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Systemic Risk in the South African Interbank System

Nicola Brink and Co-Pierre Georg

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Systemic Risk in the South African Interbank System

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Abstract

This paper analyses the network structure of the South African overnight interbank market by employing measures from network theory. A unique data set of interbank transactions from the South African Multiple Options Settlement (SAMOS) system is used. It is shown that the South African interbank system has been largely stable and resilient over the period from March 2005 to June 2010, even in times of great distress on the international financial markets. The number of banks participating in the interbank market was approximately constant over the analysed period, as well as the high level of interconnectedness. A low average path length and high clustering coefficient indicate a high level of liquidity allocation and risk sharing in the system. Furthermore a Network Systemic Importance Index (NSII) is developed to assess the systemic importance of individual banks in South Africa. This index measures each banks size, interconnectedness and substitutability by employing network theory. It is a relative index in the sense that the systemic importance of any given bank does not only depend on the properties of the bank itself, but rather on the properties of the whole network. This approach is therefore less prone to moral hazard and can be used as a tool for macroprudential oversight in addition to microprudential supervision. The NSII addresses the cross-sectional dimension of systemic risk. It has to be stressed, however, that it gives no indication of the default probability of individual banks and has therefore be accompanied by other macroprudential tools for a full picture of systemic risk.

JEL classification: E61, G01, G21, G28

Keywords: Systemic risk, interbank market, network theory, South Africa

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1 Introduction

The financial crisis of 2007/08 highlighted, among other things, the necessity of macroprudential oversight of the financial system in addition to the existing microprudential supervision. To ensure the stability of the financial system, it is important to not only monitor the strength of individual financial institutions themselves, but also to analyse the network structure that they form due to their various interlinkages. Because of the banks' dependency on access to liquidity, interbank loans are amongst the most vital interconnections between banks. In normal times, banks with excess liquidity provide loans to banks with a liquidity shortage, usually on a short-term basis and without underlying collateral. These interconnections between banks can enhance liquidity allocation and risk sharing in the banking system.

There is, however, a downside to the interconnectedness of the banking system. As was seen in September 2008, interbank markets display a "robust-yet-fragile behaviour" - the very same interconnections that lead to an enhanced liquidity allocation in normal times, can amplify shocks in times of a crisis. Central banks around the world were forced to undertake unprecedented non-standard measures to reduce money-market spreads and ensure liquidity provision to and distribution within the banking system. Even though the direct effects of the crisis on the South African financial system were very modest and the South African interbank market escaped the problems experienced in some other countries, systemic risk and contagion in interbank markets are a continuous concern for central banks. The urgency of addressing systemic risk and the soundness of systemically important financial institutions was emphasized by the Group of Twenty (G20) leaders at the Pittsburgh Summit[3], where it was agreed that *"the prudential standards for systemically important institutions should be commensurate with their systemic importance"*.

The purpose of this working paper is twofold. Firstly, it analyses the interbank network structure of the South African banking system from April 2005 until June

[3] See the Leader's Statement: The Pittsburgh Summit

2010 with measures from network theory and thereby provides a useful tool for macroprudential oversight. The analysis shows that the South African interbank market was stable both according to the number of participants and according to the level of their interconnectedness. This result is confirmed by the high clustering coefficient that has been observed and the low average path length, both indicating the high availability of liquidity in the period under investigation.

Secondly, an index to measure the systemic importance of South African banks from a network perspective is proposed. This index can be used as a building block to impose prudential requirements on firms commensurate with their systemic risk. Such prudential requirements would help to further strengthen the trust in the stability of the South African interbank market. The proposed index is a relative measure in the sense that the systemic importance of one bank depends not only on the properties of that bank, but also on properties of the whole network. This makes a particular bank's systemic significance less predictable and less constant. Banks themselves cannot be totally certain at any given point in time about their ranking in terms of systemic significance within the interbank market. As a result, the index is less prone to moral hazard, which is a major concern in the discussion of systemically important financial institutions (SIFIs).

The paper is organized as follows: After a short introduction, section two gives an overview of attempts to define systemic risk in the international context. Section three motivates the use of network theory to assess systemic risk in interbank markets while section four shows the results of various measures from network theory in the South African interbank market. Section five introduces the Network Systemic Importance Index (NSII) and shows the result for three groups of South African banks. In section six it is argued that the NSII is less prone to moral hazard, while section seven concludes.

