Evolution of the Interbank Market Network Structure: The Case of Kenya

Tiriongo Samuel
Kamau Anne
Ndirangu Lydia

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Tiriongo Samuel
Economist, the Kenya Bankers Association

Kamau Anne
Economist, the Central Bank of Kenya.

Ndirangu Lydia
Economist, the Central Bank of Kenya.

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Abstract

This study characterizes the evolution of the interbank market network structure in Kenya, as a case study of a developing money market using a network-based approach, employing overnight trading data spanning 2013 to 2020. The study extracts and describes the evolution of well-known complex network measures, including degree distribution, network density, and centrality of the players, their clustering behaviour, and clique formations, to characterize the topology of the interbank market. Study findings show that the interconnectedness among banks in the market varied over the analysis period, with large banks being the most connected as debtors and small banks exhibiting the least funding diversification. On the lending side, small banks are just as diversified as their larger counterparts, particularly before 2016. Thereafter, as counterparty risk assessments tightened, large banks dominated the market. Other microstructure market characteristics reveal several insights about the interbank market, including: an incomplete structure, with only about 1.5 percent of banks having connections with almost all other banks; a highly vulnerable structure to a few hub banks; and a varying assortativeness structure depending on the nature of the shock presented. These findings carry useful insights for understanding interbank market counterparty risk profiling and the identification of critical players in the market, which have implications for the banking sector liquidity management strategies and financial stability. Understanding the fragility of the market and the existing anchors to market stability also facilitates the monetary authority to minimize the risk of contagion and enhance the resilience of the system in the event of a shock. Overall, the interbank market is largely fragile, and thus may not be sufficiently developed to be relied on for pricing of liquidity and effective transmission of monetary policy signals.

Keywords: *Overnight Interbank market, Network Structure, Kenya*

1.0 Background

The interbank market plays an important role in monetary policy and financial stability, particularly by influencing market liquidity conditions, being the first host of the monetary policy actions of liquidity injections and withdrawals. Its efficiency in playing this role is dependent on the prevailing market structure, and the extent to which the structure influences the monetary authority's ability to utilize price-based indicators as targets for monetary policy.

The overnight interbank market in Kenya is a market purely for commercial banks to trade excess reserves.[1] Like in other money markets, the market plays three critical functions. First, it facilitates liquidity re/distribution from surplus banks to banks in deficit.[2] This helps to smooth out payments of maturing obligations of both customers and other commercial banks. Second, it enables banks to trade liquidity in order to meet their reserve requirements while avoiding keeping extra liquidity *ex-ante* to cushion themselves from liquidity shocks. This supports efficient allocation of resources and enhances financial intermediation, thereby promoting the objectives of monetary policy. Third, the market is critical in the transmission of monetary policy actions or decisions. Typically, the central bank's liquidity management operations would first hit the interbank market before they are transmitted to the rest of the financial system and economy. Hence, the overnight interbank rate is a critical anchor for the whole term structure of interest rates (Tiriongo & Kanyumbu, 2019, and Murinde *et al*, 2015). In this regard, understanding the overnight market in terms of its operational framework is crucial to policymakers in enhancing the effectiveness of monetary policy.

At the core of the interbank market is its network structure. There are several measures that describe the network structure of a market inspired by the classical network theory, often applied in natural and physical sciences (Newman, 2010, and Albert & Barabasi, 2002). These measures have also been deployed to study the topology of financial systems, particularly in terms of network completeness, span[3] and centrality[4] (*see for instance*: Boss *et al*. (2004) for Austria; Becher *et al*. (2008) on the Bank of England; Bech & Atalay (2010) for the Fed; Brink & Georg (2011) for South Africa; Peltonen *et al*. (2013) on the ECB; and Silva *et al*. (2015) for Brazil) that have implications for liquidity management and financial stability.

The most common measures of network structure, applied to describe the trading interconnectedness between and among participating banks, include network density, clustering behaviour, centrality of players, and the level of fragmentation in the market. While a network

[1] Reserves in excess of the statutory cash reserve requirements

[2] The other channel for distributing liquidity, often applied when market segmentation is entrenched, is through central banks' open market operations via repurchase agreements (repo) that mop up funds from banks with surpluses, and reverse repos that inject funds to banks with deficits.

[3] These include density/completeness, shortest path length/ distance and diameter of the network.

[4] Includes degree and strength of participant, betweenness centrality, closeness centrality, eigenvector and page-rank centrality, clustering coefficient, degree correlation/ affinity.

density measure describes the number of existing links a bank has relative to the maximum possible links it can have in a network. This is used to describe the level of completeness of a network; its clustering coefficient captures the likelihood that two banks, with a common trading partner, have a trading relation. This helps assess the level of intermediary trading in a network, which has a direct implication on the liquidity redistribution efficiency in the market. Additionally, the measure of centrality of players identifies the most important ones in a network, reflecting a bank's involvement in or contribution to the cohesiveness of the network (Newman, 2010). Being closely related to the notion of 'too-interconnected-to-fail', this measure is used to draw insights on the systemic risk and resilience to contagion from the point of view of interconnectedness (Allen & Babus, 2008; and BCBS, 2011). Network analyses also enable the establishment of the level of fragmentation/decentralization in the market, and if so, within the fragmented units, to ascertain the level of completeness of the structure. This knowledge is an important input for enhancing the central bank's design of its liquidity management practices and strengthening the resilience of the banking system. For monetary policy, finding a decentralized structure, for instance, with some banks showing a higher degree of interconnectedness/ importance in the interbank market, would have a direct bearing on the market's price discovery (Jackson, 2008; Kanyumbu, 2020).

The importance of the interbank market - and its underlying network structure - in influencing the effectiveness of monetary policy is also dependent on the operational monetary policy framework. The CBK conducts a quantity-based monetary policy framework that relies on the interbank market to redistribute bank reserves (Oduor *et al*. 2014) to achieve the monetary policy objectives primarily via the interest rate and credit channel (Misati *et al*. 2010; Sichei & Njenga, 2012). However, due to concerns of weak transmission of policy signals - attributed to unstable money demand function and unpredictable velocity of money, CBK is in the process of transitioning from the quantity-to a modern price- based targeting (CBK, 2021).[5] With this transition, the latter framework relies more on the overnight interbank market price discovery mechanism, with the overnight interbank rate centrally used as the operational target of monetary policy. Essentially, the price-based framework elevates the role of the interbank market and refocuses policymakers' attention to the implications of its network structure on the market's efficiency (Silva *et al.* 2015; Craig *et al*. 2015; and Temizsoy *et al*. 2017).

This study describes the evolution of the network structure of the interbank market in Kenya, focusing on two out of the three regimes reviewed, separated by the failure of 2 banks and the introduction of interest rate capping around the same time. It employs several network structure measures**,** which include network density, clustering, centrality, and completeness. As we explain, the structure of the network has implications on the efficient functioning of the interbank

[5] Based on arguments presented in a White paper on *Modernization of the Monetary Policy Framework and Operations,* published by CBK in 2021 (available via https://www.centralbank.go.ke/wp-content/uploads/2021/07/Modernisation-of-the-Monetary-Policy-Framework-Operations.pdf).

market and thus the effectiveness of monetary policy, particularly with the CBK's transition out of the quantity-to-price-based targeting framework of monetary policy.

1.1 Evolution of Kenya's overnight interbank market: Some stylized facts

Kenya's overnight interbank market has been active since 1995. The market is non-collateralized, and trades are dominated by local currency funds and effected on overnight tenures. There, however, exists a collateralized horizontal repo market, but its uptake and activity remain low on account of challenges in its collateral perfection framework.[6] In terms of price discovery, the overnight interbank market rate is fully market-determined and largely reflects counterparty risk assessment of participating banks that strongly define the underlying credit lines. Participating banks' adverse risk profile can present them with two consequences, manifested either individually or jointly. Either a higher price from lending banks or a punitive central bank discount window rate that is priced at 600 basis points above the Central Bank Rate (CBR), or both.

Other features of the market relate to the level of activity. Analyses of the evolution of the market between 2000 and 2020 show that the value transacted in the market grew steadily and depicted increased participation by banks across all sizes (Figure A1 in the Appendix). Over the period, the market has been active, accounting on average for about 10 percent of the banking industry assets. An eyeball inspection of the trends in activity in the market depicts three somewhat distinct regimes, particularly from 2005 through the end of 2020.

The first regime - 2005 to the end of 2010 - saw some gradual increase in the volumes traded and the number of deals, reaching a peak around 2008[7]. During this period, the average overnight interbank rate was less volatile and on a steady declining trend, with the average number of deals per day slightly above 50. The volumes traded per day were, however, the lowest when compared to the succeeding periods despite the relatively high number of deals per day, reflecting smaller trading lots (Figure A2 in the Appendix). During this period, the major development that affected market sentiments and entrenched stronger counterparty risk assessments included the subprime crisis in 2008/2009, which muted good prospects from an economic turnaround that was witnessed from 2003, following a transition of government in 2002.[8]

The second regime, from 2011 to September 2015, was characterized by a significantly high number of policy announcements by CBK that had a bearing on the interbank market. The announcements, particularly in 2011, were aimed at strengthening the capital base of financial

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[6] The collateral imperfection is underpinned by failure of the security to transfer from the borrower to lender during the transaction.
[7] It is worth noting that the Monetary Policy Advisory Committee (MPAC) was established in mid-2005. The Monetary Policy Committee (MPC) replaced MPAC in April 2008.
[8] The government transitioned from the 24 years rule of KANU to a NARC government that carried a lot of promise on economic performance and revamping governance, as covered in the *Kenya Economic Recovery Strategy for Wealth and Employment Creation, 2003-2007* (KIPPRA, 2003).

institutions licensed by CBK, restricting easy access to CBK discount window funds, amendments on the framework of cash reserve management with the introduction of reserve averaging, streamlined CBK liquidity management operations, and changes on the foreign exchange trading practices seeking to minimize arbitrage opportunities. These changes altered commercial banks' liquidity management practices, particularly with the tightening of rules on access to CBK window funds. Other changes during the period included the tightening of the monetary policy stance, reflected in a consistent upward adjustment in the CBR from 6.25 percent at the end of 2011 to 11.50 percent by September 2015. The CBK also introduced the Kenya Banking Reference Rate (KBRR) in 2015, seeking to enhance transparency in credit pricing.[9] Consequently, the interbank market witnessed declining activity in the number of interbank market deals (Figure A2 in the Appendix), and the general increase in the level, spread, and volatility of the interbank rate (Figure A3(a) and A3(b) in the Appendix). Overall, counterparty risk declined during this period, with banks having trading lines across sizes as they enhanced their internal liquidity management practices.

The third regime, covering the period October 2015 to the end of 2020, marked a distinct departure from the first two regimes. The regime depicts a stronger disconnect between the overnight interbank rate and the policy rate (see Figure A4 in the appendix). The divergence, particularly after December 2015, reflected two major events. First, is the collapse of two key medium-sized banks, which were major players in the market - one on each side of the market - between October 2015 and April 2016. This event reintroduced counterparty risk assessment among participating banks that had declined in the previous period, resulting in reduced overall activity in the market, with participation dominated by large banks. Second, is the implementation of interest rate controls from September 2016 to November 2019. This development -coming after the tightening of counterparty risk profiling- compounded the problem of ineffective transmission of monetary policy triggered by changes in the CBR and operationalized via the interbank market (CBK, 2018)[10]. While the collapse of banks reversed the gains that had been made on counterparty risk assessments and profiles of participating banks, the institution of interest rate controls triggered a disconnect between the policy rate and the interbank rate, thus reflecting a weaker transmission of monetary policy signals. Other developments during this period included

[9] For a detailed coverage of the policy announcements, see Table A1 in the appendix.
[10] Based on a paper by CBK (2018) on the 'The Impact of Interest Rate Capping on the Kenyan Economy; Highlights. Available via link: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/viewer.html?pdfurl=https%3A%2F%2Fwww.centralbank.go.ke%2Fwp-content%2Fuploads%2F2018%2F03%2FSummary-of-the-study-on-Interest-rate-Caps_February-2018.pdf&clen=585544&chunk=true

six bank acquisitions and one merger[11], and the emergence of the COVID-19 shock in early 2020 that had a bearing on the overall risk assessment and thus interbank market trading dynamics.

The above developments through the regimes had a bearing on counterparty risk profiling of participating banks and the effectiveness of the interbank market to deliver desired policy outcomes. Concerns emerge on whether the market participation structure changed considerably through the period, in response to policy actions. To the best of our knowledge, the implications of these developments alongside other related structural characteristics have not been assessed exhaustively. Ndirangu *et al*. (2021) provided the first attempt at unravelling the changes over time of the network structure of Kenya's overnight interbank market, assessing the period up to the first quarter of 2017; a period before the effects of the interest rate capping law and the collapse of the two banks had fully been manifested. Other previous studies on Kenya's interbank market have focused on various facets of network structure separately, characterizing the interbank market segmentation patterns based on event studies (Sichei *et al*. 2012 and Oduor *et al*. 2014); examining the lending relationships in the market and the inherent market disciplining mechanism that would complement prudential regulation (Murinde *et al*. 2015), and the role of market disciplining in triggering buildup in capital buffers (Tiriongo & Kanyumbu, 2019).

The rest of the paper is organized as follows. Section 2 provides a synthesis of the relevant literature, and Section 3 describes the data used for the study as well as the methodology, providing a detailed description of the network structure constructs. Section 4 discusses the results of the study, while Section 5 makes conclusions and draws some policy implications.

2.0 Literature Review

The important role of money markets in providing liquidity for the banking sector became a topical concern following the subprime crisis in 2008/09 that triggered a refocus on counterparty risk assessments in financial markets. Lack of liquidity in a bank typically originates from its asset-liability maturity mismatch, and a failure of the bank to rollover its liabilities. As a result, it may be unable to repay its creditors, and if the same creditors are facing the same liquidity shortages, this may trigger a series of repayment failures- generating a systemic failure. As a mitigation, the banks under liquidity stress may be compelled to sell less-liquid assets in order to settle the repayments. Such sales, due to the conditions under which they occur, may be concluded at a loss and thus yield a worsening of the bank balance sheets. If this process spreads in the banking system, a confidence crisis can be triggered, and the ability of the system to perform its liquidity redistribution and intermediation role is reduced, thus affecting its impact on the real economy. This propagation is critically dependent on the interconnectedness among players in the system

[11] The acquisitions involved large banks acquiring small banks, and the merger occurred between two medium sized banks - leading to the formation of a larger size bank.

(Silva *et al*., 2015). This argument has driven a lot of attention to an understanding of the network structure of interbank markets, especially after the global financial crisis, during which the linkages created by liabilities among banks and other financial institutions played a crucial role and yet were poorly understood (Brunetti *et al*., 2015).

The study of interconnectedness involves an assessment of the complex networks underpinned by the intersection between graph theory and statistical measures (da F. Costa *et al*. 2005). The application of the network-based approach confers several benefits, from its unique ability to capture topological and structural characteristics of the relationships to permitting the unification of the structure, dynamics and functions of a system represented by the network (Albert & Barabasi, 2002, Albert *et al*. 2000). The network approach has been applied to examine systems that depict nontrivial topology and are composed of a large number of connections/ vertices (Newman, 2010 and Silva & Zhao, 2015).

From the onset, four universal properties are typical in a complex network[12] are identified. First, a node (bank) in the network would be connected to several other nodes in a free-scale distribution, so that nodes that have few connections depict a highly concentrated hub. Second, nodes may describe a clustering pattern where there is some probability that two nearest neighbors or nodes are connected. Third, any node in the network may also be reached from any other node with minimal nodes in between (only a few steps), and fourth, nodes tend to be assortative, that is connect with nodes of similar type/degree (Newman, 2003; and Albert & Barabasi, 2002). Typically, the set of financial operations in a market is a complex system best represented by networks that commonly exist in the payments system and the interbank market (Castro Miranda *et al*. 2014).

Focusing on the interbank market, a relevant channel of financial contagion is the overlapping claims that institutions have on each other. A default of a given market player could generate a domino-like effect if subsequent defaults arise based on exposures to the defaulting player. Fundamentally, this places network topology at proximity and relations to systemic risk and financial stability (Allen & Gale, 2000; Frexias *et al*., 2000). Green *et al*. (2016) note that the structure of the interbank market has implications for its liquidity re-distributive role, its pricing outcomes, and determines the vulnerability of the network to contagion. This is affirmed by Kanyumbu (2020), who establishes that the structural characteristics impacting liquidity distribution and contagion, as well as pricing, have implications for monetary policy.

Some empirical studies have delved into the specific network topological features and their implication on contagion effects. For instance, Nier *et al*. (2007) show that the degree of

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[12] Examples of complex network structures include the internet, the World Wide Web, biological neural network, social networks, food webs, metabolic networks, and financial networks

connectivity among players in the interbank market has an effect on contagion, but the effect is non-monotonic. This implies that initially, a small increase in connectivity increases the contagion effect, but beyond a certain threshold, connectivity acts as a buffer for shocks, thus supporting stability. This notion is confirmed especially where the players face small shocks (Acemoglu *et al*. 2015).

In a related study, Silva *et al*. (2015) examine three main features of the interbank market network structure. First, is the degree of assortativeness of the market to specifically ascertain whether banks tend to connect with other banks of a similar type in the interbank market. They show that highly connected players are easily connected to other players who carry very few connections. They associated a disassortative structure with the existence of money centers, which act as hubs to other players, particularly the non-large banks. Second, they examined the substitutability of players in the market, based on analyses of the weighted clustering coefficient measure of the network in a money market with both banks and non-bank players. Their findings showed that large banks were more substitutable than large non-banks, particularly on the borrowing side. Finally, they also established, based on the classical criticality measure of vulnerability, that large banks were more critical to the rest of the players; a finding particularly true during crisis periods. Large banks were also noted to behave like a 'rich-club', forming near-clique structures, and playing the role of liquidity providers in the money market, with this behavior more evident in specific crisis periods.

Similar studies have found a high degree of concentration of links in a smaller number of banks (Boss *et al*., 2004 for Austria; Soramäki *et al*., 2006 for the Fed, Imakubo & Soejima, 2010 for Japan, and Martínez-Jaramillo *et al*., 2014 for Mexico). The concentration of links on a smaller number of nodes gives rise to hub-like nodes in the network. These types of networks, despite appearing robust, are fragile because random disturbances are easily absorbed, whereas targeted attacks on the hub-like nodes have a significant effect on the entire network (Albert *et al*. 2000; Newman, 2003). Such findings highlight the importance of examining the time series dynamics of the interbank market network structure metrics, as these features tend to vary over time, with implications on the functioning of the money market.

Several studies have also focused on the measures of centrality in the interbank market networks to examine the degree and strength of participants (Fricke and Lux, 2013; Craig & Von Peter, 2014; Craig *et al*., 2015; Temizsoy *et al.,* 2017). Frick and Lux (2013) examine interbank data on the e-MID trading platform for the Italian interbank market and find a core-periphery structure that places banks in specific positions within the network. Moreover, the core banks were more concentrated on the borrowing side rather than on the lending side. This finding was corroborated by Craig & Von Peter (2014) for the German interbank market structure case. A further examination of this finding by Craig *et al*. (2015) showed that a bank's position in the network was important since it affected its bidding aggressiveness during auctions, and thus the overall pricing outcomes. In particular, central lenders in the money market were observed to bid more aggressively in the auctions, as banks with a diversified borrowing structure bid less aggressively and paid less for liquidity in the auctions. In further examining the centrality issue, specifically comparing the borrowing costs and lenders' premiums, Temizsoy *et al.* (2017) show that while banks' borrowing costs increase with borrowing links, the premiums for lenders reduced. In addition, as banks' centrality go up, they receive discounts on their borrowing. In an extreme case, some banks in the network may grow their centrality to such levels as to be 'too-interconnected-to-fail'. Thus, interconnectedness and a bank's position in the structure played a key role in enabling it to meet its liquidity needs.

Consistent with the argument that a bank's positioning in the network matters in determining its ability to meet liquidity needs, Brassil and Nodari (2018), pointed out that the positioning can be disrupted by shocks. They argue that during episodes of financial crises, such as during the global financial crisis that disrupted counterparty risk profiling of financial institutions, this triggered changes in the centrality of players in money markets. Using data for the Australian interbank market for the period 2005-2016, they examined the density-based measure of network centrality and established that the number of core banks declined from eight to five in the network as lending relationships reduced significantly during the global financial crisis period. Their estimated density-based measure of centrality was 0.25, indicating a sparse network of overnight loan relationships. In addition, they concluded that a bank's positioning in the interbank market is also important in determining pricing of liquidity, so that a bank would pay more for liquidity if it on-lends to a centrally located bank. This argument was consistent with earlier assertions by Afonso et al (2011), Iyer & Pedro (2011), Craig *et al. (*2015), and Temizsoy *et al* (2017).

