2.The liquid liability ratio controls for bank liquidity risk. The higher the ratio is, the lower will be the direct funding risk. 3. The ratio of total loans to assets and the ratio of non-interest revenue to total revenue capture business model diversification. 4. The tier one capital to total assets ratio and the tier one capital to total capital ratio reflect the impact of financial regulation. 5. To account for bank risk, we also include the ratio of net charge-offs to equity in the logarithmic form. 6. The log of a bank's market share indicates competition level, expecting that a bank with a larger market share faces less competition and is, therefore, more stable.

Table A2
Stage two panel diagnostic test results

Test	
Firm effects (F-test)	F (30, 1294) = 3.32 ***
Hausman Test	9.03

*** significant at 1%.

Table A3
Strict exogeneity test results

	Coeff.	t-stats	
constant	−0.111	[−3.19]	
edge(t)	0.002	[1.17]	
avrate(t)	−0.045	[−4.11]	***
path(t) *1000	0.000	[−0.24]	
P2c(t)	0.156	[2.32]	**
Net-strength(t)* 1000	−0.107	[−1.63]	
out_centr(t)	0.596	[0.88]	
betweeness(t)	−3.284	[−1.33]	
kgipo	0.118	[2.77]	***
saipo	−0.254	[−1.06]	
elec	−0.094	[−0.47]	
gfc	−0.226	[−1.23]	
inf	0.073	[1.05]	
kgb	−0.262	[−4.5]	***
edge (t+1)	0.001	[1.07]	
avrate (t+1)	0.027	[2.02]	**
path (t+1)*1000	0.000	[−1.33]	
P2c(t+1)	−0.088	[−1.23]	
Net-strength (t+1)* 1000	0.000	[1.22]	
out_centr (t+1)	−0.109	[−0.12]	
betweeness (t+1)	1.077	[0.37]	***
$H_{0:}\rho_1 = \rho_2 = 0$	F (6, 1312) = 1.71		

Note: Based on the strict exogeneity test (Wooldridge, 2002), we add the one quarter leading variables of all the explanatory variables (excluding event dummies) in the baseline model. The insignificant F-test result on all the leading variables supports exogeneity.

Table A4
The combined results of Tables 7 and 8

	Coeff	Z stats	
Network measures			
avrate	0.193	[8.03]	***
edges	0.099	[46.23]	***
path *1000	−5.639	[−30.68]	***
avrate (t−1)	−0.132	[−12.07]	***
edges (t−1)	−0.007	[−20.53]	***
path *1000 (t−1)	0.466	[25.41]	***
Node measures			
Net-strength* 1000	−0.146	[−2.63]	***
betweenness	−6.188	[−1.87]	*
out_centr	0.936	[1.26]	
P2c	0.148	[0.82]	
Net-strength* 1000 (t−1)	0.092	[2.34]	**
betweenness (t−1)	1.540	[1.13]	
out_centr (t−1)	−0.652	[−1.46]	
P2c(t−1)	−0.063	[−0.88]	
Liquidity shock dummies			
kgipo	−46.626	[−44.31]	***
saipo	−15.991	[−33.52]	***
elec	10.458	[27.86]	***
gfc	−5.010	[−33.5]	***
inf	0.154	[0.53]	
kgb	−0.106	[−1.25]	
shock dummy interactions with topology measures			
kgipo_net_strength	0.173	[1.11]	
saipo_net_strength	−0.088	[−2.14]	**
ele_net_strength	−0.023	[−0.53]	
gfc_net_strength	0.059	[2.51]	**

(continued on next page)

Table A4 (*continued*)

	Coeff	Z stats	
inf_net_strength	0.094	[0.69]	
kgb_net_strength	−0.003	[−0.02]	
kgipo_avrate	6.148	[45.21]	***
inf_avrate	−0.227	[−1.9]	*
saipo_betweenness	4.570	[2.84]	***
kgipo_betweenness	−2.136	[−1]	
ele_betweenness	−3.397	[−1.14]	
gfc_betweenness	−1.959	[−0.93]	
inf_betweenness	300.380	[12.41]	***
kgb_betweenness	−216.038	[−8.34]	***
kgipo_out_centr	2.248	[3.06]	***
saipo_out_centr	1.305	[4.21]	***
ele_out_centr	−0.047	[−0.03]	
gfc_out_centr	−1.430	[−1.24]	
inf_out_centr	−0.506	[−0.43]	
kgb_out_centr	0.803	[0.81]	
kgipo_p2c	0.021	[0.34]	
saipo_p2c	0.787	[12.78]	***
ele_p2c	0.209	[2.99]	***
gfc_p2c	−0.834	[−12.41]	***
inf_p2c	0.348	[3.38]	***
kgb_p2c	−0.486	[−5.25]	***
square of topology measures			
avrate_squ	−0.025	[−12.98]	***
edges_squ	−432.217	[−37.94]	***
path_squ	2.578	[31.74]	***
net_strength_sqr	−0.015	[−1.73]	*
betweenness_squ	21.591	[0.87]	
outcentr_squ	1.070	[0.77]	
p2c_squ	0.018	[0.1]	
constant	−1.749	[−32.4]	***
overall R squ	0.102		
Robust standard error	Yes		
Standard error clustered at	bank level		
Time effect	Yes		

Note: 1. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
2. Detailed explanations of the variables refer to Table 1.
3. Table A3 presents combined results of Tables 7 and 8 The results are largely consistent with Tables 7 and 8 results.

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