2 Systemic Risk

In the literature there are a large number of definitions of systemic risk, each emphasizing a certain aspect of it. Similarly, according to the Financial Stability Board, International Monetary Fund and Bank for International Settlements (2009), most G20 countries do not have a formal definition of systemic risk either. Most commonly accepted, however, is the distinction between a broad and a narrow sense of systemic risk, as described by De Bandt *et al* (2010). In this classification, contagion effects on interbank markets pose a systemic risk in the narrow sense, whereas in the broad sense it is characterised as a common shock to many institutions or markets. This distinction is followed by the Financial Stability Board (FSB) who defines systemic risk as *"a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy"*. The European Central Bank (ECB) suggests that systemic risk can be described as the risk of experiencing a strong systemic event that adversely affects a number of systemically important intermediaries or markets (European Central Bank, 2009). The trigger of the event could either be a shock from outside or from within the financial system. The systemic event is strong when the intermediaries concerned fail or when the markets concerned become dysfunctional. Since all these different dimensions of a systemic event interact with each other, it is clear that systemic risk is a highly complex phenomenon. In its analysis, the ECB focuses on three main forms of systemic risk namely contagion risk, the risk of macroeconomic shocks causing simultaneous problems at many financial institutions or markets and the risk of an abrupt unravelling of imbalances that have built up over time.

According to Acharya and Yorulmazer (2003) as well as Nier *et al* (2008), informational contagion is another form of systemic risk that has to be taken into account. Especially in times of crises financial markets exhibit a herding behaviour. The insolvency of a bank can increase the cost of borrowing for the remaining banks quite drastically in these situations. The insolvency of the US investment bank Lehman Brothers in September 2008 led to a breakdown of interbank markets not only because of the direct losses that were associated with it, but mainly because it was a signal to financial market participants that their own risk perceptions were incorrect. This led to a surge in risk-awareness and risk-aversion and ultimately to the breakdown of interbank money markets. While informational contagion clearly deserves more attention, currently there exists no model to properly assess it.

Following the approach of the ECB (European Central Bank, 2010), it is possible to distinguish between four broad analytical approaches to assess the different dimensions of systemic risk. Firstly, financial stability indicators can measure the current state of instability in the financial system. Secondly, early warning models can help assess the likelihood and severity of systemic crises. Thirdly, stress-tests of the financial system can be used to analyze the impact of macro-shocks. Lastly, contagion and spillover models can be employed to analyze how initial shocks spread throughout the financial system. While central banks today have to employ all four types of models to properly assess systemic risk, the academic literature is at different stages in the development of those tools.

It was recently emphasized by e.g. Borio (2010) that the distinction between the time- and cross-sectional dimensions of aggregate risk is critical. In the time-dimension leading indicators of financial distress are needed, while in the cross-sectional dimension a robust quantification of the contribution of each institution to systemic risk is necessary. There exists a growing literature on cross-sectional measures to assess systemic risk (see e.g. Tarashev et al. (2009) and (2010), Huang et al. (2010), Acharya et al. (2010), Goodhart and Segoviano (2008), or Adrian and Brunnermeier (2009)). The NSII proposed in this paper falls into the second strand of models as it contributes the systemic risk in the interbank to individual institutions.

3 Network Theory

3.1 Financial Networks and Systemic Risk

A new approach to assess systemic risk in financial markets originates from network theory and has been widely applied to Ecology, Neuroscience, Biochemistry, Epidemology, Social sciences and Computer science. The neural network of the worm C-Elegans, the structure of the World-Wide-Web, the power grid of the United

States and the spreading of the HI Virus have all been analysed using network theory. The increase in computing power in recent years has led to a vast increase in the research of large and complex systems and some of the results, especially from Epidemology, can be applied to the analysis of financial networks.