The interbank market network structure's implications on the pricing of liquidity is argued to be based on the underlying lending relationships established between participating banks (Finger & Lux, 2017; Liu *et al*., 2017). Banks are argued to establish lending relationships with those they perceive as not presenting any form of direct or indirect risk, and also based on their past/historical lending relationship, which may be anchored on any other factors such as ownership structure. Lending relationships create the credit lines/links in the network and are noted to have implications on the ability of the interbank market to appropriately pick up monetary policy signals. Oduor *et al*. (2014), employing an event study methodology to analyze the bilateral lending relationship patterns in the interbank market in Kenya, concluded that the interbank market in Kenya exhibited a segmented structure depicting an incomplete network that was inefficient in picking policy signals in the short run, more so during periods when liquidity was volatile.

The dichotomy between small and large banks and how they trade with each other is described by Cocco *et al.* (2009) and Bech and Atalay (2010). The studies show that while small banks in the Portuguese market rely on large banks to borrow funds, large banks tend to hold consistent relationships with familiar counterparties because of lower interest premiums. For the U.S market, small banks are net lenders while large banks are net borrowers. Evidently, banks' role variations across markets are noted. In addition, Heider *et al*. (2009) find evidence of liquidity hoarding among banks in the interbank network when they are faced with the challenges of assessing counterparty risk, particularly during periods of crisis. Afonso *et al.* (2011, however, argue that it is not so much a case of liquidity hoarding but the case of heightened concerns on counterparty risk that leads to reduced liquidity and increased cost of finance for weaker banks; a feature that causes an increase in the interest rate spreads between the larger and the smaller banks during a crisis.

The interbank market network structure is also argued to have implications on the fragility of the financial system. Ye Bai *et al*. (2021), employing the interbank market trading data for the period 2003 to 2012, show that Kenya's interbank market became more closely interconnected with increasing network size from 2006 to late 2009. This coincided with a series of liquidity shocks that affected liquidity demand in the banking system. During periods of liquidity shocks, large, foreign, and listed banks not only increased their importance in the network as borrowers but also formed a higher density of connections in the direct neighborhood as borrowers. This study also shows that in an environment of heightened asymmetric information and increased uncertainty, more reputable banks are able to satisfy credit profiling by other banks and get access to liquidity. In addition, the presence of an incomplete interbank market structure, coupled with a high degree of interconnectedness, can facilitate the spread of liquidity shocks; thus, reflecting the impact of interconnectedness on banking sector contagion.

Using quarterly data for the period 2008q4 to 2017q2 and selected cross sections, Ndirangu *et al.* (2021) explore the various measures from network theory to uncover a number of microstructure characteristics of the interbank market in Kenya. The study concludes that the Kenyan interbank market was fragmented, consisting of local clusters with hub-like and periphery banks; features that became more prominent with time. They also find the structure of the interbank market to be incomplete -consistent with conclusions of Oduor *et al*. (2014) - with each bank in the network linked to another in not more than three steps (maximum of two banks in between). Based on the short-path length[13] measure, contagion in the market can spread with ease as exposure is only about two banks away in the network. With reference to the study period, this study, however, fails to fully account for the developments during the post-interest rate controls period[14], particularly on the banks' pricing of liquidity and assessment of counterparty risks.

Typically, networks are argued to be commonly incomplete in the sense that each player can only exchange assets with a limited number of other players. But the greater the incompleteness of the network, the more intermediation is required to transfer the assets between players. The uncertainty of trade in networks constitutes a potentially important market friction that manifests in the

[13] The path length measure reflects the number of links passed to get from one node to the other, reflecting the number of connections needed to transfer liquidity form one node (bank) to another.
[14] The interest rate controls law was applicable from September 2016 to November 2019.

mispricing of liquidity (Gale and Kariv, 2009), which impedes the transmission of monetary policy.

From the foregoing, it is established that the state of the interbank market structure - as measured by its varied constructs - has implications on the efficiency of the market in pricing liquidity - and by extension the effectiveness of monetary policy, and the fragility/stability of the financial system as inferred from its effects on contagion. Against this background, this study uses data spanning January 2013 to December 2020 to examine the evolution of the market network structure in Kenya. The period covered is of particular relevance allowing for a comprehensive review of the impact of various market and policy developments that include: the implementation of the interest rate controls between September 2016 and November 2019; increasing relevance and focus of the role of interbank market as the central bank shifts to price based forward looking monetary policy framework; and a period when three medium sized banks were put under liquidation in between 2015 and 2016.

This study examines the implications of these developments on the interbank market counterparty risk assessments, interbank market lending /borrowing exposures, and liquidity pricing in the market, which are important pillars for effective monetary policy and banking sector stability. In particular, it uncovers the topology/microstructure of the interbank market, the evolution of the network structure measures through various phases of market developments, and provides insights into their implications on the conduct of monetary policy and stability of the financial system.

3.0 Data and Methodology

3.1 Data

The study analyzes the structure of the interbank market network in Kenya using daily interbank trading data that shows the participating banks, volumes traded, and interest rates charged for each of the trades spanning the period January 2013 to December 2020. The selection of this period was informed by the availability of continuous data through the period[15] . In this regard, data from 36 banks were used in the study out of a total of 39 banks. Data was obtained from the Central Bank of Kenya and analyzed based on the CBK bank tier classifications. In this classification, there are 21 tier-three (small) banks with a market share (in terms of assets) of 8 percent, 9 tier-two (medium-sized) banks whose market share was 17 percent, and 9 tier-one (large-sized) banks with a market share of 75 percent of total assets as of 2020.

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[15] Prior to April 2012, CBK interbank market trading was stored in legacy systems before the Bank implemented the T24 core banking system from 2012Q2. This limits the detailed structure analysis of the interbank market to only a part of the second regime (from 2013Q1) and the whole of the third regime described in section 1.1.

3.2 Methodology

The objective of this study is to assess and uncover the evolution of Kenya's interbank market aggregate network structure measures over the study period. In terms of network topology, the interbank market is assumed to consist of a set of banks (nodes) that are connected via some relationship (edges), through lending or borrowing. The number of nodes and links measures the size of the network and the density of the connections. Overall, indicators of network structure are borrowed from standard network theory, often applied in natural and physical sciences (Strogatz, 2001, and Alber & Barabási, 2002), and have increasingly been applied in financial networks in advanced economies over the last two decades. In this section, we present the network indicators/ metrics that are used to characterize the role of each bank in the interbank market.

Here, the interbank network is characterized by the liability (or exposure) square matrix 'D' represented by an N x N matrix, where N is the number of banks (**Figure 1**). The entries *d(i,j)* represent the nominal obligation of bank i to bank j within a certain period. The diagonal elements of 'D' are zero as banks would not hold liabilities against themselves. Off-diagonal elements are positive in the presence of trading and zero otherwise.

The sum of row (a_{ij}) shows banks i's interbank claims towards all the other banks, and sum of the columns (l_{ij}) show the sum of liabilities for each bank. A bank can either be a net borrower or net lender and the links are therefore directed, that is, the direction of the flow matters so that $d(i,j) \neq d(j,i)$. The analyses would therefore reflect the overnight bilateral liability matrix of all banks overtime.

Figure 1: Interbank-Lending Matrix

		Sum of row (Total assets)
	$\begin{pmatrix} 0 & d_{1j} & d_{1N} \\ d_{1l} & 0 & d_{iN} \\ d_{N1} & d_{Nj} & 0 \end{pmatrix}$	a_{1j}
		$\vdots$
		a_{ij}
		$\vdots$
		a_{Nj}
Sum of column (Total liabilities)	$l_{1j} \ldots\ldots\ldots l_{ij} \ldots\ldots\ldots\ldots l_{Nj}$	

To construct the network, let γ depict the set of vertices (banks) and, the set of edges. The cardinality of N = $|\gamma|$, represents the number of banks in the network. Assume a matrix L that represents the liabilities matrix (weighted adjacency matrix), in which the (*i, j*)-th entry represents the liabilities of the bank (vertex) i towards j. The set of edges θ is given by the following filter over **L**: $\theta = \{(i, j);\ \boldsymbol{L}_{ij} > 0: (i,j) \in \gamma^2\}$. We assume in our analysis that, there is no netting between i and j^2; implying that if an arbitrary pair of banks owe each other, then two directed independent edges linking each other in opposed directions will emerge. This ensures that in the network, if a bank defaults, its debtors remain liable for their debts. Additionally, we define the matrix of exposures between the banks as $A = L^T$, where T is the transpose operator. We now describe the network structure metrics briefly, based on Strogatz (2001), and seek to provide economic meaning to each measure in the context of the interbank market[16].

Measures of centrality in network theory applied in interbank market studies enable an understanding of how banks are distributed in the network and also determine their influence, power, and control within a network. To measure how banks are linked to each other in the network, the measure of *degree*[17] is computed, which may be 'in degree' denoted as $k_i^{(in)}$, reflecting the number of banks bank i borrows, or its funding diversification; or 'out degree' denoted as $k_i^{(out)}$, that captures the number of banks bank i lends to or its investment diversification. The intensity of the bank's interactions in the network is measured by the amount transacted or *strength*. This can also be in form of 'in-strength' $s_i^{(in)}$, or 'out-strength', $s_i^{(out)}$ for directed networks, respectively corresponding to amount borrowed or lent. The analysis of degree is also done based on bank tiers. Additionally, a ratio of out-to-in degree for banks by tiers uncovers which side the banks lean towards more, as either lenders or borrowers. As such, a higher out-to-in degree implies that the banks are more on the lending than borrowing side or are more diversified in investments compared to funding.

Measures of cohesion in the network show important relationships within the interbank market in terms of connectivity. To do this, the study uses the *density/completeness* measures. Density is derived by dividing the number of observed links at a given time with the total number of possible links. A high density in an interbank liability market, implies an active interbank market with numerous lending relationships. It is also a measure of completeness of a network, where for a complete network, all possible links would be present. The density for directed networks is given in equation 1:

$$d = \frac{m}{n(n-1)} \qquad [1]$$

where *m* is the number of transaction links and *n* is the number of banks in the network, with 0<d<1. The closer *d* is to 1, the more complete the network, while as density tends to zero the network is said to be sparse (Newman, 2010). Whereas a high network density portends greater

[16] See the appendix B for a further definition of the metrics. Also, other in-depth measures of network structure of interest, which include degree, strength, density/completeness, shortest path length/ distance and diameter, clustering coefficient, centrality, and network assortativity are discussed.
[17] Gives the number of edges connected to a node: number of banks linked to it in the network.

risk diversification and stability, more interlinkages may not guarantee greater stability since it depends on the nature of a shock facing the network. In the presence of large shocks, a dense interbank linkage may yield a fragile system and thus facilitate contagion.[18]

Related to the concept of density is the *clustering coefficient ($cc_{i,}$),* which measures the probability that two banks (nodes) sharing a common neighbor, share a link. In the interbank market, $cc_{i,}$ indicates the probability that two banks linked to each other in trading have a common trading partner. In order to have a triangular connection between three banks, at least one bank must lend to one counterparty and borrow from another. The $cc_{i,}$ provides a means to assess the extent of intermediary trading. It also quantifies how close the particular bank and its neighbours are to being a clique and therefore, and thus a measure of network cohesiveness. The cc_i lies between 0 and 1. The closer the local cc_i is to 1, the more likely it is for the network to form clusters. A high clustering coefficient also may indicate existence of stable and lasting relationships among the banks, with all the potential consequences that it entails, which can be either positive (so that there is an enhanced resilience to random and relatively mild shocks) or negative (that is, a higher level of contagion when facing targeted and intense attacks).

From a lending perspective, a high cc_i means that bank i is easily substitutable because its neighborhood has other nearby options to invest in. Conversely, a low cc_i means that few options are available for the neighbours of i suggesting that bank i is important in the neighborhood because its removal would significantly reduce the trading options for its nearby links. Consequently, cc_i can be viewed as a measure of diversification of the counterparties of i. It can also help identify important institutions in the network that may act as bridges between different clusters allowing liquidity or contagion to spread out. The clustering coefficient of a single node can be extended to the entire network by averaging the $cc_{i,}$ over the network banks.

In order to ascertain how quickly information (liquidity or contagion) spreads through an entire interbank network, the study analyses the *average path length* and *network diameter*. A path is any connection between two banks, and the length of the path between the two is the number of links passed to get from one bank to the other along this path. The shortest path length (or distance) is the minimum number of banks it takes to get from any bank A to another bank B. The maximum distance of a bank is the longest path to any other bank. The diameter of a network is the maximum distance across all banks. A lower measure of average path length and network diameter implies increased market efficiency in distributing funds or increased vulnerability to contagion risk, as a sudden shock would be transmitted through fewer banks. Higher-density networks tend to yield a smaller average shortest path length (ASPL). The more crowded a network gets with links, the fewer steps it takes to get from one bank to another. The path length aids in the identification of

[18] Nevertheless, the impact of a shock may be contained if banks' capital levels can quickly absorb it (Acemoglu *et al*, 2015).

important or most central banks in a network. Some of the most popular shortest-path-based measures include *betweenness centrality* and *closeness centrality* measures.

Betweenness centrality, on the other hand, quantifies how frequently a bank lies on the shortest path between two other banks (Newman, 2010). Typically, a bank with a high betweenness centrality would have an important influence on other banks as it can stop the flow of funds/information that passes through it. It thus shows which banks act as 'bridges' or intermediaries between other banks in a network. If a bank is part of many paths that connect other banks to each other, then it is likely to have informational or relational importance within the network since it is vital in connecting banks. On the other hand*, closeness centrality* measures how far away a bank is from the other banks based on the average length of the shortest paths connecting it to others. It evaluates the importance of banks according to their position in the network. The closer a bank is to others, the higher its closeness centrality, and the more it is likely to quickly transmit to other banks any risk of failure. Such banks (also called close centers) have better sight of the flow of information in a network and would be quite efficient in distributing liquidity. This measure of centrality conveys information on the importance of a bank based on its own characteristics.

A bank's importance can also be ascertained via the importance of the banks it connects to. This is measured by the *Eigenvector* and *PageRank centrality*. These measures help uncover influential or important banks whose reach extends beyond just their direct connections. They are useful because they indicate not just their direct influence, but also the implied influence through the specific bank's connections. For instance, a bank may have a high degree score (i.e., many connections) but a relatively low *Eigenvector*/ *PageRank* centrality score, if many of those connections are with similarly low-scored banks. Also, a bank may have a high *betweenness* score (indicating it connects disparate parts of a network) but a low *Eigen/PageRank* centrality score because it is still some distance from the center of power in the network. The difference between the two metrics is that, while the *PageRank* score accounts for the direction of the link when identifying the importance of a bank, the *Eigenvector* does not. For this reason, this study focuses on the *Pagerank* measure. Stress in any bank with a high *PageRank* score can easily be transmitted to the rest of the market.

An additional critical measure of the interbank network structure is the *assortativity measure.* This captures the affinity between banks or the likelihood of a bank to trade with those of its type or those carrying similar characteristics. This measure is strongly related to the degree metric. A network is said to be assortative if high (low) degree banks form links to other high (low) degree ones (Newman, 2003) and disassortative, otherwise. In an assortative network, there is more resilience against directed attacks on high degree banks (hubs) compared to disassortative networks that depict some vulnerability. Conversely, disassortative networks are more efficient in transmitting information/liquidity and therefore, supporting effective pricing. However, available literature points to the existence of both assortative and disassortative features in every market, but their effect on stability and efficiency of liquidity distribution and its pricing would differ (Jackson, 2008).

Nonetheless, various studies have shown that interbank networks are disassortative, a fact that seems to account for the often-observed core-periphery structures (see for instance, Craig and von Peter, 2014; Fricke and Lux (2012; and Brede et al., 2009). They argue that the prevalent core-periphery structure is an accommodation between network efficiency and resilience. This finding of disassortativeness (particularly in developed economies' markets) seems to be quite common and thus emphasizes the importance of identifying the centrally important banks/hubs.

In this study, we compute the measure of assortativeness as suggested by Newman (2003), by examining the correlation (Pearson's) measure (r) of the degree of a bank in each connected pair. Positive values of *r* indicate that the network's pairs have similarity in degree, while negative values indicate divergencies. Being a correlation measure, $r\epsilon\ [-1,1]$. When $r = 1$, the network has perfect assortative mixing patterns, while it is completely disassortative in the case $r = -1$. Negative assortativity of a financial network is often associated with the existence of hubs or money centers. A more detailed description of this network measure and its importance for the interbank market is also provided in *Appendix B.*

4.0 Discussion of Results

Considering the magnitude of data involved, the analyses have been done on a quarterly basis spanning the period Q1: 2013 to Q4:2020, covering two of the three regimes discussed. We examine the time series evolution and tease out the persistent trends in the measures of the interbank market network structure. Individual measures of the network structure were computed, as described in section 3 (*and appendix B*), and the results are summarized and discussed per construct. Graphs are deployed to visualize the evolution of the measures of network structure.

4.1 Measures of Network Centrality

Degree and Strength

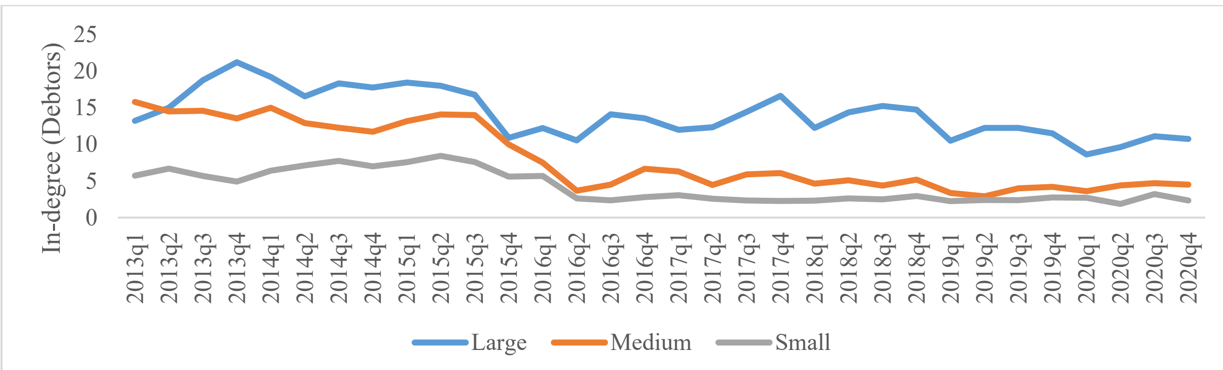
The simplest and most common measures of centrality of a bank within a network is its *degree* and *strength*. The degree measures are examined to obtain information on the roles played by the market participants. Banks with higher degrees and strength are considered to be closer to the center of the lending/borrowing network, and therefore are interpreted as the most important players within the interbank market. Figures 2 and 3 show the evolution of the average in- and out-degree measures based on bank tiers.[19]The in-degree represents the number of banks that have

[19] Bank tiers are based on the Central Bank of Kenya's classification.

funded bank i in the market (reflecting funding diversification), and the out-degree denotes the number of banks that bank i has invested in (investment diversification).

Based on the findings displayed in Figure 2, it is evident that large banks are the most connected as debtors, while the small banks have the least funding diversification. On average, only 7 banks were exposed to small banks between 2013 and 2015, compared to 18 and 14 banks for large and medium banks, respectively. This reflects differentiated access to funding opportunities that banks, based on their size, are presented with. However, as counterparty risk assessments were tightened in late 2015/ early 2016 following the collapse of the two medium-sized banking institutions, the general level of funding diversification declined, and more so for the medium-sized banks. The interest rate caps in September 2016 may have sustained this behaviour.

Figure 2: Evolution of in-degree (funding diversification) by tier group



However, on the lending side, small banks were, on average, just as diversified as the larger banks before the general drop in 2015q4 (Figure 3). The market instability created by the collapse of the two institutions between late 2015 and early 2016 is associated with a general decline in investment diversification, more evident among the smaller banks that preferred to remain liquid. Generally, the market remained dominated by the large banks, especially on the borrowing side (Figure 4).

Figure 3: Evolution of out-degree (investment diversification) by tier group

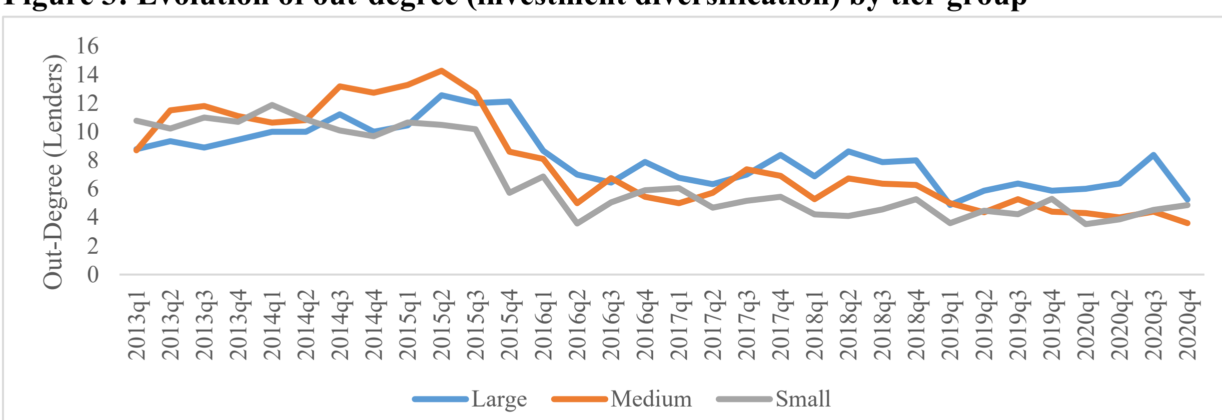
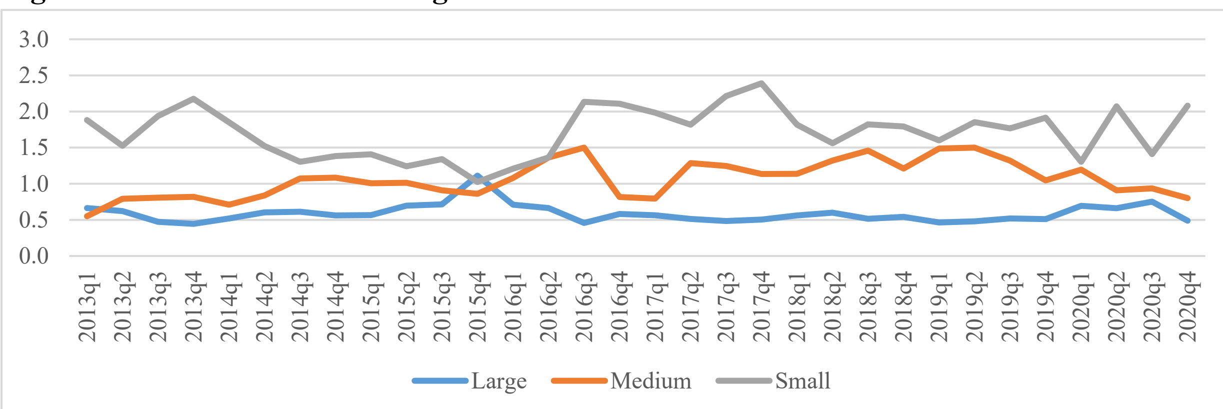


Figure 4 shows the ratio of the out-to in-degree, that is, the ratio of investment to funding diversification. The out-degree for small banks is, on average, about 1.7 times higher than the in-degree. This means they trade with more counterparties when lending liquidity than when borrowing, which can be attributed to their lack of power to choose those that can lend to them. This feature appears evident even for medium-sized banks, particularly from 2016q3 onwards, coinciding with the capping of the interest rates and the period following the placement of the two medium-sized banks, which were active participants in the interbank market, under statutory management. On the contrary, large banks have more creditors than debtors, as this ratio remains at about 0.6 throughout the period, reflecting their sustained market power (to obtain funders) throughout the study period.

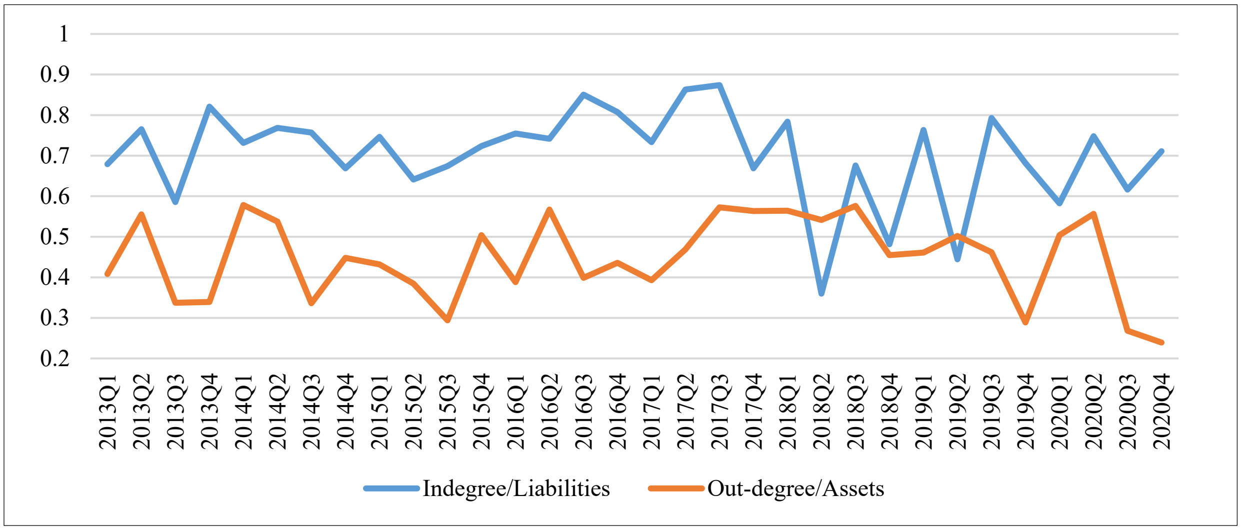
Figure 4: Ratio of Out-to-In-Degree



These findings are consistent with those of other studies that have explored interbank bilateral exposures from the perspective of bank behavioral preferences, as well as some that have examined such relationships in times of crisis. Bech and Atalay (2010) observe that, while small banks in the US overnight interbank market tend to be net lenders, large banks tend to be net borrowers. However, Cocco *et al.*(2009), in examining the Portuguese interbank market, provide additional insights on the dichotomy between small-and large-banks' exposures, noting that small banks rely on large banks to borrow funds, while large banks tend to hold consistent relationships with familiar counterparties because of the lower interest premiums they can afford. For the Kenyan case, large banks borrow more (than they lend) from a large number of creditors, mostly smaller banks.

A few additional insights can be drawn from examining the relationship between *degree* and *strength*. Figure 5 shows a high correlation between in- degree and liabilities (in-strength). The higher correlation between in-degree and in-strength suggests that banks that had large value interbank liabilities had the liabilities with many counterparties. As such, the risk of default by one of these banks would thus be spread to many counterparties. The size of the contagion would, however, be contingent on the impact the non-repayment by such a bank would have on the ability of its creditors to meet their interbank obligations, as well as the size of the bank affected by the initial shock, with smaller banks affected more than the larger banks (Iyer & Pedro, 2011). For the case of Kenya, the capping of the interest rates in September 2016 appears to have affected this relationship, evident in the increased volatility of the in-degree/liability ratio from 2017 onwards.

Figure 5: Correlation between the Degrees and Strength



The changes observed in the interbank market from 2016 are consistent with those observed in advanced economies after the global financial crisis. It was nearly impossible to restore stability in the interbank lending markets despite efforts by central banks to inject massive amounts of liquidity in these countries. While Heider *et al*. (2009) attribute this rigidity to liquidity hoarding by banks, mainly due to challenges among banks at the time to adequately conduct counterparty credit risk assessments, Afonso *et al.* (2011) provided evidence against liquidity hoarding, and argued that heightened concerns about counterparty risk reduced liquidity and increased the cost of finance for weaker banks, leading to an increase in the interest rate spreads between the larger and the small banks.

Similarly, the observed rise in interest spreads in the Kenyan interbank market after the collapse of the two banks in 2015-2016 is consistent with these findings (as shown in Figure A3 in the appendix), indicating that concerns about elevated counterparty risk may have triggered an increase in the cost of finance for weaker banks.

Network Density and Path Length

From the analysis above, it is observed that trading activity and links in the interbank market declined in the third regime. This is also demonstrated by the decline in the network density measure from an average of 0.25 to about 0.15 (Figure 6). This depicts increased sparseness of the network as some banks suspended trading with some of their counterparts. This finding is akin to that of Brassil and Nodari's (2018) for the Australian interbank market, who observed a sparse density (0.25) and a significant decline in lending relationships after the global financial crisis that tightened counterparty risk assessments.

For the Kenyan case, before the markets could recover from the distortions caused by the collapse of the two institutions, the interest rate capping law was introduced in late 2016, which is noted to have further undermined risk pricing (CBK, 2018).[20] The interest controls hindered recovery in the interbank trading as reflected in the trend of the density after 2016q3. The declining density is also associated with longer *path lengths*.

Figure 6: Density of the Interbank Market, 2013-2020

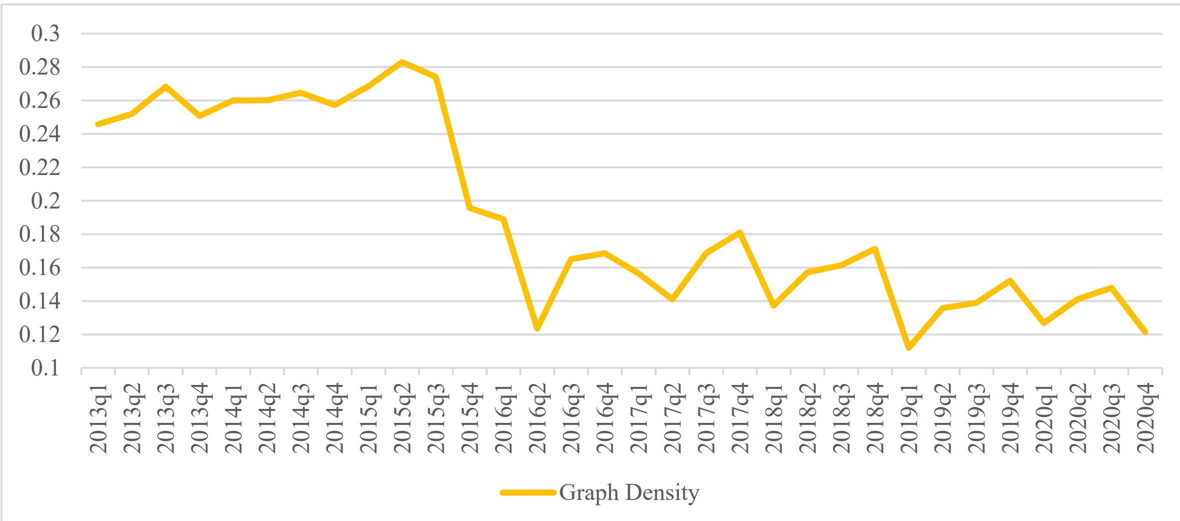


Figure 7 shows the estimated average shortest and maximum path lengths (diameter) connecting two banks as having also increased slightly from 2016 onwards. While the average shortest path stood at about 2 links (*circa* one bank in-between); the maximum average distance increased from 3 to about 4 steps. Even with the increase in network diameter, the fact that the average short path length remained at about 2 links implies that contagion could still spread with ease. At the maximum, each bank could be linked to all other banks in the network in 4 steps (with 3 banks in between).

Consistent with the evolution of the market network density, the clustering coefficient, which reflects the level of connectedness of the network, also declined from an average of 0.4 before 2016q1 to an average of 0.20 thereafter, with some elevated volatility (Figure 8). This implies that the probability of two banks that share a trading partner having a trading line among themselves declined from 40 percent to 20 percent. The notable decline, particularly after the 2016 q1 and 2016q3 follows the observed trend in the density, which coincides with the collapse of the two

[20] See arguments by a CBK paper on the Impact of the Interest rate Capping on the Kenyan Economy (2018) (available via: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/viewer.html?pdfurl=https%3A%2F%2Fwww.centralbank.go.ke%2Fwp-content%2Fuploads%2F2018%2F03%2FSummary-of-the-study-on-Interest-rate-Caps_February-2018.pdf&clen=585544&chunk=true)

banks and the implementation of interest rate capping, respectively. These two events triggered credit line reassessments in the market, leading to the loss of credit lines for some banks.

A decline in the clustering coefficient implies that a majority of banks had trading neighbours who had fewer options. This would confer increasing importance to some banks in the network. A further decline in the clustering coefficient is noticeable in 2019q1, a phenomenon that may be attributed to tight liquidity conditions in the market that arose from a Ksh 60 billion bond floated about this time and payments of quarterly taxes. The downward trend was maintained until late in 2019q4 when the interest rate capping law was repealed, and it started to edge upwards.[21]

Figure 7: Network Diameter and Average Shortest Path Length

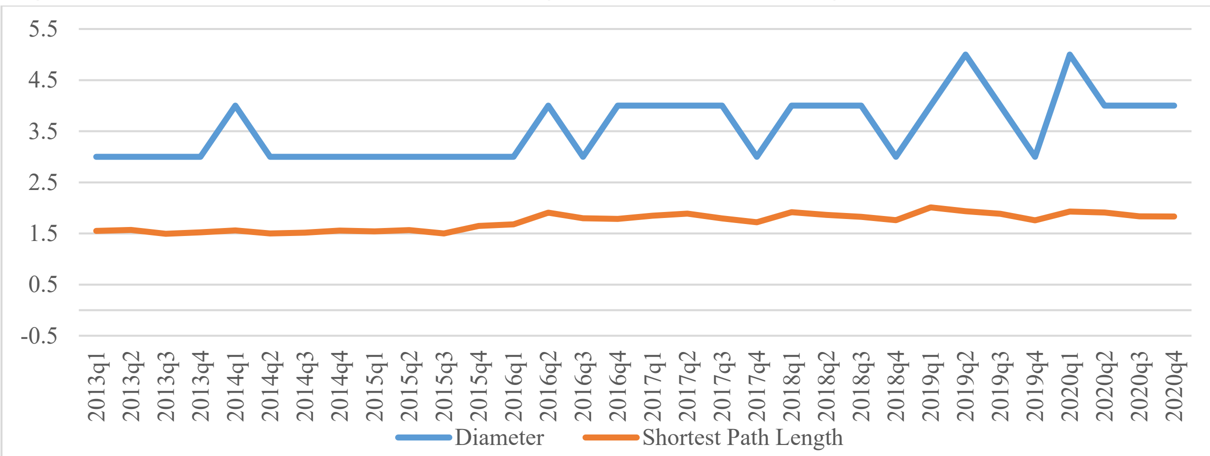
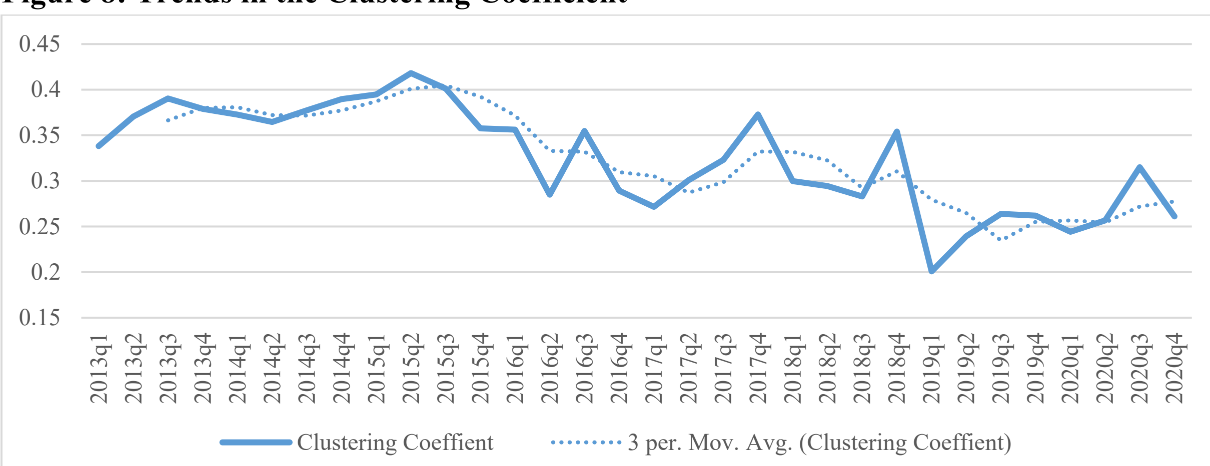


Figure 8: Trends in the Clustering Coefficient



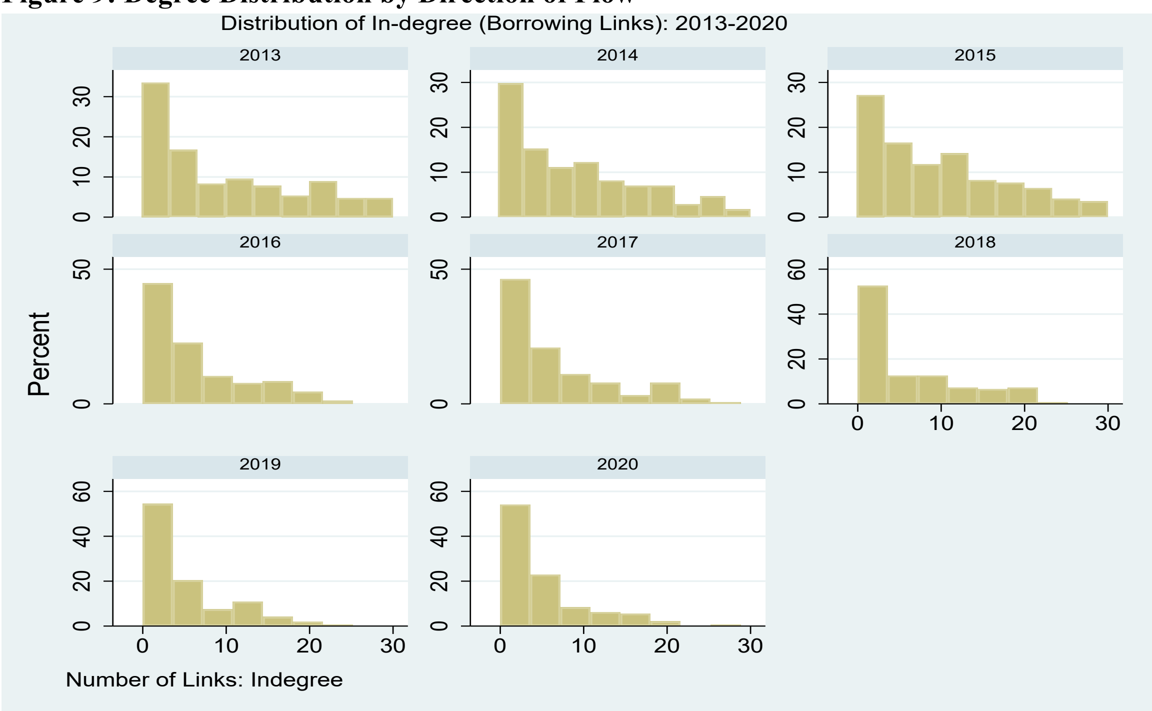
[21] An increase in the indicator is visible thereafter although the emergence of COVID-19 in early 2020 may have moderated the recovery. The first case of COVID-19 infections was reported in Mid-March 2020.

4.2 Measures of Degree Distribution

The analysis of the interbank market microstructure can be enriched by examining the distribution function of the in- and out-degree. This helps in ascertaining the concentration of borrowing/lending relationships in the interbank market and identifying any significant movements/changes in the distributions over time. The evolution of degree distribution has implications for the stability of a network.

Figure 9 shows considerable asymmetry in the degree distribution, especially for the borrowing transactions. As of 2013-2015, about 30 percent of the banks had 3 or fewer connections, while about 5 percent of them were connected to almost 30 banks (based on analyses of the right tail of the distribution). This skewness worsened over the years, so that by 2017 and 2018, almost 50 percent of the banks had 3 or fewer connections. Although the out-degree distribution measure tends to be more evenly distributed, the distribution also becomes slightly right-skewed from 2016 onwards.