A financial network consists of a set of banks (nodes) and a set of relationships (edges) between the banks[4]. Even though many relationships exist between banks, this note focuses on relationships that stem from interbank lending. For the originating (lending) bank the loan will be on the asset side of its balance sheet, while the receiving (borrowing) bank will hold the loan as a liability. As for example Allen and Babus (2008) argue, linkages between financial institutions stem from both the asset side (through holding similar portfolios) and the liabilities side (by sharing the same mass of depositors). These linkages can be direct (as in the case of interbank loans) and indirect (as in the case of similar portfolios). The authors investigate the resilience of financial networks to shocks and the formation of financial networks. Network theory has been successfully applied in the analysis of payment systems (see e.g. Soramäki and Galbiati (2008), or Markose *et al* (2010)). Castren and Kavonius (2009) apply network theory to study accounting-based balance sheet interlinkages at a sectoral level. Canedo and Jaramillo (2009) propose a network model to analyse systemic risk in the banking system that seeks to obtain the probability distribution of losses for the financial system resulting both from the shock/contagion process. Nier *et al* (2007) construct a network model of banking systems and find that (i) the better capitalised banks are, the more resilient the banking system is against contagious defaults and that this effect is non-linear; (ii) the effect of the degree of connectivity is non-monotonic; (iii) the size of interbank liabilities tends to increase the risk of knock-on default; and (iv) more concentrated banking systems are prone to larger systemic risk. In Gai and Kapadia (2009) the authors investigate systemic crises with a network model and show that on the one hand the risk of systemic crises is reduced with increasing connectivity on the interbank market. On the other hand, however, the magnitude of systemic crises increases at the same time. Georg and Poschmann (2010) employ network theory to analyze contagion and common shock effects in a model of interbank markets with

[4] For an extensive overview of financial networks see e.g. Allen et al. (2010)

central bank activity. They show that common shocks are not subordinate to contagion, but pose instead a greater threat to systemic stability.

Contagion in interbank markets emerges if, for example, Bank A, which has an interbank loan from Bank B, is hit by a shock and goes into insolvency. Bank B then suffers a loss on its assets and might itself become insolvent if it does not have enough bank capital. If Bank C now has an exposure to Bank B, this could also cause solvency problems for Bank C. Now Bank C faces problems, even though it had no immediate interconnection with Bank A, which was the root of the shock. Even from this very simple example one can see that microprudential supervision and regulation is inadequate on its own to identify potential routes of contagion and assess the stability of a financial system.

The situation is even more complex when other interlinkages between banks are taken into account, caused for example by investing into a similar class of assets. To illustrate this form of systemic risk (Whelan, 2009) considers three banks - Bank A, B and C – whose balance sheets are shown in Table 1. Now assume that Bank A makes an initial loss of 5 on its loan book. This will reduce its equity capital to 5 and increase its leverage ratio from 200/10 = 20 to 195/5 = 39, putting it close to, or below, the capital adequacy ratio. This very modest initial loss then forces A to sell some of its securities. Originally its securities were worth 40 but since Bank A has to do away with them in a fire-sale, the bank sells half of them and recoups only 18 instead of their original value of 20. The reduced value of Bank A's securities will reduce its equity capital to 1, as it suffers a loss of 2 on the securities it sold and a mark-to-market loss of 2 on the remaining securities. Now Banks B and C are hit with two problems: since Bank A has been selling its securities in a fire-sale, the securities of Bank B and Bank C are now worth only 36. This reduces their equity capital from 10 to 6. Needing to shrink their balance sheets and worried about Bank A's solvency, they decide to not roll-over their loans to A. Bank A now has to repay the loans to Bank B and Bank C but with almost no equity and the value of its securities falling, it fails to do so. Banks B and C now suffer losses on their own loan book as well as on their securities and are then just as vulnerable as Bank A, even without directly suffering the initial loss.

Table 1 Example balance sheets

Bank A

Assets		*Liabilities*	
Loans to Customers	100	Retail Deposits	130
Loans to B	30	Borrowing from B	30
Loans to C	30	Borrowing from C	30
Other Securities	40	Equity Capital	10
Total	200	Total	200

Bank B

Assets		*Liabilities*	
Loans to Customers	100	Retail Deposits	130
Loans to A	30	Borrowing from A	30
Loans to C	30	Borrowing from C	30
Other Securities	40	Equity Capital	10
Total	200	Total	200

Bank C

Assets		*Liabilities*	
Loans to Customers	100	Retail Deposits	130
Loans to A	30	Borrowing from A	30
Loans to B	30	Borrowing from B	30
Other Securities	40	Equity Capital	10
Total	200	Total	200

Source: Whelan (2009)

There are various attempts to assess systemic risk in a broad context. Brunnermeier et al. (2009) propose to apply leverage, maturity mismatch or the rate of expansion to measure systemic risk. Lehar (2005) estimates the risk of a common shock by the correlation between institutions' asset portfolios. Acharya (2009a) recommends to measure an institution's contribution to aggregate risk based on its marginal value at risk and its marginal expected shortfall. Acharya (2010) proposes to assess the systemic expected shortfall, which indicates how much an institution is prone to undercapitalize when the financial system is also undercapitalized. Haldane (2009) suggests to measure contagion based on the interconnectedness of each institution within the financial system, whereas Adrian and Brunnermeier (2009) focus on CoVaR, which is the value at risk of the whole financial sector in times of crisis. They argue to interpret the difference between CoVar and the institution's specific value at risk as the institution's contribution to systemic risk. Tarashev *et al* (2009) propose to apply the Shapley value methodology to asses this contribution. Thomson (2009) provides a scoring model to categorize each institution according to its contribution to systemic risk. Eligible criteria are size, contagion, correlation, concentration and economic conditions.