Figure 9: Degree Distribution by Direction of Flow



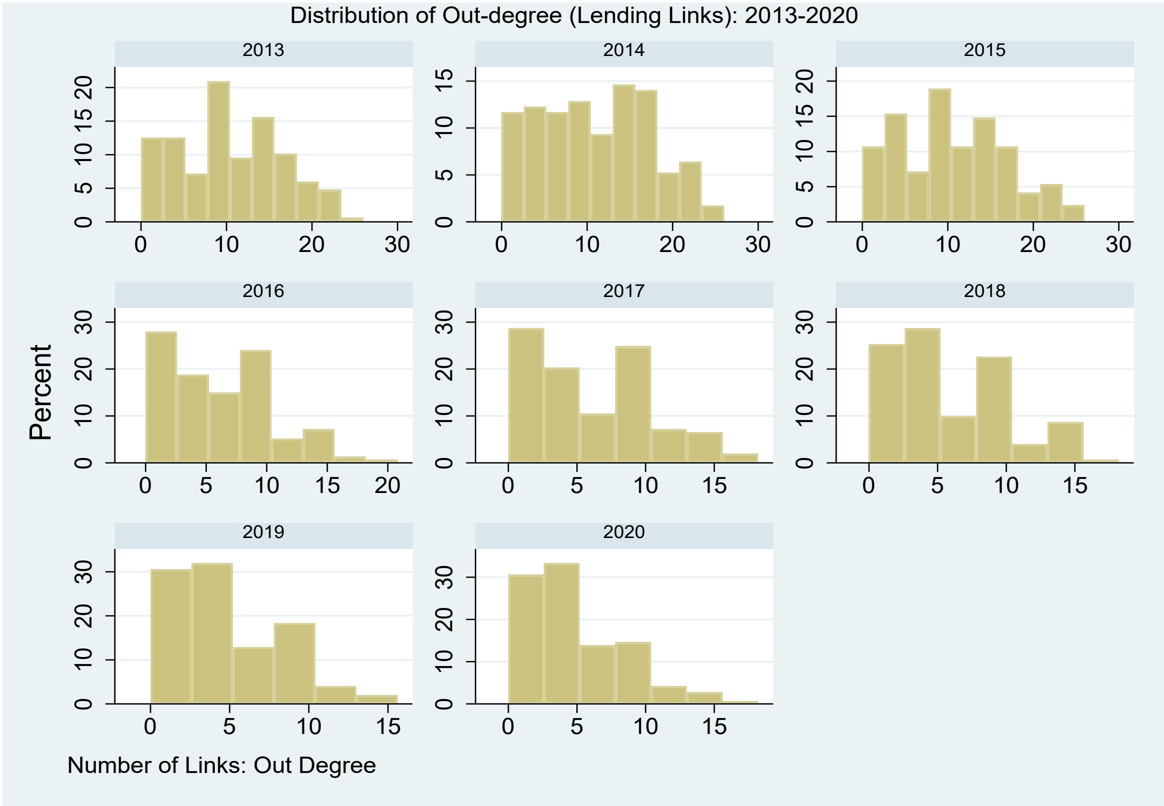
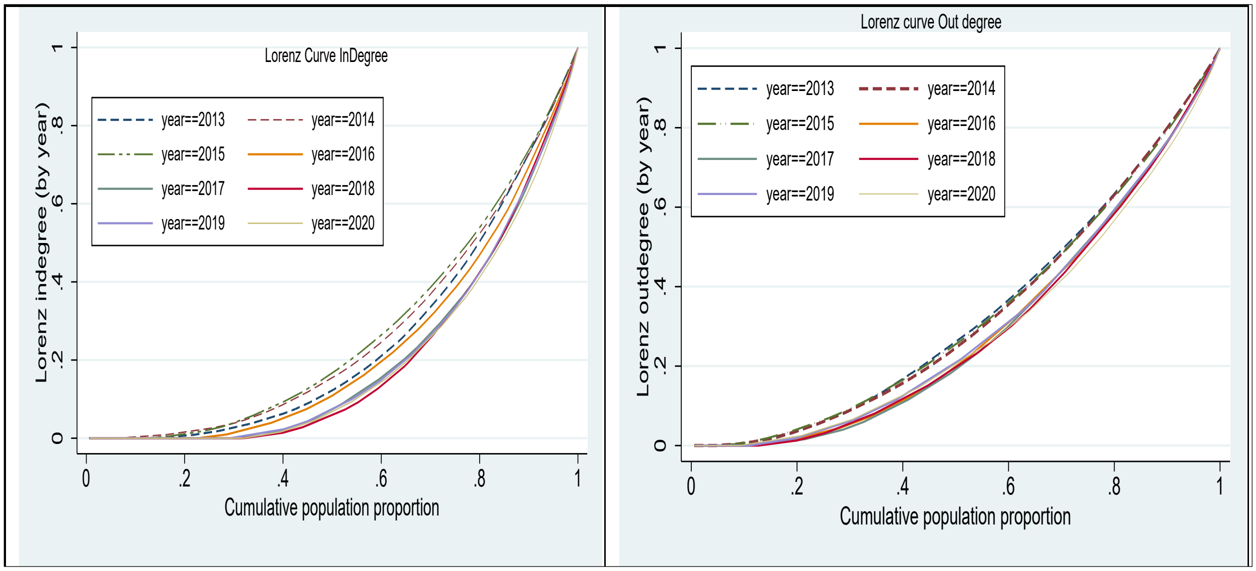


Figure 10 also reveals similar information using the *Lorenz* curve of the degree distribution. The in-degree is much more unequal than the out-degree, and the concentration increases over the years, especially from 2016, with 2018 recording the highest (the outermost curve) for in-degree distribution.

Several studies have shown that many interbank networks have similar degree distribution with links concentrated in a small number of banks (see for instance, Fricke and Lux, 2013 for Italian overnight market; Boss *et al*., 2004 for Austria; Soramäki *et al*. 2006 for the Fed, Imakubo & Soejima, 2006 for Japan, and Martínez-Jaramillo *et al*., 2014 for Mexico). The concentration of links on a smaller number of nodes gives rise to hub-like nodes in the network. One important feature of such networks is that they can be described as robust, yet fragile (Albert *et al*. 2000; Newman, 2003). This is because random disturbances are easily absorbed, whereas targeted attacks on the hub-like nodes have a significant effect on the entire network.

This highlights an important feature for the attention of policymakers. That is, while such a network might experience long stable periods during which disruptions are confined to peripheral banks and can thus be absorbed easily within the entire system, such periods could be a misleading indicator of the overall stability of the system. This is because it is only when a hub (a bank with many connections) is subjected to stress that the true network dynamics emerge (Haldane, 2009). In light of this, this study provides a detailed visualization and characterization of the interbank market network to be able to identify such hub-like banks.

Figure 10: Lorenz Curves for In- and Out- Degree Distribution, 2013-2020



4.3 A Description of the Network Microstructure

A more detailed visualization and characterization of the interbank market for each year from 2013 to 2020 are shown in Figure A5 in the Appendix. The analysis exploits the notion of community/clique detection in complex networks, consistent with the approach of Newman and Girvan (2004). Each community is defined as a sub-graph whose nodes have many interconnecting links, but are sparsely connected with the rest of the network. The revealed patterns help uncover hidden relationships within the network.

For ease of identification, each cluster of banks is marked in a different colour. The algorithm used to extract the clusters identifies communities of banks that have at least four members linked to each bank. Knowledge of the cliques[22] can help predict behaviour and the roles of individual banks in the network, which is their "structural signatures". Based on the charts in Figure A5 in the appendix, a decentralized network[23] is observed, characterized by the existence of several hubs (core) and periphery banks.[24] These are the 'wildcards' in Column 1, as Column 2 shows the expanded cliques.[25]

It is also observed that the density within each cluster is much higher than the average for the entire network. For instance, the average density for the largest cluster is about 78% over the study

[22] A clique represents a group of banks with known characteristics/behaviour and supports a description of the nature of segmentation that exists in the interbank market.

[23] A decentralised network is one without any overall dominant central hub. But instead, a network that has some nodes with a higher degree of connectivity than others, giving the overall topology of local clusters with local hubs. Although there may be some overall centre to it, the network is still defined largely by what is happening at the local level (Baran, 1964).

[24] A hub is represented by a subset of nodes which are highly connected with other hub members, while the periphery banks tend to have very few links with the rest of the market.

[25] The inter-group links have been omitted to de-clatter the graph.

period, and at least 70% of the banks can reach every other bank in that cluster through a borrowing and lending link. This implies that reciprocity is quite high in the largest cluster over most of the study period. These clusters are highlighted in bold in Table 1 and can generally be considered as the core of the interbank market in each period.

Table 1: Most Connected Cluster (core) of the Interbank Market, 2013-2020

	2013	2014	2015	2016	2017	2018	2019	2020	
Number of Banks Trading									Average
Cluster 1	13	17	17	12	11	11	9	9	
Cluster 2	7	4	5	7	4	5	5	4	
Cluster 3	4	4	4	4	4	4	4	4	
Cluster 4	4	4	4	4	4	0	4	0	
Cluster 5	4	0	0	0	0	0	0	0	
Periphery	11	15	13	15	19	19	18	20	
Cluster Density									
Cluster 1	**0.69**	**0.74**	**0.85**	**0.82**	**0.82**	**0.71**	**0.81**	**0.78**	**0.78**
Cluster 2	0.79	0.92	0.65	0.69	0.50	0.75	0.55	0.67	0.69
Cluster 3	0.67	0.92	0.83	0.50	0.58	0.58	0.50	0.58	0.65
Cluster 4	0.58	0.67	0.75	0.58	0.75	0.00	0.58	0.00	0.65
Cluster 5	0.83								
Reciprocity									
Cluster 1	**0.56**	**0.64**	**0.82**	**0.78**	**0.78**	**0.59**	**0.76**	**0.71**	**0.70**
Cluster 2	**0.73**	**0.91**	0.46	0.55	0.00	0.67	0.18	0.50	0.50
Cluster 3	0.50	0.91	0.80	0.00	0.29	0.29	0.00	0.29	0.38
Cluster 4	0.29	0.50	0.67	0.29	0.67	0.00	0.29	0.00	0.45
Cluster 5	0.80								
Proportion of Amount Lent (%)									
Cluster 1	**24.9**	**41.3**	**34.8**	**76.1**	**43.2**	**42.3**	**54.7**	**25.1**	**42.8**
Cluster 2	**33.2**	6.1	12.2	3.9	5.7	0.9	2.5	1.5	8.2
Cluster 3	13.0	23.5	2.5	4.4	7.1	6.2	6.1	2.1	8.1
Cluster 4	4.4	4.6	29.3	1.6	1.4	0.0	2.3	0.0	7.3
Cluster 5	4.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.7
Periphery	19.7	24.4	21.1	14.0	**42.6**	**50.6**	**34.5**	**71.3**	34.8
Proportion of Amount Borrowed (%)									
Cluster 1	**46.9**	**74.4**	**63.8**	**77.8**	**83.5**	**80.6**	**67.1**	**75.2**	**71.2**
Cluster 2	2.4	9.0	19.8	1.2	3.6	2.7	4.0	5.3	6.0
Cluster 3	3.6	2.8	8.1	2.6	4.3	5.4	18.5	3.9	6.1
Cluster 4	41.4	1.3	2.2	7.3	1.0	0.0	7.1	0.0	10.0
Cluster 5	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.3
Periphery	4.4	12.5	6.2	11.1	7.7	11.3	3.3	15.6	9.0
Spread % (Lending - Borrowing Rate)									
Cluster 1	-0.16	-0.14	-0.48	**0.39**	**0.22**	**0.65**	**0.48**	**0.32**	
Cluster 2	**0.27**	**0.11**	-0.83	-0.07	0.14	0.21	0.60	-0.27	
Cluster 3	0.07	0.23	-1.66	-0.55	-0.95	0.47	-1.08	0.59	
Cluster 4	-0.18	0.19	-0.11	0.22	0.37		0.79		
Cluster 5	-0.06								
Periphery	0.31	-0.04	3.30	-0.46	-0.36	-0.67	-0.46	-0.14	

Banks in the large clusters tend to be net borrowers, accounting for about 70% of funds borrowed and about 43% of the lending over the study period. However, this pattern was disrupted during the period of market instability in 2016. The 12 banks in the largest clique hardly traded with the rest of the market, as about three-quarters of the borrowing and lending transactions were solely within this clique of banks, depicting entrenched segmentation.

Regarding the lending rates, banks in the largest clique depicted some market power, reflected in the average positive margins most of the period, compared to the rest of the market, as indicated by the interest rate spreads in Table 1. Conversely, banks in the periphery that are net lenders tend to borrow at a relatively higher cost than they lend. A close examination of the lending and borrowing patterns shows that these banks mainly lend to the core cluster. The fact that the interest spreads generally widened after 2016 is indicative of rising financing costs for weaker banks as counterparty risk increased.

4.3.1 Identification of Important Banks and Changes in Centrality over Time

The clustering shown in Figure A5 in the appendix also allows identification of the most important actors in the network over time. These are best identified in column 2 by the size of the node (representing a bank) as measured by the betweenness centrality measure that depicts the strategically linked banks.

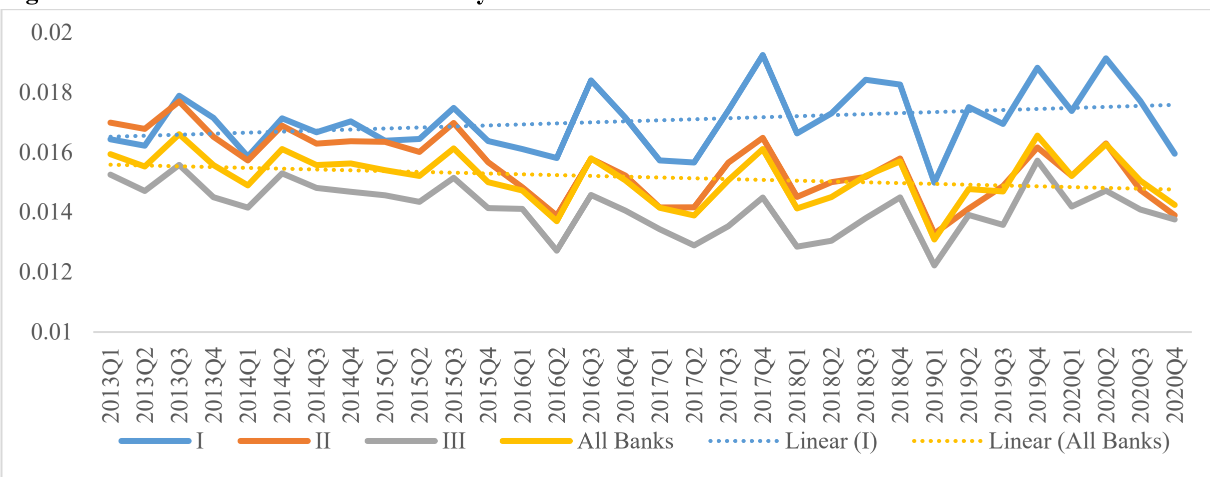
Here, we proceed to identify the particular banks in each trading year around which others in the clique cluster or the most central in each clique. For instance, in 2013, the four banks cluster around bank number 46 (the dark green clique), as 13 banks in the largest clique (navy blue) cluster around bank number 12 and number 4; the right blue clique around bank number 7, and the light green clique with 4 banks cluster around bank number 23. These banks have the highest betweenness centrality and in-degree measures, and the lowest clustering coefficient in each clique. Their low clustering coefficient can also be explained by the fact that they have many links to the peripheral banks. Removal of such a bank from the network would significantly reduce the trading options for other banks in its sub-network. We also find a high betweenness centrality in some of the periphery banks because their removal would cut off some other periphery members from the network. For instance, bank number 22 is very central since it is only through it that bank 28 connects most of the time to the rest of the market. While Bank 22 cannot be considered as central based on its interconnectedness, it is much more important to the network because of this aspect. A deeper scrutiny of this bank's business model indicates that it serves as a niche market.

The evolution of the cliques between 2013 and 2016 shows that the bank clustering was quite stable, just as was the average density in this period. Thereafter, the number of banks forming the major/core clique declined from 17 banks in 2015 to 10 by 2017; a trend consistent with that of Brassil and Nodari (2018) for the case of the Australian interbank market when counterparty risk assessment was tightened. The changing market structure is also depicted by the other measures of bank centrality, that is, the closeness and betweenness centrality.

Despite a notable decline in the average closeness centrality measure in the third regime (Figure 11a), the critical market players varied as the cohesiveness of the large banks increased. The trend of betweenness centrality across the bank tiers, shown in Figure 11(b), indicates that as the average market density declined, the large-tier banks appear to have become very central to the network, since their average betweenness centrality substantially increased, while that of the whole market declined. The market seems to have split into two main segments after 2016q2; one for large banks and the other for the rest of the banks.

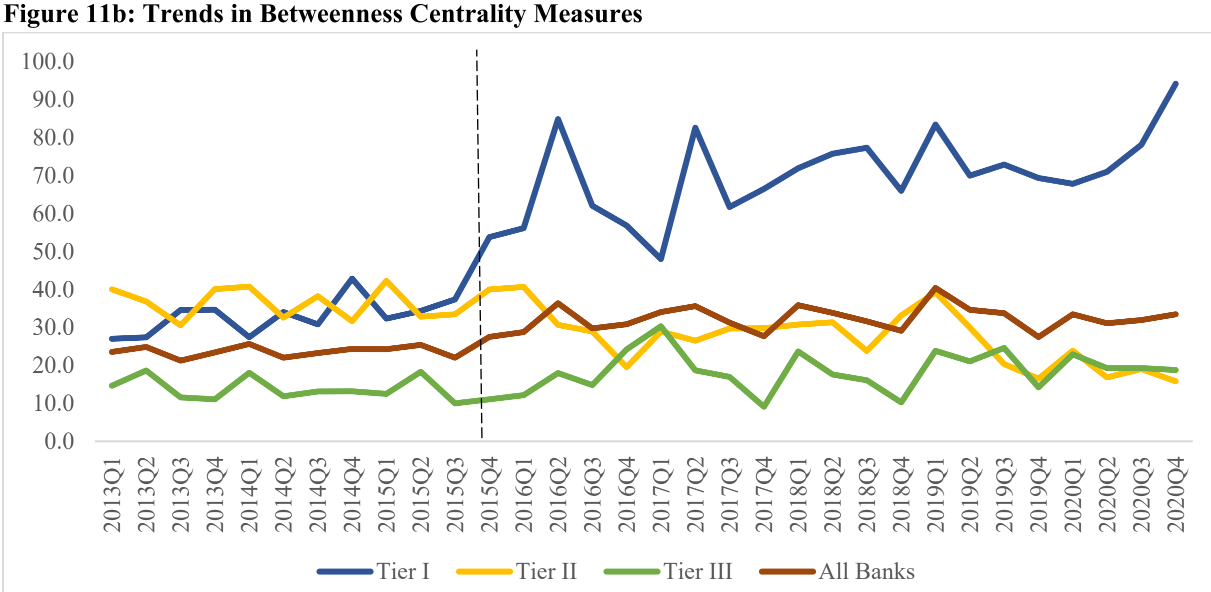
The specific banks whose importance rose over time can also be identified by examining the association between the various measures of centrality (*Figures 12a and 12b, and Figures A6 to A8 in the Appendix)*.

Figure 11a: Trends in Closeness Centrality Measures



Note: I, II and III respectively represent the closeness centrality measures for the large (Tier 1), medium (tier 2) and small (tier 3) bank tiers.

Figure 11b: Trends in Betweenness Centrality Measures



Figures 12a and 12b show the relationship between the local clustering and the in-and out-degree for each bank by tier group. Banks located in region *A* have a small number of connections (degrees) but tend to have counterparties that are more connected to each other, as the clustering coefficient measure is higher. These represent the highly connected banks in the periphery, which also link this region to the hubs, for instance, Bank 22, as depicted in Figure A6 in the appendix. Banks located in area B have a small number of transaction partners and a low clustering coefficient. These banks possess very few links to the hub and form part of a local, small-scale, fragmented network in the periphery.

Banks located in area C contain some of the most centrally located banks in the interbank market, given their high measure of the betweenness centrality (See Figure A7 in the Appendix). They have a high number of links but a low clustering coefficient, which is indicative of their importance in their neighborhood. A closer examination of each of the cliques (Figure A5 in the Appendix) shows that banks around which other market players cluster are found in this area. These banks also constitute the major borrowers in the market. The large banks (labeled 1) dominate area C from 2016 onwards. Banks that specialize in lending are found in area C, shown in Figure 12(b), with more of the small banks (labelled 3) appearing in this area. However, we also find some large banks here, especially in the third regime – that is, after October 2015. A closer scrutiny of these banks reveals that the large banks are local banks that intermediate liquidity from large bank counterparts to smaller banks in the periphery. This may highlight the uniqueness in terms of the operational framework of local large banks in their treatment of counterparty risk, which allowed them to intermediate liquidity from their large counterparts to banks in the periphery. All banks that acquired others are generally found in area C, which may point to the market stabilising role of this move, given the changing operating environment.

Figure 12 (a): Clustering Coefficient versus In-degree by Tier Group

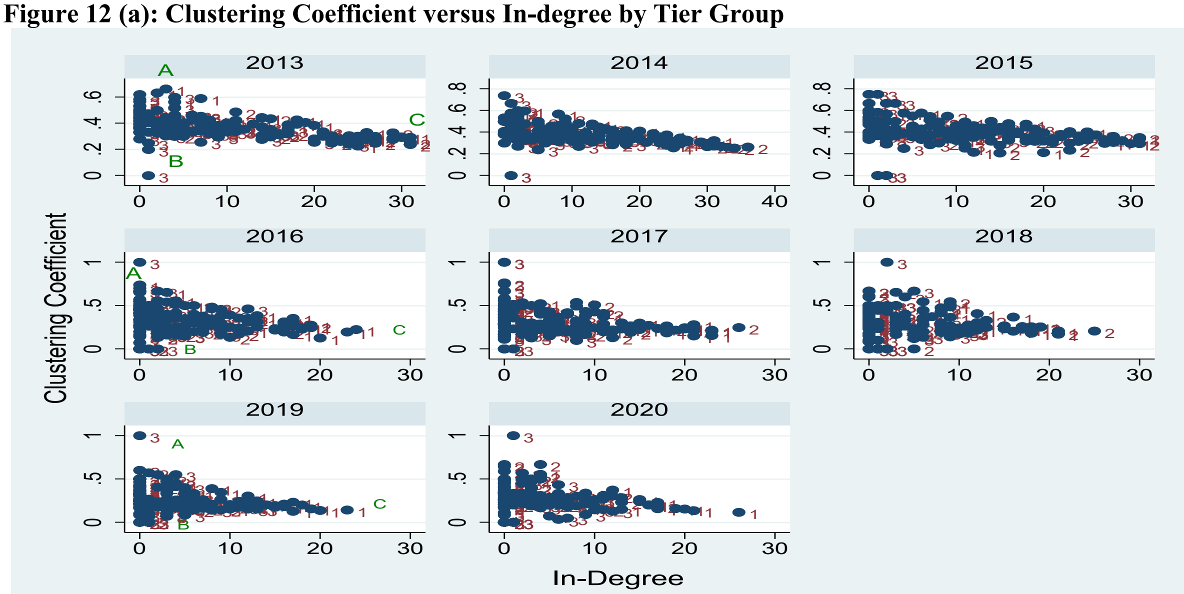
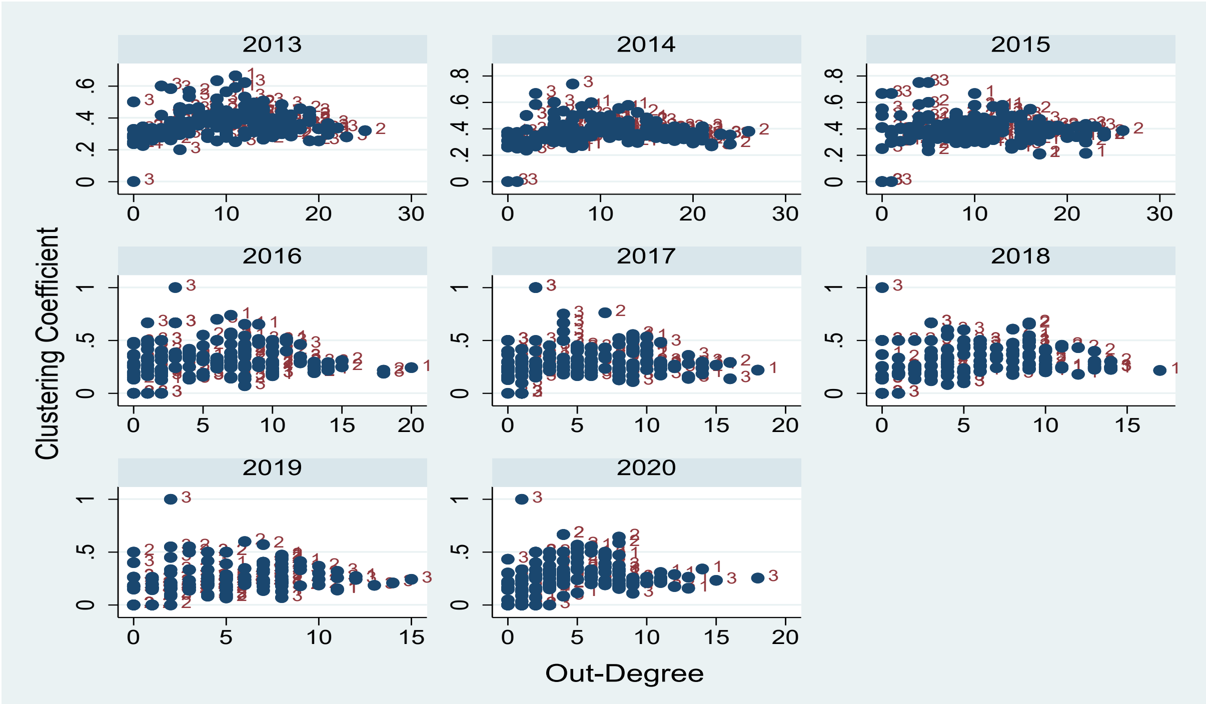


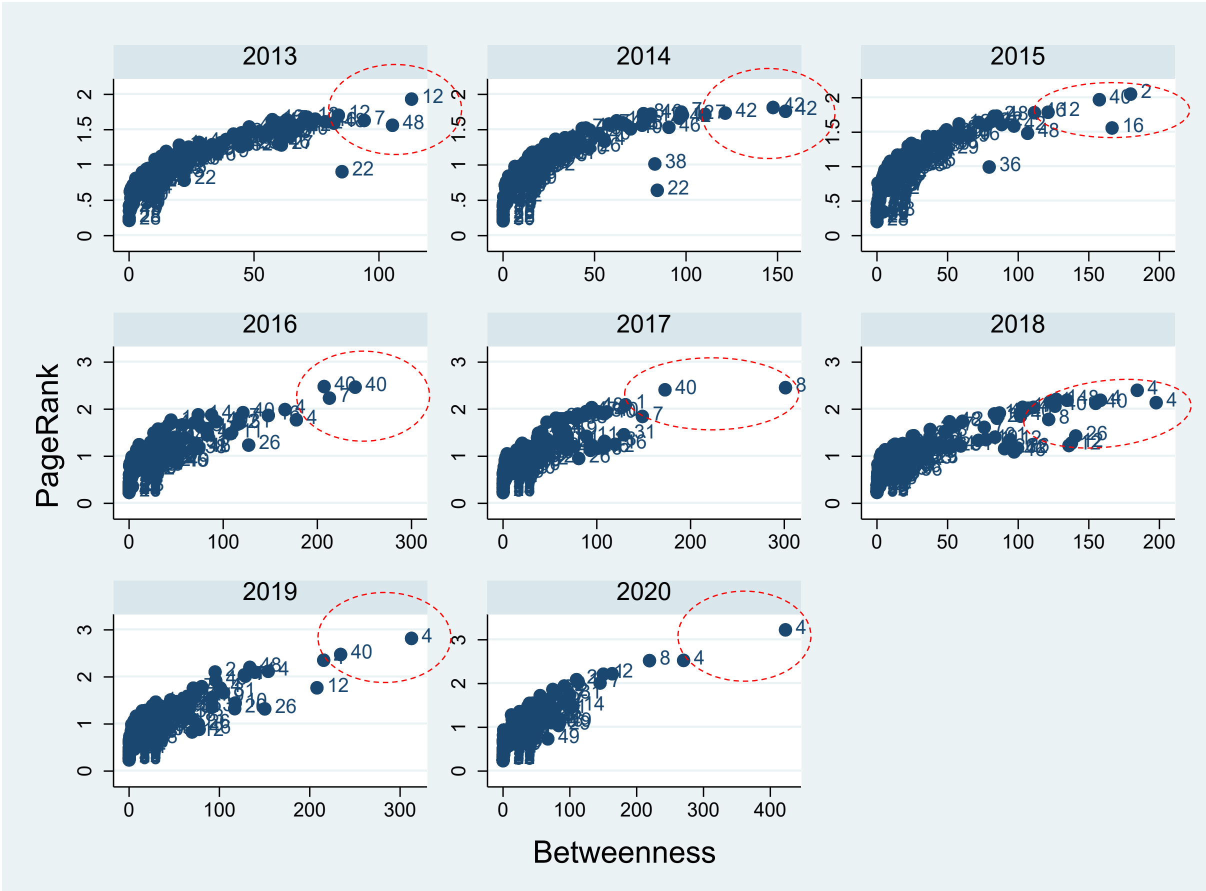
Figure 12 (b): Clustering Coefficient Versus Out-degree by Tier Group



PageRank

The centrality of the banks in area C above is also demonstrated by a plot between the *PageRank centrality* and *betweenness centrality* (circled banks in Figure 13) measures (Figures A7 and A8(a & b) in the Appendix). The importance of the PageRank measure lies in the fact that, unlike other centrality measures (e.g., degree and betweenness), it considers the relevance of neighbours to determine the importance of a bank (node) in the network. Most influential banks, i.e., those with high PageRank measure, also have high betweenness centrality. This implies that distress in any of such banks can easily be transmitted to the rest of the market.

Figure 2: PageRank and Betweenness Centrality



Network Affinity/Assortativity

The study analyses assortativity measures of banks in terms of their degree, that is, whether banks tend to trade with those with similar linkages or otherwise, and if so, in which direction. As noted in section 3.2, this notion has implications for the network stability and efficiency in the distribution of liquidity. Figure 14(a) shows the trend of the lending and borrowing affinity measures. Negative values show a disassortative structure (where banks tend to have relationships with those not necessarily of their type), while positive values show an assortative structure. With respect to the borrowing affinity, it is evident that the market was disassortative over the period 2013 to 2016q2, despite the financial instability caused by the collapse of the two banks and foreign exchange market volatilities. During this period, a bank has a high degree of counterparties with few borrowing links.

However, after the second quarter of 2016, the values became positive, just as was the case for lending links, whose values were positive during most of the study period. Here, the market became assortative; a development that is linked to the introduction of interest rate capping in September 2016, which entrenched counterparty risk assessments and pushed banks to trade more with those of their type in terms of risk characteristics. As such, we observe a market that was disassortative amidst shocks before interest rate capping, shifted to become assortative during the interest rate capping period, so that those with high degrees tended to trade with those with high degrees and vice versa. Like social networks, banks could only trust their type after interest rate capping was implemented.

An assortative network structure implies that loosely connected banks, revealed in the clustering analysis above, would therefore rarely lend among themselves. For the highly connected banks, the risk of lending to each other was shared among many lenders. While this may have been desirable for the stability of the interbank market, it may not have been the most efficient way of distributing liquidity within the market, as those with few links were rationed out completely; a scenario evident over the period 2016-2019 [the high skewness depicted in Figures 9 and 10]. As a mitigation measure, the CBK provided liquidity to the underserved banks during this period.

Figure 14(a): Trends in Network Assortativeness (In-In and Out-Out)

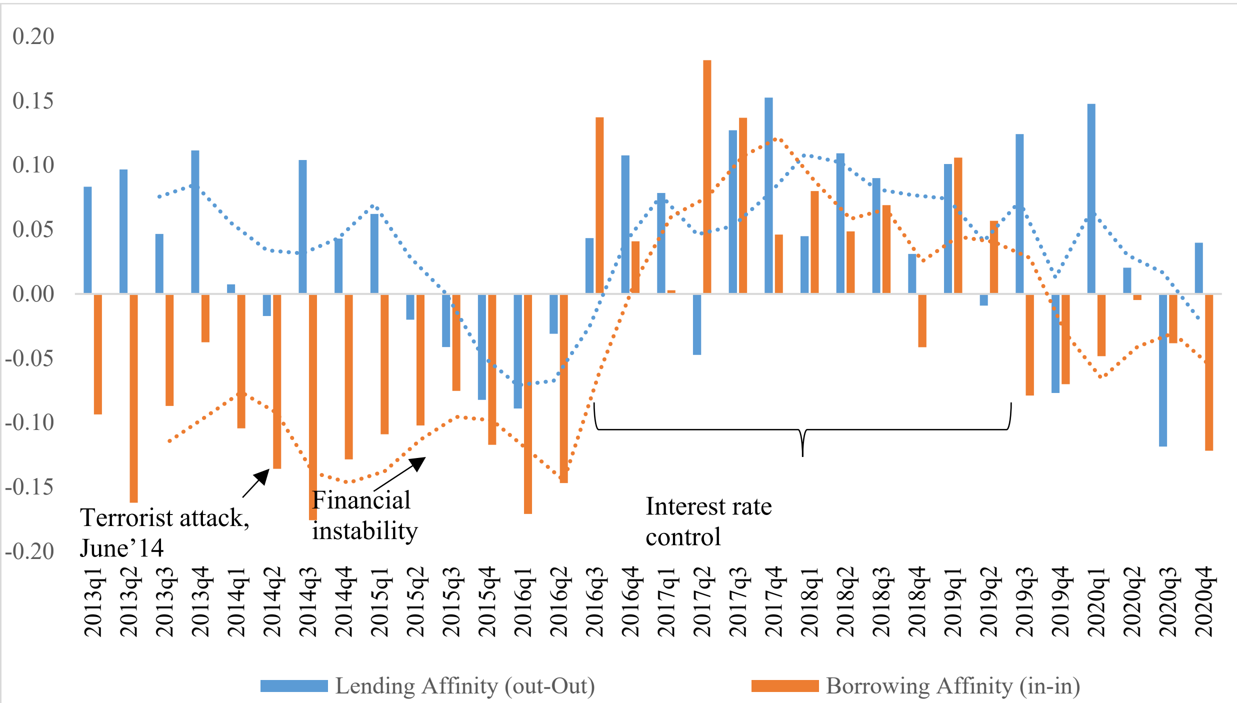
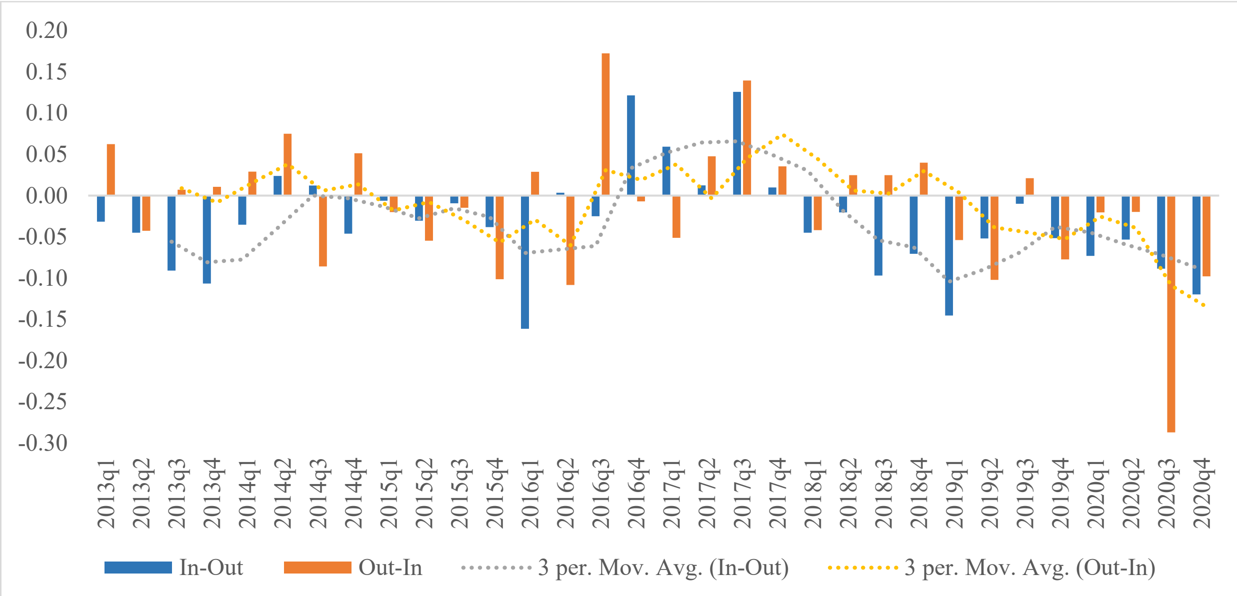


Figure 14(b) shows trends in the in-out and the out-in degrees of assortativeness. On average, banks with many borrowers tended to borrow from banks with low in-degree, i.e., more disassortative when borrowing, which was indicative of banks that served as money centers. However, the out-in links tended to oscillate between positive and negative assortativeness but with a tendency to be more negative during a distressful period. In both cases, the tendency for the whole market to be assortative between 2016 and 2019 was still apparent. The market turns disassortative after the removal of the interest rate caps in 2019Q4. The seemingly increased disassortativeness in 2020 can be attributed to the COVID-19 pandemic that presented a stress-test to the banking sector resilience, altering the counterparty risk profiles as banks explored alternative models to remain afloat with liquidity, as overall credit risk increased.

Figure 14(b): Trends in Network Assortativeness (In-Out and Out-In)



5.0 Conclusions and Policy Implications

The study characterizes the evolution of the network structure measures of Kenya's overnight interbank market between 2013 and 2020 using daily trading data. Several measures borrowed from the network theory are computed on a quarterly basis and tracked over time to uncover several microstructure characteristics. The interbank market is characterized as a network where banks are regarded as nodes and the claims and liabilities between them are treated as links in a network. Applying network-based theory facilitated the examination of the topology and the evolution of the interbank market, analysis of the structural characteristics of the data relationships, which are valuable inputs for the appropriate design of the central bank's liquidity management actions, and enhanced resilience of the banking system.

Measures derived from the topology of the interbank network suggest that during the period covered by the study, large banks were the most connected as debtors, with the difference between tier groups becoming more pronounced after 2016. Beyond 2016, while the funding diversification of small banks worsened, the difference in investment diversification across bank tiers was not as pronounced. For small banks, their investment diversification was about 1.7 times higher than their funding diversification, implying that they were linked to the network more through lending than borrowing activities. This indicates that small banks, following the tightened counterparty risk assessments, engaged more in being liquidity suppliers than investing in alternative assets, as their counterparty risk status would not allow them to access borrowed funds in the interbank market. This highlights the vulnerability of small banks to shocks, and the fact that small banks are affected more by shocks than their larger counterparts; an argument consistent with that of Iyer & Pedro (2011).

Based on the distribution function of the banks' borrowing and lending links, it was observed that close to 40 percent of banks had less than 5 connections during the study period, and only 1.5 percent were connected to almost all other banks in the network. This was evident across most of the years covered by the study and reflects a disjointed interbank market network and the presence of money hubs/centers. This finding implies that while such a network might experience long periods of stability - particularly when disruptions are confined to peripheral banks - indicators of overall stability of the system during such episodes may be misleading. This is because, when a hub bank is faced with stress, it exposes the entire system's fragility. This may have been the likely scenario that unfolded in Kenya's interbank market, following the placement of two key players under statutory management between October 2015 and April 2016.

Analyses of the average path length, which is an indicator of the speed of contagion in the system, showed that even when two peripheral banks are not linked to the same hub bank, they can be linked via 2 to 3 steps, particularly because the hubs form a near-complete network. While this feature implies that the hub banks provide an efficient shortcut for peripheral banks to access liquidity in the network, it also indicates that contagion can spread with ease. This has adverse implications on the financial stability of peripheral banks in the event of a shock, particularly one hitting a hub bank. As a mitigation, the identification of the peripheral banks allows the central bank to target the peripheral players with liquidity and safeguard their survival during a shock.

Based on the analysis of the evolution of network density over the period, it was also observed that the network cohesion declined after 2015, which coincided with the collapse of two key banks in the network. Consistent with the decline, network clustering and closeness centrality generally also declined towards the end of 2015. The outcome of these changes resulted in large banks becoming more central (important) in the network from 2016 as counterparty risk assessments were tightened. This study establishes that the market was split into two: one for large banks and another for the smaller banks. The study also indicates that the systemically important banks use the *PageRank* centrality measure. The identification of the most central players in the interbank market can also inform central bank liquidity management strategies, particularly in targeting to quell industry liquidity distortions/imbalances employing the role of the most influential /connected players.

In addition, based on the measures of degree of assortativeness, on average, the Kenyan interbank market was largely disassortative during periods before and after interest rate controls. That is, there was evidence of trading across bank types, especially when banks were borrowing. A disassortative structure points to the existence of money centers. However, capping of the interest rates wiped out the gains that had been made by the market in allowing trading across bank types, significantly leading the network to an assortative structure, where banks retreated to trading extensively with counterparts only of their type (degree). While assortative trading yields a more stable network structure of the interbank market[26], it is inefficient in liquidity redistribution, as those with few links would be starved of liquidity. In this environment, the central bank (as it did) would have to support the liquidity distribution role of the interbank market, with targeted interventions on the underserved banks.

The above features of the interbank market network have several implications. First, the need to identify the most important players in the market, on both sides of the market, could inform the liquidity provision and redistribution strategies of the central bank, with favorable implications of supporting the effectiveness of monetary policy. Second, there is a need to continuously monitor the performance of highly connected banks – the hub banks, since their failure would have ramifications on the stability of the system. Third, there is a need to appreciate the nature and role of shocks in destabilizing the interbank market network and provide appropriate interventions to avert systemic instabilities. Fourth, it is evident that the market is highly fragile, especially given the way segmentation became more entrenched after the market instability caused by the collapse of two key institutions between late 2015 and early 2016.

In light of the above occurrences and vulnerabilities of the interbank market, we conclude that the market remains disjointed and fragile. In this regard, its liquidity distribution role is not fully developed to support an effective price discovery mechanism - a necessary and sufficient condition for the success of price-based monetary policy frameworks. Nonetheless, understanding the fragility of the market – such as the triggers of tightening/loosening of counterparty risk assessments- and the existing anchors to market stability – such as the clique formations and patterns of assortativeness- can be used by the central bank to minimize the risk of contagion and enhance resilience of the system in the event of a shock. As such, a lot more effort could therefore be directed at enhancing the resilience of the system by reducing counterparty risks and any incentives for clique formations, particularly during periods when there is a shock.

[26] Georg (2013) compares different interbank network structures and concludes that money-centre networks (a key feature for disassortative networks) are more stable than random networks.

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Appendices

A. Table A1: Chronology of Events / Announcements with relevance to the Interbank Market

YEAR	REFORM/ ANNOUNCEMENT
Feb. 2009	The Banking regulations on Credit Reference Bureau of 2008 became effective. The Regulations require all licensed banks to share information on Non-Performing Loans (NPLs) through a Credit Reference Bureau (CRB) licensed by CBK. The role of licensed CRBs is to collect, collate and process data received from approved sources of information and generate credit reports used by lenders. This was aimed at reducing the cost of credit in the market by minimizing information asymmetry.
1st Jan. 2011	Introduction of definition of "significantly undercapitalized" and "undercapitalized bank" in the Banking Act, the Central Bank Act and the Microfinance Act which would enable the Central Bank to determine whether an institution is weak in its capital base hence trigger prompt corrective action by CBK. In line with this, the Central Bank was given powers to take swift action when an institution exhibits weakness in its capital base or regulatory obligations.
29th Jun. 2011	CBK revised rules that guide the CBK window operations. In particular, delinked the CBR from being the operational interest rate for the CBK discount Window and set the discount Window rate at 8%. Also announced that this rate would be reviewed from time to time and posted on the CBK website daily at 9.00am. Also announced stiff penalties for banks using funds from the CBK Window to trade in the interbank market.
11th Jul. 2011 (*effective 12th July 2011*)	CBK further revised guidelines on the use of CBK discount Window, by requiring that: Banks' lending in the interbank barred from accessing Window funds on the same day; In a week (Monday-Friday) banks were restricted to borrow from the Window a maximum of their statutory cash reserves; Window rate reviewed downwards to 6.25% from 8.00% ; and banks were also required to consider liquidating their Treasury bills, bonds or foreign currency positions prior to resorting to CBK Window.
28th Jul. 2011	CBK announced MPC decisions which included: Retention of CBR at 6.25% and introduction of weekly (five day) averaging on cash reserves instead of the daily and banks were allowed to deviate from the 4.75% provided the five-day average of 4.75% was met.
12th Aug. 2011(*effective 15th Aug. 2011*)	CBK issued further guidelines on the operations of the CBK discount window, including: Any bank accessing funds from the CBK Window were not allowed to lend in the interbank market either on the same day or the following day; computation of the window rate shall be : Window rate = CBR + (Average interbank rate for the previous day-CBR) + 3% Penalty; Eligibility to access funds from CBK Window would be determined by among other things, individual bank's foreign exchange trading behaviour over the previous four trading days; and Reverse repos were suspended until the stance on monetary policy was changed.
26th Aug. 2011 (*effective 29th Aug 2011*)	CBK issued guidelines on liquidity management and CRR. The guidelines reviewed the formula for Window rate to reflect market conditions by introducing a weight for the gap between average interbank rate and CBR and expanded the period for the average interbank rate component. (*Average period was not announced but was actually 2 days). CBR was the floor.* Further, the new guidelines expanded averaging of cash reserves from weekly to monthly but limited the deviation to a minimum of 3% failure to which penalties would be effected.
15th Sept. 2011	MPC held a special meeting due to volatilities in the interbank market and the economy at large that impeded effectiveness of monetary policy. The meeting adjusted the CBR upwards from 6.25% to 7.00% to rein in inflation and exchange rate instability.

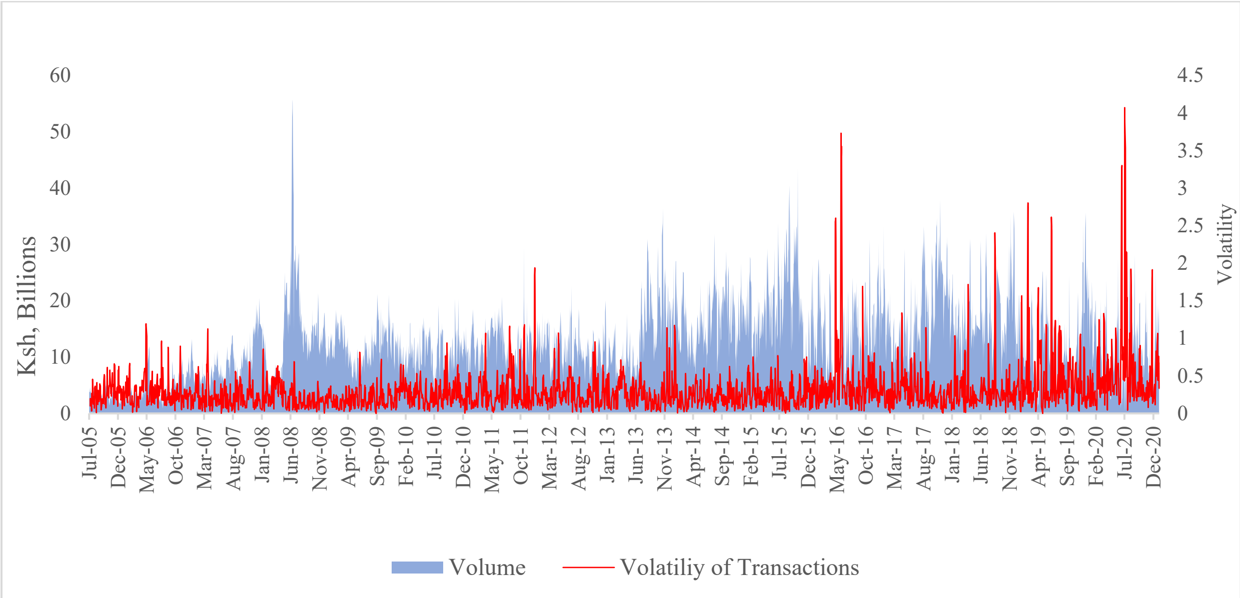
27th Sept. 2011	CBK announced direct support to corporate demand for foreign exchange by allowing direct purchases of foreign exchange from major corporate earners and direct sales to major importers in the oil sector (*direct sales were however not effected*).
6th Oct. 2011	MPC decision to adjust the CBR upwards from 7.00% to 11.00% to tame inflationary pressure, stabilize exchange rate and re-establish a strong growth base. The MPC also changed its meeting frequency from bi-monthly to monthly and fixed it on the first week of the month.
13th Oct. 2011	CBK issued further guidelines on foreign exchange transactions by banks. The guidelines stipulated that the reverse carry transactions that had been introduced into the market, and were unrelated to economic activity, and which have not been utilized for domestic purposes were limited to a minimum tenor of one year; foreign currency swaps involving Kenya shillings were limited to a minimum tenor of seven days; and the foreign exchange exposure limits were reviewed downwards from 20% to 10% of core capital. (*banks were given a week to implement this*)
18th Oct. 2011	CBK clarified on the foreign exchange guidelines; that foreign currency swaps and forward transactions involving Kenya shilling for non-resident financial institutions will be limited to a minimum tenor of one year.
2nd Nov. 2011	MPC decision adjusted the CBR upwards from 11.00% to 16.50% to provide an enhanced monetary policy tightening stance, effective immediately. Further, the CRR was adjusted upwards from 4.75% to 5.25% effective from 15th December 2011.
2nd Dec. 2011	MPC decision adjusted the CBR upwards from 16.50% to 18.00% to ease inflation and contain inflationary expectations that were building up.
2nd Feb. 2012	MPC decision maintained CBR at 18% to allow the full impact of a tight monetary policy stance to filter through the market and deliver lower inflation.
6th June 2012	MPC decision to maintain CBR at 18% to allow the full impact of a tight monetary policy stance to filter through the market and deliver lower inflation. MPC also introduced multiple longer tenors on Term Auction Deposits (TAD) of 14, 21 and 28 days as additional instruments for liquidity management. The price ceiling of the TAD was fixed equal to the prevailing CBR level. All other operational terms on TAD remained unchanged.
6th July 2012	MPC decision to adjust CBR downwards from 18.00% to 16.50% following the decline of inflation towards its short-term target of 9.00%. The MPC also announced a resumption of its bi-monthly meetings.
6th Sept. 2012	MPC decision to further lower the CBR from 16.50% to 13.00% to provide a stronger signal for lower interest rates in the market.
8th Nov. 2012	MPC decision to adjust CBR downwards from 13.00% to 11.00% to provide a stronger signal for lower interest rates in the market.
11th Jan. 2013	MPC decision to adjust CBR downwards from 11.00% to 9.50% to provide realign market interest rates and enhance credit uptake for increased economic activity.
8th May 2013	MPC decision to adjust CBR downwards from 9.50 percent to 8.50 percent to provide an additional signal that interest rates should continue declining to encourage the private sector to participate in growth-augmenting activities. In the same month, CBK purchased a net of USD 191 million from the market to build its foreign exchange reserves following stability in exchange rate market.
May 2014	CBK sold USD 165.5 million in line with the CBK's exchange rate policy of minimizing exchange rate volatilities. The Bank also announced the introduction of a Kenya Banks' Reference Rate (KBRR), which was developed as an outcome of discussions led by the Treasury between the stakeholders and. This was part of recommendations to enhance the supply of private sector credit and mortgage finance in Kenya by facilitating a transparent credit pricing framework.
May 2015	The maximum acceptable rate on the Term Auction Deposit instrument of monetary policy implementation was raised to 250 basis points above the CBR. This was targeted at enhancing the effectiveness of the instrument.

June 2015	MPC raised the CBR from 8.5% to 10.0% to anchor inflation expectations (*A new CBK Governor was appointed*).
July 2015	Tight market conditions due to a fiscal cash crunch and foreign exchange market instability
July 2015	MPC decision to raise CBR from 10.0% to 11.50% to provide a stronger signal that CBK was enhancing its effort to anchor inflation expectations. Furthermore, the KBRR was revised upwards from 8.54% to 9.87%. In order to enhance the instruments for effective liquidity management, MPC introduced a 3-day repo.
Aug. 2015	MPC decision to retain CBR at 11.50% in order to anchor inflation expectations. During the same month, one bank (Dubai bank Ltd) was placed under receivership.
Sept. 2015	MPC decision to retain CBR at 11.50% in order to anchor inflation expectations.
Oct.2015	One medium size Bank (Imperial Bank Limited) was placed under receivership by the CBK.
Nov.2015	CBK placed a moratorium on the licensing of new commercial banks until further notice. This moratorium, however, does not apply to cases relating to resolution, amalgamation and acquisition of banks.
Dec.2015	CBK signed an agreement with two banks (Kenya Commercial bank and Diamond Trust Bank) to provide depositors of the collapsed Imperial Bank access to their deposits (capped at *Ksh 1 million*).
March 7, 2016	CBK announced the sale of IMPERIAL BANK Ltd (in receivership since October 2015) shares in IMPERIAL BANK (Uganda) Ltd to Exim Bank (Uganda), in an effort to recover funds for the benefit of all IBL depositors. In addition, CBK announced its continued collaboration with Kenya Deposit Insurance Corporation (KDIC) to ensure funds held by the collapsed entity were safeguarded to protect the financial system.
April 7, 2016	CBK placed Chase Bank Ltd (a medium size bank) under receivership, for a period of 12 months, following the bank's failure to meet its financial obligations as a result of liquidity difficulties, which arose from a run on the bank triggered by adverse social media reports and the stepping aside of two of its directors.
July 16, 2016	CBK announced the acquisition of 51% stake of Oriental Commercial bank ltd by M Holdings Limited to form a Non-Operating Holding Company under Section 13 (1) (e) of the Banking Act. Consequently, Oriental Commercial Bank ltd became M Oriental Commercial Bank Limited. The transaction and consequent changes were expected to be completed by September 2016.
July 28, 2016	CBK announced the receipt of notification that the Banking (Amendment) Bill, 2015, had been amended by parliament on July 28, seeking to regulate interest rates that are applicable to banks' loans and deposits. While appreciating the underlying sentiments about the need to lower the overall cost of credit, CBK expressed its concern on the adverse consequences of capping interest rates, that would include, inefficiencies in the credit market, credit rationing, promotion of informal lending channels, and undermining the effectiveness of monetary policy transmission. The law became effective in September 2016.
August 10, 2016	CBK announced the receipt of a Memorandum of Understanding (MOU) from the banking sector, through the Kenya Bankers Association (KBA), detailing the steps that banks would take to lower interest rates, in line with the adjustments in the CBR and KBRR. Banks also committed, to eliminate some non-interest charges that hinder customers from gainfully benefiting from positive market developments. This step would also allow for interest rates to be more responsive to market conditions.
February 17, 2017	CBK announced that I&M Bank Ltd. (I&M Bank) had acquired 100% of Giro Commercial Bank Ltd. (GCBL), effective *February 13, 2017*. Following this acquisition, I&M Bank that was ranked 9th before the acquisition (in terms of market share) as of December 31, 2016, would control 5% of market share after the acquisition.

April 28, 2017	CBK announced the licensing of DIB Bank Kenya Limited (DIB) and highlighted that DIB's entry would expand the product offerings in the market, particularly in the nascent Shariah compliant banking niche.
May 11, 2017	CBK announced the completion of the acquisition of a majority stake in Fidelity Commercial Bank Limited (FCB) by SBM Africa Holdings Limited (SBM Africa), on May 10, 2017, following the requisite regulatory approvals. CBK noted that SBM wound deploy its experience and expertise from Mauritius and other markets, to enhance the competitiveness and resilience of Kenya's banking sector.
June 22, 2017	CBK and KBA announced the official launch of Cost of Credit website. The website provides information on fees and charges relating to loan products offered by commercial banks and microfinance banks; specifically, *personal secured loans*, *personal unsecured loans* and *mortgage loans*.
June 23, 2017	CBK announced the licensing of Mayfair Bank Limited to conduct banking business in Kenya and indicated that the entry of Mayfair Bank Limited would broaden the choices available to the Kenyan banking public and enhance the competitive environment in the banking sector.
June 28, 2017	CBK announced 100% acquisition by Diamond Trust Bank Kenya Limited (DTB) of Habib Bank Limited Kenya (HBLK), effective August 1, 2017.
April 10, 2018	CBK announced the implementation of interoperability of mobile phone financial services from April 10, 2018. Customers would be able to transfer funds across networks in real time, at low cost, and in a secure environment.
August 20, 2018	CBK announced the acquisition by SBM Bank (Kenya) Limited of a significant proportion of the assets of Chase Bank (Kenya) Limited (In Receivership); allowing resumption of a range of services to customers through its branches.
September 26, 2018	CBK published the names of Dr. Benson Akong'o Ateng', Dr. Margaret Kwengwa Chemengich, Prof. Jane Wanjiku Kabubo-Mariara and Mr. Humphrey Mugambi Muga, following their appointment on August 24, 2018, as members of the Monetary Policy Committee (MPC) of the Central Bank of Kenya. CBK stated that the new Members had extensive experience in economic policy and banking sector matters and would therefore enhance the MPC's role in formulating monetary policy.
September 2, 2019	CBK announced the approval of the acquisition of 100% shareholding of National Bank of Kenya Limited (NBK) by KCB Group PLC (KCB Group), indicating that the acquisition would strengthen both institutions leveraging on their respective well-established domestic and regional corporate, public sector and retail franchises.
September 27, 2019	CBK announced the merger of Commercial Bank of Africa Limited (CBA) and NIC Group PLC (NIC) effective September 30, 2019, indicating that the merger would strengthen both institutions leveraging on their combined market share of 9.9 percent and customer base of over 40 million in four East African countries where the two institutions were present.
October 2, 2019	CBK announced the successful completion of the withdrawal (demonetization) of the older series KSh.1,000 notes that started on June 1, 2019, targeted at mitigating illicit financial flows, and the emerging risk of counterfeits.
January 17, 2020	CBK announced 100% acquisition of the shareholding of Transnational Bank Plc by Access Bank Plc effective February 1, 2020.

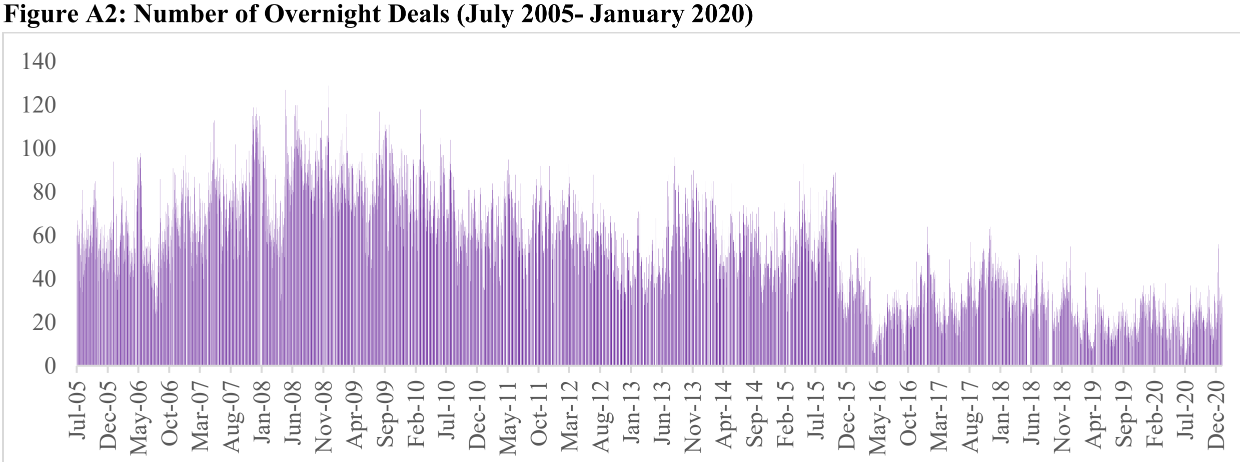
March 16, 2020	CBK, in consultation with payment service providers, announced a set of measures that would facilitate increased use of mobile money transactions instead of cash, and reduce the risk of transmission of COVID-19 (Coronavirus) by handling banknotes. The measures included : no charge for mobile money transactions up to Ksh.1,000; increased transaction limit to Ksh.150,000 and the daily limit (and mobile wallet limit) to Ksh.300,000; eliminated the monthly total limit for mobile money transactions; retained the maximum tariffs for mobile money transactions and eliminated charges transfers between mobile money wallets and bank accounts.
March 18, 2020	CBK published emergency measures to mitigate the adverse economic effects on bank borrowers from the coronavirus pandemic. The measures that were targeted at facilitating banks to increase lending to borrowers, included: a lowering of the CBR to 7.25%; a lowering of the CRR to 4.25%; allowing flexibility on CBK liquidity management facilities with the maximum tenor of Repurchase Agreements (REPOs) extension from 28 to 91 days; and flexibility on CBK requirements for loan classification and provisioning for loans that were performing on March 2, 2020 and whose repayment period was extended or were restructured due to the pandemic.
April 9, 2020	CBK preferred penalties on Absa bank foreign exchange trading, suspending its trading between April 9-15, 2020, following Absa Kenya's failure to provide information about some specific foreign exchange trades that it conducted in March 2020. CBK indicated that Absa Kenya had failed to ensure that the standard checks on AML/CFT and KYC requirements were applied.
April 14, 2020	CBK published the Credit Reference Bureau Regulations, 2020 (CRB Regulations), which provide for the licensing and supervision of Credit Reference Bureaus (CRBs) by CBK, as well as a framework for the exchange of borrowers' credit information between commercial banks, microfinance banks, Savings and Credit Societies (SACCOs), other credit information providers approved by CBK, and CRBs.
April 24, 2020	CBK announced the acquisition of 51% of the shareholding of Mayfair Bank Limited (MBL) by Commercial International Bank (Egypt) S.A.E (CIB) effective May 1, 2020.
April 29, 2020	The MPC announced its decision to lower the CBR form 7.25% set in March 2020 to 7.00% to augment its accommodative monetary policy stance.
May 22, 2020	CBK announced the acquisition of assets valued at Ksh.3.2 billion and assumption of liabilities of the same value of Imperial Bank (Kenya) Limited (In Receivership) (IBLIR) by KCB Bank Kenya Limited (KCB Bank) effective June 2, 2020.
August 7, 2020	CBK announced the acquisition of 90% of the shareholding of Jamii Bora Bank Limited (JBB) by Co-operative Bank of Kenya Limited (Co-op Bank) effective August 21, 2020.
September 18, 2020	CBK announced the licensing of the Kenya Mortgage Refinance Company Plc (KMRC) as the first mortgage refinance company in Kenya. KMRC's principal objective was to provide long term finance to primary mortgage lenders (commercial banks, mortgage finance companies, microfinance banks and Savings and Credit Co-operatives) to increase the availability and affordability of mortgage loans to the public.
October 1, 2020	CBK announced the expiry of the Suspension of the Listing with credit reference bureaus of negative credit information, which had been implemented for six months from April 14, 2020, for affecting borrowers whose loans had become non-performing after April 1, 2020. This measure announced the resumption of full disclosure of credit profiles of customers.

Figure A1: Daily Value and Volatility of the Interbank Transactions (January 2000- December 2020)



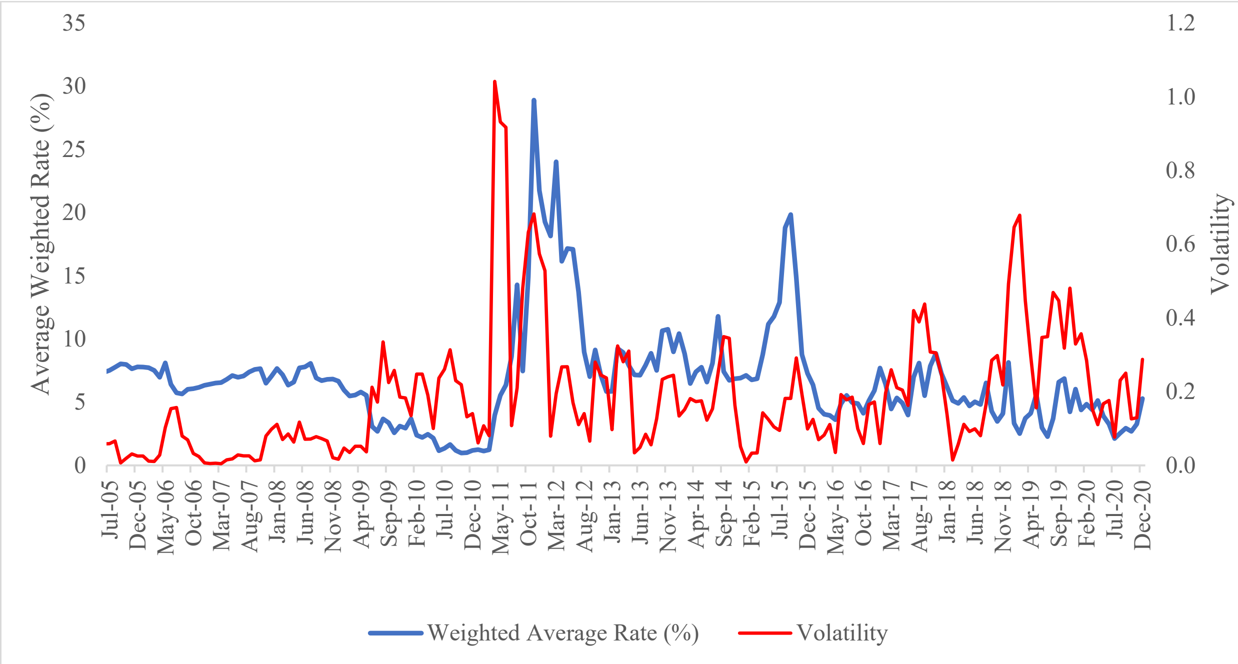
Note: Volatility of transactions is based on a 3-month moving standard deviation.
Source: Central Bank of Kenya

Figure A2: Number of Overnight Deals (July 2005- January 2020)



Source: Central Bank of Kenya

Figure A3 (a): Overnight Interbank Interest rate



Note: Volatility is based on a 3-month moving standard deviation.
Source: Central Bank of Kenya

Figure A3 (b): Overnight Interbank Interest rate Spread

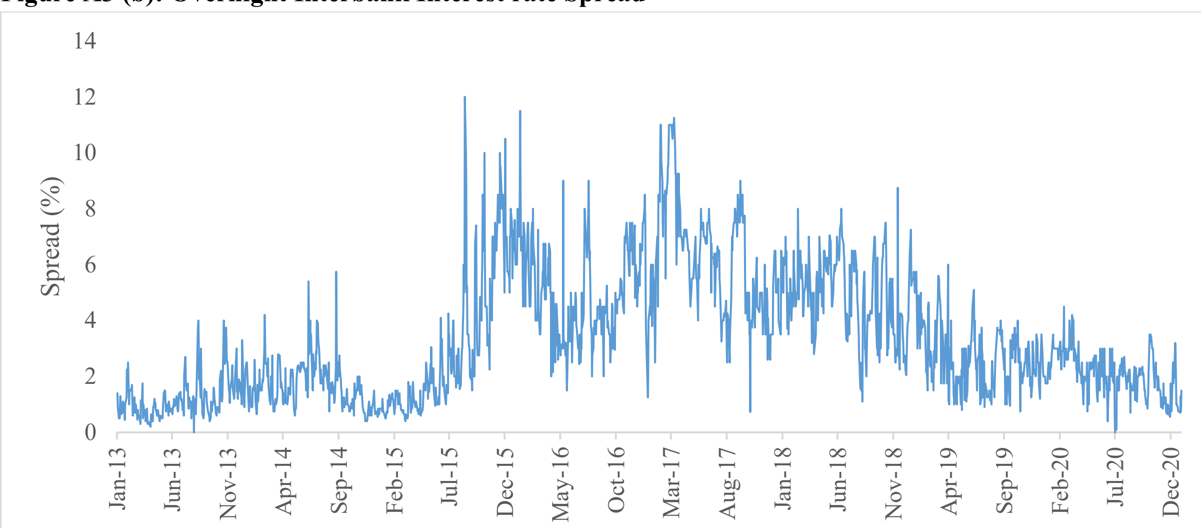
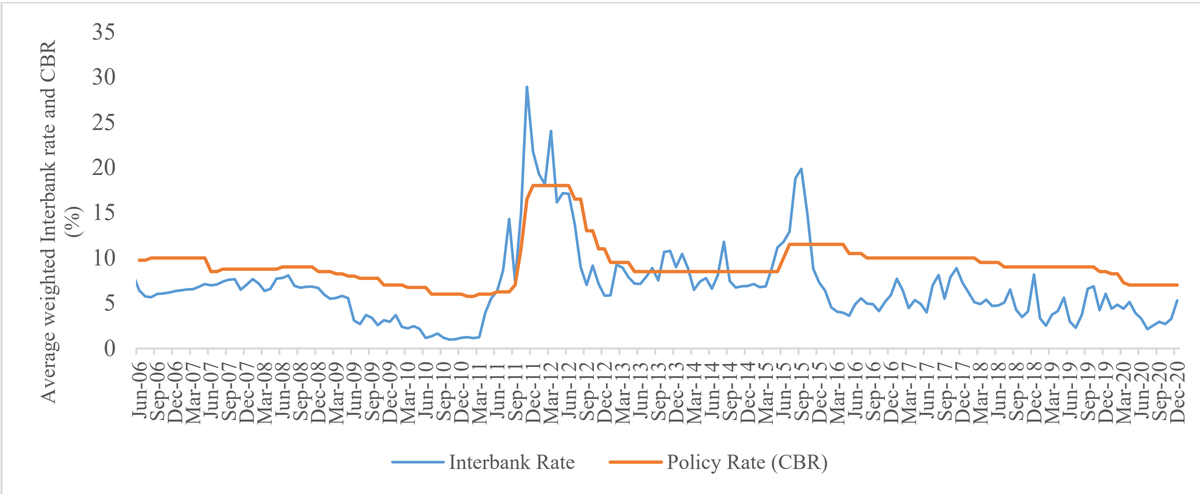


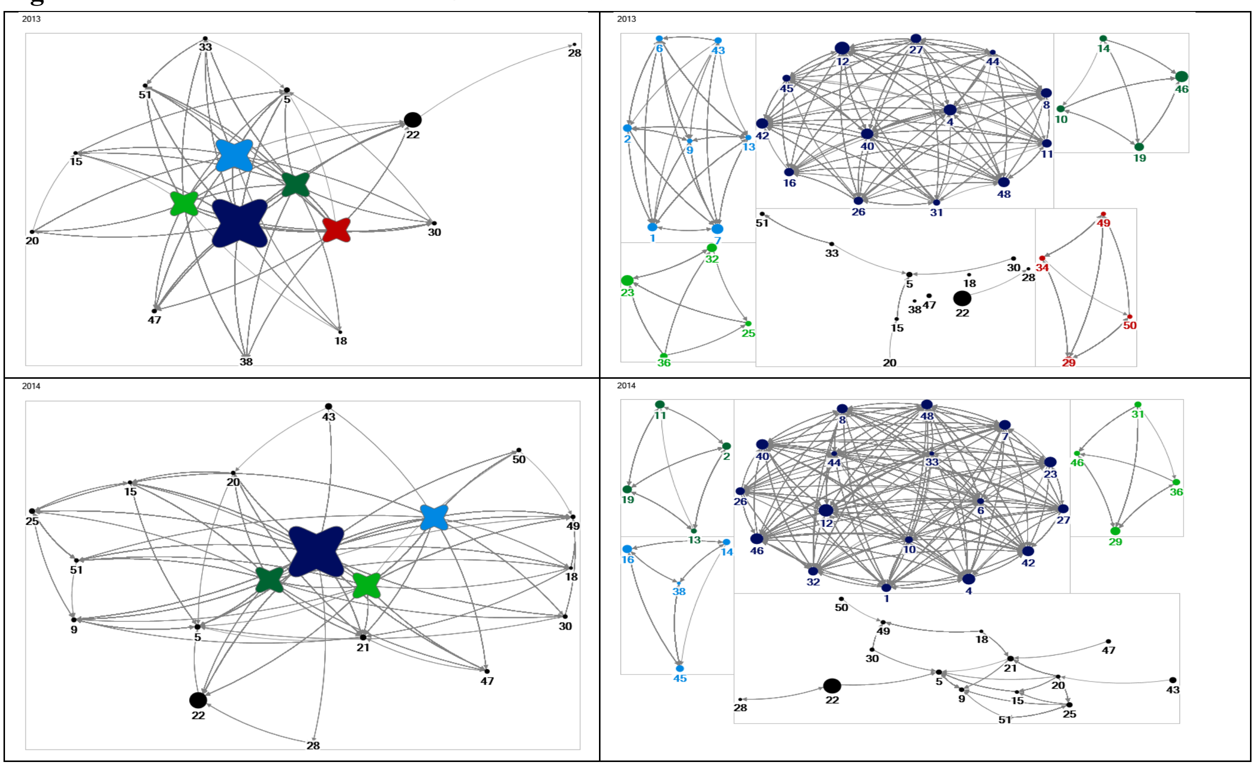
Figure A4: Interbank Rate and the Policy Rate

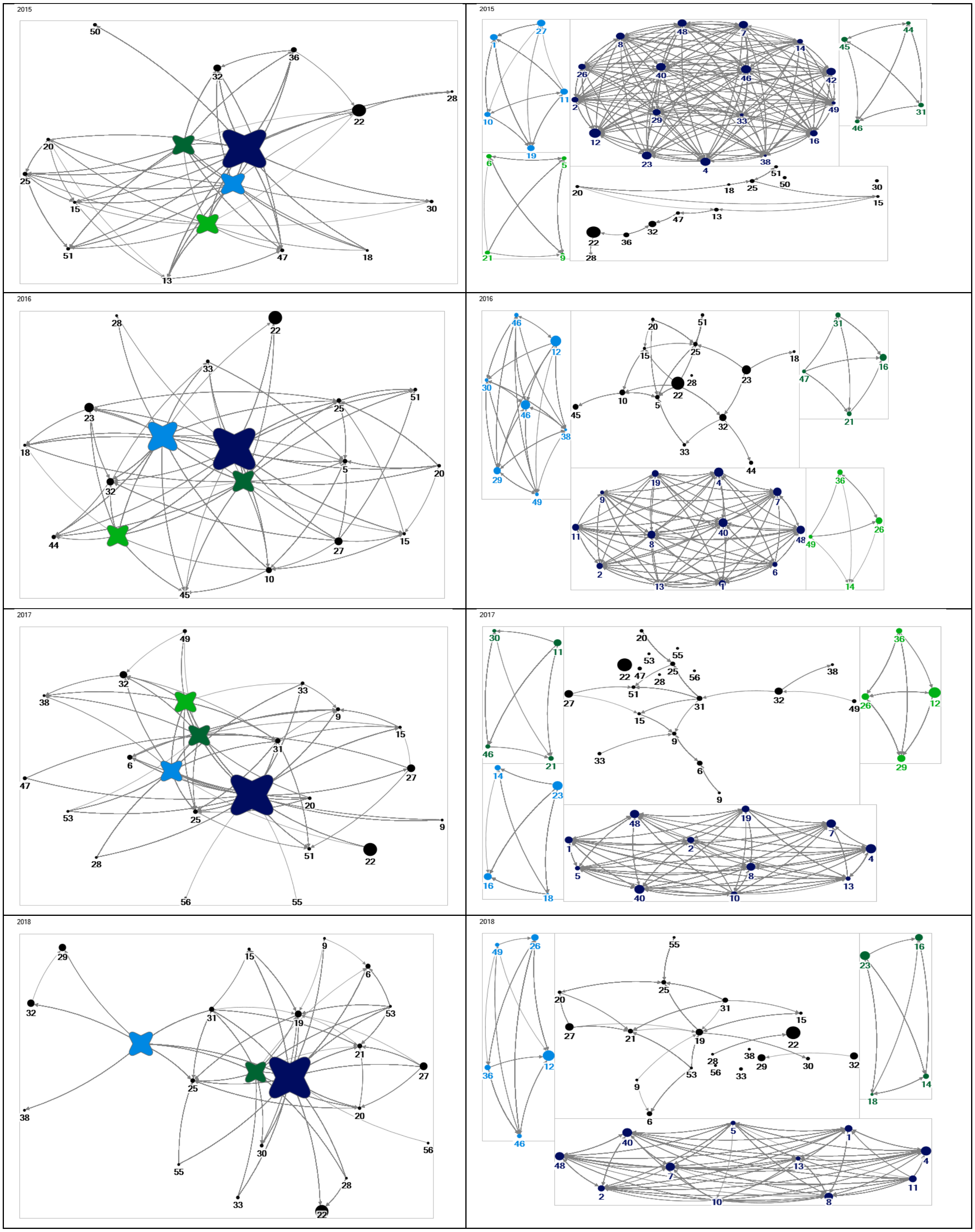


Source: Central Bank of Kenya

Note: The CBR was launched in June 2006

Figure A5: Evolution of Interbank Cluster: 2013-2020

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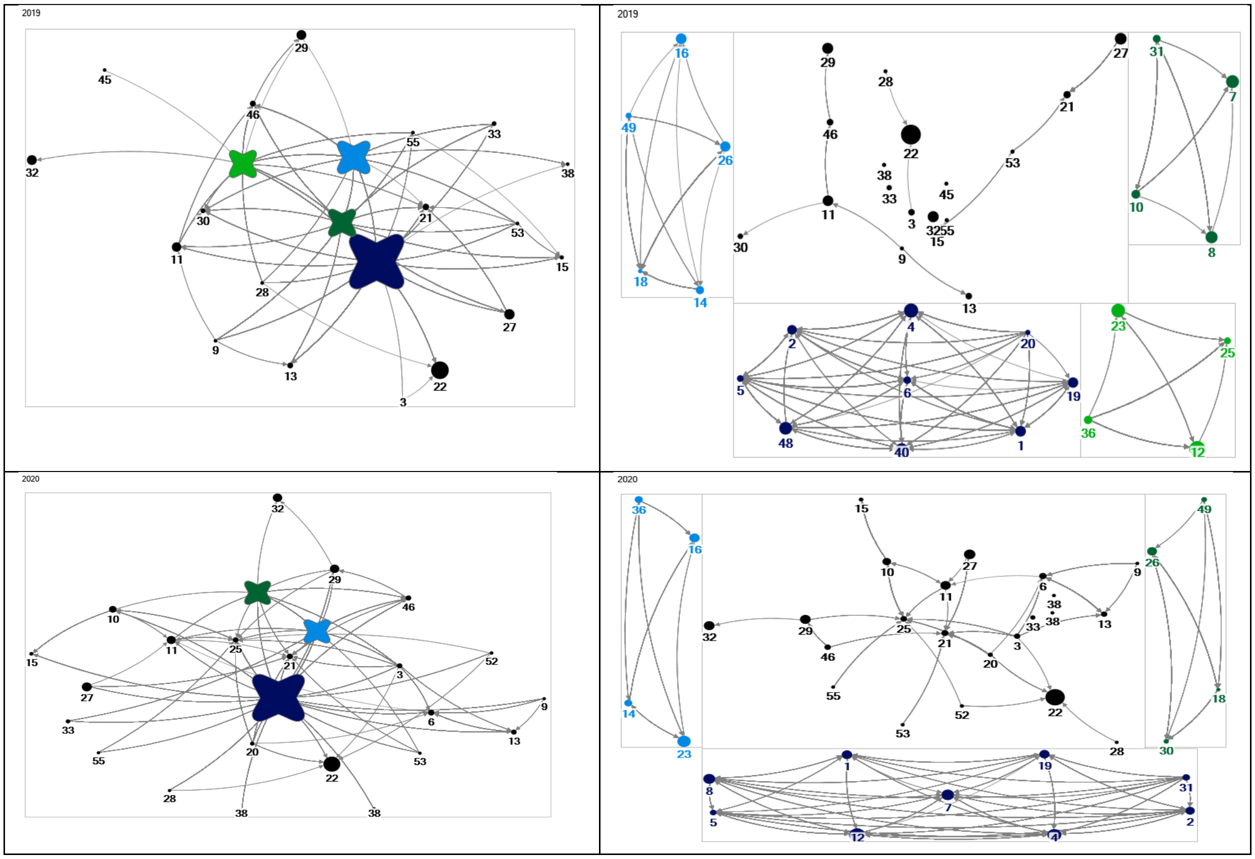

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Figure A6: Clustering Coefficient and Indegree

Figure A7: Betweenness and In-degree

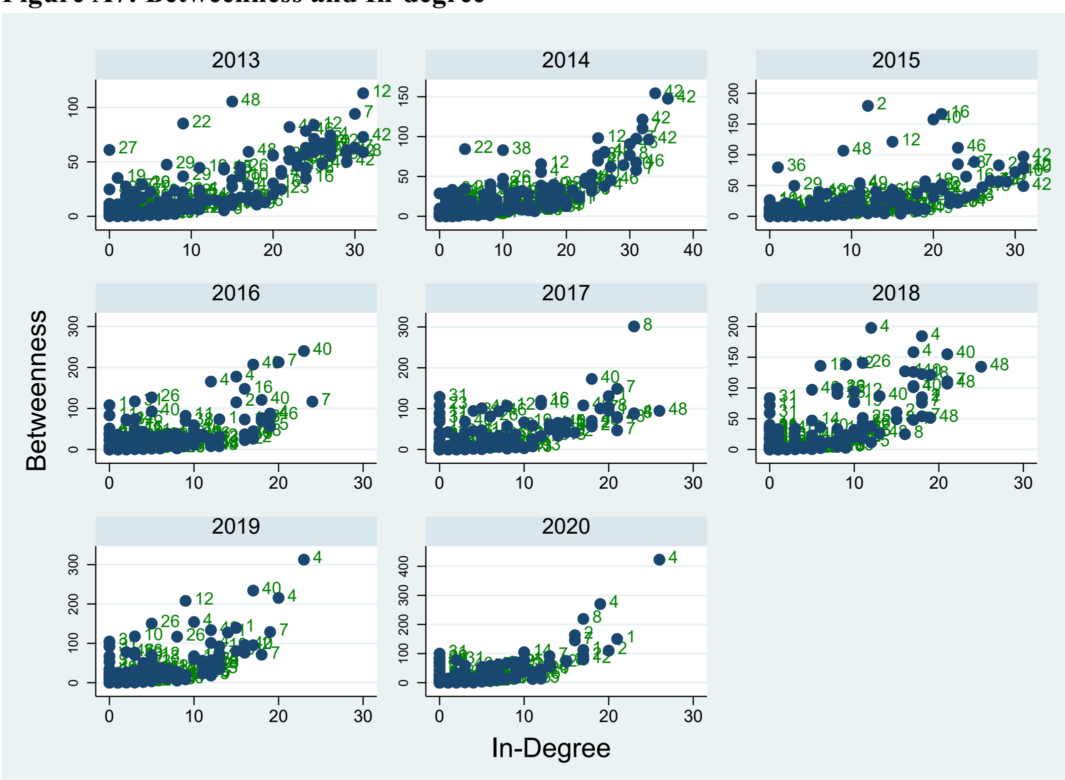


Figure A8 (a): PageRank and In-degree

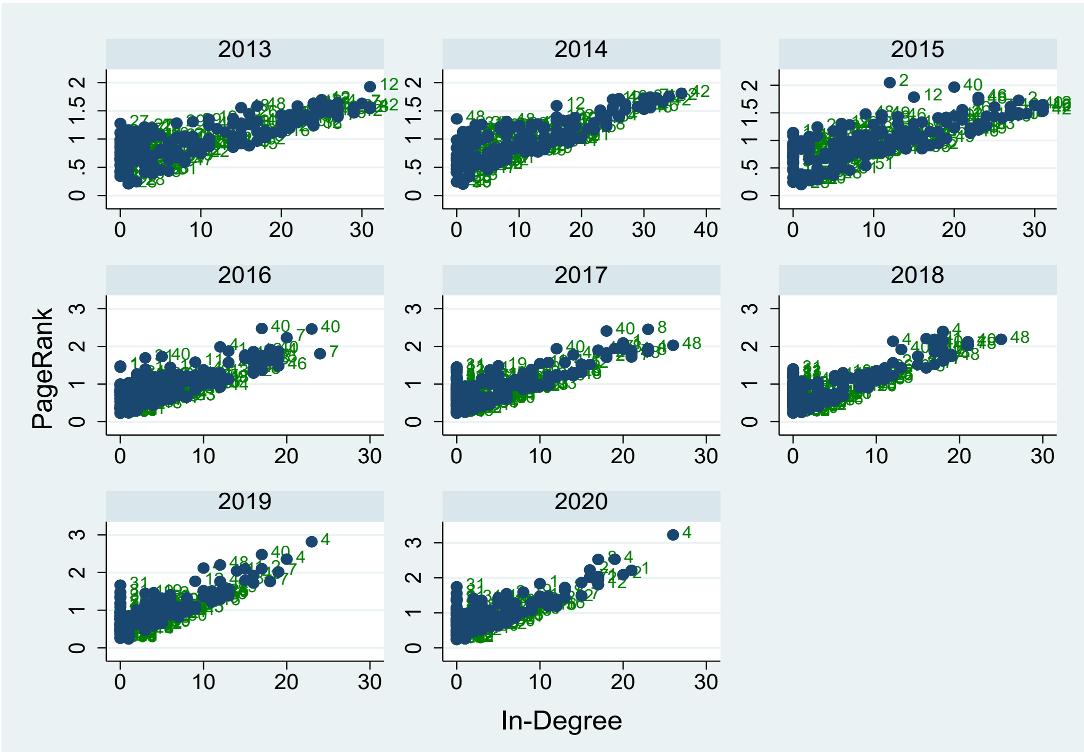
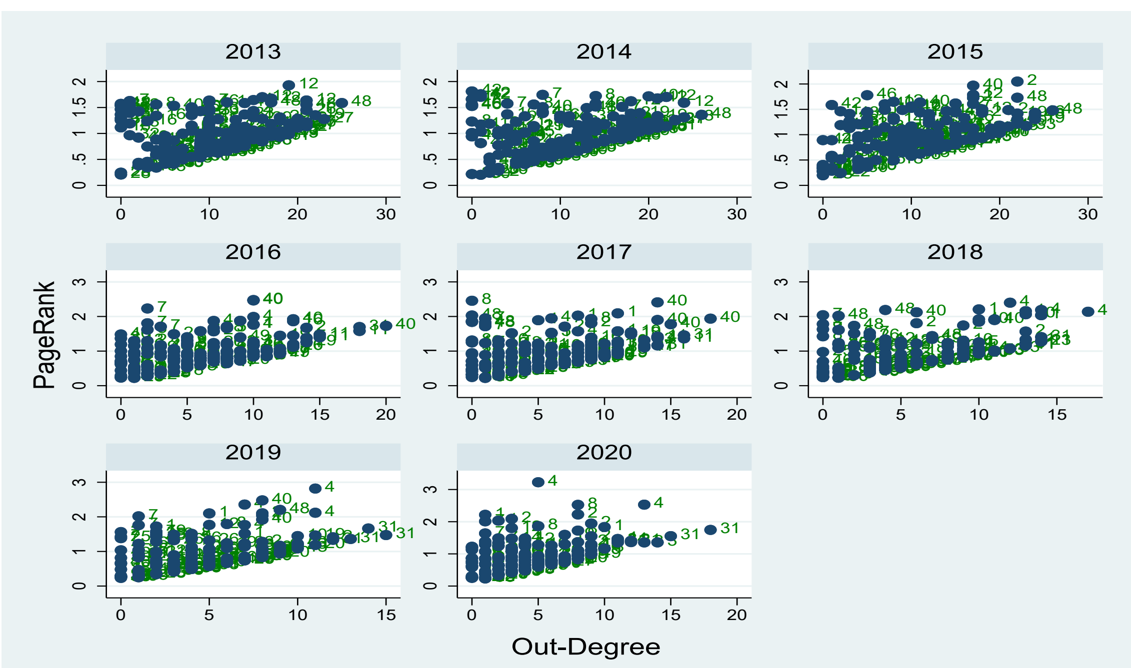


Figure A8 (b): PageRank and out-degree



B. Description of Measures used in Network Structure Analysis

In studying the network structure, we use a set of measures borrowed from the complex network theory to extract topological information about the interbank market. The measures can be classified into three broad classes depending on the information they depend on, and include: strictly local measures, quasi-local measures and the global measures.

More specifically, the strictly local measures relate to the inherent characteristics of the vertex (bank) itself, and include measures of degree, strength and link distribution.[27] The quasi-local measures consider the neighborhood's structural or topological characteristics to render information. The most important examples of the quasi-local measures include the weighted clustering coefficient of vertices and criticality measure. In these measures, if a reference vertex is considered, the neighborhood may be treated as either direct neighbors, or indirect neighbors. For the latter case, the indirection must be limited. If it were unlimited, the measure would be classified as global, which makes use of all of the relationships contained in the network to derive information. Examples of global measures include the weighted clustering coefficient of the network and measures of assortativity. All these measures are described in much detail below.

Description of the Network Measures

i) Degree

The degree represents the simplest characterization of the network. The degree of a vertex $i \epsilon \gamma$, indicated by k_i, is related to its connectivity, or number of links, to the remainder of the network. This measure can be decomposed further into the in-degree, $k_i^{(in)}$, and out-degree, $k_i^{(out)}$, such that the identity $k_i = k_i^{(in)} + k_i^{(out)}$ holds. The domain of k_i corresponds to the discrete-valued interval $\{0, \ldots, 2(N-1)\}$. When $k_i = 0$, we say that vertex *i* is a singleton vertex. Conversely, when k_i is Sufficiently large, we say that vertex *i* is a hub. The in-degree of the vertex *i* is defined as $k_i^{(in)} = \sum_{j \epsilon \gamma} 1_{\{L_{ji>0}\}}$, where $1_{\{A\}}$ represents the Heaviside function that yields 1 if the logical expression A evaluates to true, and 0, otherwise. In the liabilities network L, the in-degree represents the number of banks from which bank i has borrowed from (its creditors). Hence, it can be regarded as a measure of funding diversification. With a similar reasoning, the out-degree of the vertex i is defined as $k_i^{(out)} = \sum_{j \epsilon \gamma} 1_{\{L_{ij>0}\}}$. The out-degree symbolizes, in a network of liabilities, the number of banks bank *i* has lent to (its debtors). As such, it can be an indicator of investment diversification. Here, if a bank has many interbank creditors (debtors), it is said to have a high in-

[27] These measures ignore the neighbouring and the global features.

degree (out-degree). The banks that have higher in-degree measures are the most systemically relevant, while those with higher out-measures are the most important sources of funds (or money centers).

ii) *Strength :* The strength measure is an extension of the degree and takes the size of the liabilities and exposures into account. It can be interpreted as a measure of intensity of the interaction. The strength of a vertex $i \epsilon \gamma$, indicated by s_i represents the total sum of weighted connections of bank *i* towards its neighbours. Like for the case of degree, the notion of strength can be further decomposed into the in-strength, $s_i^{(in)}$, and out-strength, $s_i^{(out)}$, such that the identity $s_i = s_i^{(in)} + s_i^{(out)}$holds. The domain of s_i corresponds to the continuous interval $[0, \infty)$.The in-strength of the vertex *i* is defined as $s_i^{(in)} = \sum_{j\epsilon\gamma} L_{ji}$. In a network of liabilities, the in-strength represents the amount of money that a bank has borrowed from the market, or its dependency on the market. In contrast, the out-strength of the vertex *i* is defined as $s_i^{(out)} = \sum_{j\epsilon\gamma} L_{ij}$. This is an indicator of the extent to which a bank has invested in the market. It is noted that the strength is a generalization of the degree measure for weighted networks. When dealing with non-weighted networks, the strength reduces to the degree concept.

iii) *Density/Completeness:* The density *d* of a network is the ratio of the number of existing links and the number of the maximum possible links. Based on Newman (2010), it is a measure of completeness of a network, where for a complete network all, possible links are present. The density for directed networks is defined as:

$$d = \frac{m}{n(n-1)}$$

where *m* is the number of links (transactions) and *n* is the number of nodes (banks) in the network, with 0<*d*<1. The closer *d* is to 1, the more complete the network.

iv) *Shortest path length/distance and diameter:* A path is any connection between two nodes and the length of the path between any two nodes is the number of links passed to get from one node to the other along this path. The shortest path length (or distance) is the minimum number of nodes it takes to get from any node A to another node B. The maximum distance (or eccentricity) of a node is the longest path to any other node. The diameter of a network is the maximum distance across all nodes. Higher density networks tend to yield smaller average shortest path length (ASPL). The more crowded a network gets with links, the less steps it takes to get from one node to the other. The path length (L_g) is represented by equation 5:

$$L_g = \frac{1}{n(n-1)} \sum_{i \neq j} d\,(v_i v_j) \qquad [5]$$

Where $d(v_i v_j)$ is the length of shortest path which exists between vertices.

v) *Clustering coefficient:* The clustering coefficient (c_i) is a measure of the probability that two nodes which are neighbours of the same node, themselves share a link (i.e., the three nodes form a triangle). In social networks, this is equivalent to the observation that two people each of whom is your friend, are likely to be friends with each other. The local c_i, of node i is the ratio of the number of directed connected neighbours of i and the maximum possible number of connections among neighbours. The c_i, is thus a measure of connection density around a node.

In the context of the interbank markets, c_i, indicates whether there is a link between two banks which have a common trading partner. In order to have a triangle in the payments system, at least one bank must lend to one counterparty and borrow from another. The c_i, provides a way to assess the extent of this kind of intermediary trading. It also quantifies how close the particular bank and its neighbours are to being a clique. The closer the local c_i, is to 1, the more likely it is for the network to form clusters. From a lending perspective, a high c_i means that bank i is easily substitutable because its neighborhood has other nearby options to invest in. Conversely, a low c_i means that few options are available for the neighbours of i suggesting that bank i is important in the neighborhood because its removal would significantly reduce the trading options in the nearby surroundings. Consequently, c_i can be viewed as a measure of diversification of the counterparties of i.

The clustering coefficient of a single node can be extended to the entire network, by averaging the c_i, over the network banks. An interbank network with a low clustering coefficient has several entities which are not easily substitutable. The converse is the case for a network with a high average clustering coefficient. As discussed above, the clustering coefficient metric can either be related to a vertex or the entire network. In terms of the notations, the clustering coefficient of a vertex is a measure of the extended degree to which vertices in a graph tend to cluster together, which quantifies the number of loops of order three (transitivity). Originally designed for non-weighted networks, it has been extended and adapted to weighted directed networks, as is the case of the interbank market network. The weighted clustering coefficient of a vertex $i \epsilon \gamma$ is given by equation (1) (adopted from Barthelemy *et al*., 2005):

$$CC_i = \frac{1}{s_i(k_i-1)} \sum_{(j,k)\epsilon\gamma^2} \frac{W_{ij}+W_{ik}}{2} A_{ij} A_{ik} A_{jk}, \qquad (1)$$

in which $CC_i \epsilon [0,1]$; W_{ij} is the edge weight from i to *j*; $A_{ij} = 1_{\{W_{ij}>0\}}$. When $CC_i \rightarrow 1$, vertex i presents dense topological structures in the vicinities in the sense of triangular modules. In contrast, when $CC_i \rightarrow 0$, it only contains sparse structures, possibly with long linear chains of vertices.

With respect to the interbank markets, the clustering coefficient can be conceptualized both for the borrowing and lending perspectives. From the borrowing perspective, the edge weights in (1) are set to $W_{ij} = L_{ij}$, and the strengths s_i are set to $s_i^{(out)}$. From the lending perspective, we fix $W_{ij} = (L^T)_{ij}$ and $s_i = s_i^{(in)}$. A high CC_i means that bank *i* is easily substitutable because the neighborhood of bank i has other nearby options to invest in (lending perspective) or borrow from (borrowing perspective). This is because neighbors of i communicate with each other as well. Conversely, if CC_i is small, few options are available for the neighbors of *i*, implying that bank *i* is important in the neighborhood because its removal would drastically reduce the investment or funding alternatives in the nearby network surroundings. Consequently, CC_i can be seen as a measure of the diversification of the counterparties of *i.*

With respect to the weighted clustering coefficient of the Network, and picking from equation (1) that quantifies the clustering coefficient of a single vertex, the idea can be extended to the entire network by averaging the weighted clustering coefficient over all of the network vertices (as suggested by Newman (2003), so that:

$$CC = \frac{1}{N} \sum_{i \epsilon \gamma} CC_i, \qquad (2)$$

in which CC assumes the same domain of CC_i, i.e., $CC \epsilon [0,1]$, because (2) is a convex combination of terms in the region [0;1]. A financial system network with low CC has several entities with singular properties, i.e., they are not easily substitutable. Conversely, if CC is high, almost all of the participants have alternative options to invest in or borrow from and, therefore, the majority of banks are substitutable.

vi) *Centrality:* A key issue in network analysis is identification of nodes that are most important or central than others in the network (Borgatti, 2005; Newman, 2010). For the interbank networks, measures of centrality summarize a bank's involvement in or contribution to the cohesiveness of the interbank network. The larger the centrality measure, the greater importance such a node/bank has in the network. The concept of centrality is closely related to the concept of 'too-interconnected-to-fail 'as one of the components in the determination of systemic risk is interconnectedness (see BCBS, 2011). According Martinez-Jaramillo, *et al*. (2012), a financial institution is considered important in a network if it has the following characteristics: possesses many linkages to other members of the network (degree); the total amount of its assets, liabilities in the network is very large (strength); there are many paths which pass through it (betweenness); its failure could transmit contagion in a few steps (closeness); and its counterparts are considered also as relevant (*eigenvector and PageRank*).

With respect to the concept of degree and strength, these are the most easily understood statistics for measuring the centrality of a node within a network. Banks with higher degree and strength are considered to be closer to the center of the debit/credit network, and therefore more important players within the financial system. The degree is a local measure, i.e., it does not consider the global structure of the network, but only the local neighborhood of the node. Thus, while the degree is a sensible centrality measure for small networks, it can miss important global characteristics of the importance of the node in large networks. The common global centrality measures, include; betweenness, closeness, Eigenvector and PageRank centrality.

Betweenness centrality is one of the most popular centrality measures (often simply referred to as betweenness). It measures the number of times a node lies on the shortest path between other nodes (Newman, 2010). It shows which nodes are 'bridges' between nodes in a network or the ability of a node to act as an intermediary for other nodes. It is a useful for identification of players who influence the flow around a system and therefore regarded as a measure of others' dependence on a given node. This measure of centrality is particularly important in a payment system network because a bank with a high betweenness centrality would have an important influence on other banks as it can stop the flow of funds/information that passes through it. For instance, consider two banks A and B with the same degree, but bank A has a higher betweenness centrality. It means that, relative to bank B, it is located on a more important path in the network. It is more likely to be involved in the transmission of a liquidity shock if it is unable to pay a transaction and more likely to have a larger impact on the network. It is thus a measure of contagion. The more important a bank is as a debtor, the greater is its tendency to have a high betweenness centrality and thus occupy an important position within the network.

Closeness centrality has the interpretation of independence in social networks in terms of communication control or from potential control by intermediaries. The closer a node is to other nodes, the greater is its closeness centrality. Such nodes have better vision on the flow of information. In this latter sense, closeness centrality is also regarded as a measure of access efficiency. A bank with high closeness centrality would depend less on other intermediary banks to receive funding/information. In the context of financial contagion, closeness centrality can be associated with capacity of the bank to spread contagion.

The Eigenvector and PageRank Centrality, like degree centrality, measures a node's influence by counting the number of links it has to other nodes within the network, but goes a step further to show a bank's importance in its connections to other important banks in the system. We can think of degree centrality as awarding one "central point" for every network neighbor a bank has but appreciate the fact that not all neighbours are equal. In this regard, instead of awarding to a node just one point for each neighbor, Eigenvector centrality gives each node a score proportional to the sum of the scores of its neighbours. A high Eigen centrality score indicates a strong influence over other nodes in the network. It is useful because it indicates not just direct influence, but also implied influence over nodes more than one 'hop' away. A node may have a high degree score (i.e., many connections) but a lower Eigen centrality score if many of those connections are with similarly low-scored nodes. Also, a node may have a high betweenness score (indicating it connects disparate parts of a network) but a low Eigen centrality score because it is still some distance from the center of power in the network. In the analysis of financial networks, eigenvector centrality corresponds to the importance of nodes as recipients (or sinks) of spillovers.

PageRank, like Eigen centrality, can help uncover influential or important nodes whose reach extends beyond just their direct connections. The main difference is that PageRank takes link direction and weight into account. So, links can only pass influence in one direction, and pass different amounts of influence.

From the foregoing, the measures of centrality help to single out important banks within the market. They capture well characteristics associated with the too-connected-to-fail. However, they may fail to capture concentration risks from counterparty exposures which are normally associated with too-important-to-fail risk. Added to these include the community detection metric, which appreciates that the systemic importance of a node does not depend on its number of connections but rather on the node's ability to have a substantial impact on its neighbours, even if the impact is largely contained within a local neighborhood, i.e., a subgraph of the larger graph characterizing the network. To complement the centrality measures, let us consider the identification of subgraphs or communities within a network and the critical nodes around which such subgraphs form or other nodes cluster. One of the measures for community detection is the clustering coefficient described earlier. In this study, we interact the clustering coefficient for each of the bank with the calculated centrality measures to further identify important banks in the network.

vii) *Network Assortativity:* Assortativity is a network-level measure that, in a structural sense, quantifies the tendency of vertices to link with similar vertices in a network. The assortativity coefficient r is computed as the Pearson's correlation of degrees of vertices in each connected pair. We compute the correlation between out- and in-degrees of links between debtor and creditor banks and examine the extent to which banks trade with similar ones. A network is said to be assortative if high (low) degree nodes form links to other high (low) degree ones (Newman, 2003). Positive values of r indicate that the network's pairs of vertices have vertices in the endpoints with similar degrees, while negative values indicate endpoints with different degrees. In general, $r \epsilon [-1,1]$. When $r = 1$, the network has perfect assortative mixing patterns, while it is completely disassortative in the case $r = -1$. Negative assortativity is often correlated with the existence of hubs or money centres in financial networks.

Understanding the assortative mixing patterns in complex networks is important for interpreting vertex functionality and for analyzing the global properties of the networks' components. Concerning the interbank market network, assortativity is important for the following reasons:

i) When the network indicates high disassortative mixing, i.e., $r \to -1$, the majority of banks connect with other entities with dissimilar degrees. Considering that, in these types of networks, only a few banks have several connections (money centres), the onset of a default in these money centres directly affect a large portion of the network vertices. In this configuration, all of their neighbours that are vulnerable may, in turn, default, leading to the beginning of a contagion process throughout the network. Since there are many highly connected money centres, the network diameter tends to be small, favouring the spread of the contagion process. However, if a bank with small degree defaults, it may also affect money centres in a direct manner. But since the latter's capital buffers are high, they are likely to absorb all loses coming from that defaulted entity. As such, the chaining effect of subsequent defaults is retained by money centres.
ii) When the network indicates high assortative mixing, i.e., $r \to 1$, we expect that two types of clusters or communities will emerge in the interbank network: communities of high- and low-degree vertices. In each community, there will be more edges connecting each pair of banks of the same group than edges cross-connecting different communities. We expect that the network will not present money centres, in the sense that they are a few highly connected banks. The high-degree community tend to be an almost complete (clique) graph, because the number of large institutions is small, and they almost connect to all of their similar pairs. With regard to the low-degree community, because there is only a small quantity of edges per each vertex, it is expected that the network structure will present long linear chains of banks (large network diameter), so that each bank in the group will exhibit very low diversification. If a member of the high-degree community defaults, it will affect all of the connected high-degree neighbours and also a few low-degree vertices, which are more likely to be vulnerable given their lower diversification. Additionally, because the low-degree community has long linear paths of less-diversified banks, if they are vulnerable (have low capital buffers and larger exposures), there is a higher probability that the process will cascade through the neighbours in a domino effect, onsetting a process of contagion with long paths. On the other hand, if a default occurs in a member of the low-degree community, then it is very unlikely that it will propagate to the money centre cluster. However, depending on the bank's vulnerability, the same domino effect that was previously described may occur in the low-degree community. In any case, financial networks very frequently do not present positive assortativity.
iii) When the network does not indicate edge attachment preferences in a global sense, we expect the graph will have a slight mixture of assortative and disassortative trends in its various different regions. During the calculation of the assortativity, these terms are

cancelled out, resulting in $r \approx 0$. In this configuration, we do not expect to encounter communities in the strong sense, as in the previous case.

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African Economic Research Consortium
Consortium pour la Recherche Economique en Afrique
Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org