3.2 Data Gaps

Despite the importance of macroeconomic shocks to financial stability, policy makers and academia are faced with huge information and data gaps. A number of suggestions on how to close these gaps have been made in the past two years (Financial Stability Board and International Monetary Fund, 2009), but the issue is far from resolved. The unavailability of data makes it impossible, for all practical purposes, to properly measure the systemic risk that is associated with cross-correlations amongst banks' portfolios. Yet, it is clear that structured finance and derivatives have increased the number of cross-correlations between different portfolios. In South Africa, the fraction of derivative financial instruments to the total balance sheet volume is much smaller than in the United States, the United Kindom or the Euro-area, for example. This is not to say that there are no cross-correlations amongst the portfolios of the South African banks. Especially the large banks all depend heavily on short-term wholesale funding, which effectively introduces cross-correlations between their portfolios that have to be taken into account when assessing the vulnerability of the South African banking system to macroeconomic shocks.

3.3 Literature Review

Even with the aforementioned limitations, network theory can provide valuable information about the health and stability of the banking system. This is underlined by the large number of countries that have employed network theory to assess systemic risk. Basically there are two strands of literature. One strand follows Eisenberg and Noe (2001) who develop a liabilities matrix for a financial system and show that it has a unique clearing payment vector. Sheldon and Maurer (1998) construct a matrix of interbank loans for Switzerland based on known marginal loan distributions and the principle of entropy[5] maximisation. Blåvarg and Nimander (2002) construct the matrix

[5] Entropy is a measure of the disorder that exists in a system.

of interbank exposures from the reports of Swedish banks to the Riksbank. Upper and Worms (2004) analyze the risk of contagion in the German interbank market using data from banks submitted to the Bundesbank. They apply the principle of entropy maximisation to construct the matrix of interbank exposures. Wells (2004) constructs the matrix of bilateral exposures by using data on UK-resident banks money market loans and deposits with other UK-resident banks. Degryse and Nguyen (2007) use detailed information on aggregate interbank exposures of individual banks and on large bilateral interbank exposures of the Belgian banking system to construct the matrix of interbank exposures. They analyse the years 1993 - 2002 and find that the structure of the Belgian banking system has changed from a complete structure to a "multiple-money-centre" structure. Van Lelyveld and Liedorp (2004) use several data sources, including monthly balance sheet data, large exposures and survey data from an *ad hoc* survey obtained from the largest ten banks in the Netherlands to construct the matrix of interbank exposures. Boss *et al* (2004) study the Austrian interbank market with a combination of actual interbank exposures (for large loans) and an estimation technique, and were able to show that the degree distribution of the interbank network shows two different power law exponents, relating to two different sub-network structures, differing in the degree of hierarchical organization. They identified the Austrian interbank network to be a small-world network.

Another strand of literature uses payment system data and actual interbank exposures to analyze systemic risk. Furfine (1999) examines the likelihood that a failure of one bank would cause the subsequent collapse of a large number of other banks in the US using the Federal Reserve's large-value transfer system Fedwire. Mistrulli (2007) uses actual interbank exposure data from the Bank of Italy Supervisory Reports database to analyze the risk of contagion in the Italian interbank market. The results are compared to the analysis of contagion in the Italian interbank market if the maximum entropy method is used. It is shown that the maximum entropy method leads to an overvaluation of the severity of contagion, which is in contrast with the common view that complete markets are more resilient to financial contagion. Memmel and Stein (2008) use data from the German credit register and of the regulatory reports filled in by the banks, to analyze contagion risk in the German interbank market. Gabrieli (2010) analyzes the functioning of the overnight unsecured euro money market during the ongoing crisis in terms of operational efficiency of monetary policy implementation, efficient reallocation of banking systems reserves and developments in the pricing of interbank loans using data on unsecured euro-denominated loans executed through the e-MID platform (which represents roughly 17% of the total turnover of the overnight segment). The results suggest that monetary policy implementation has been hampered by the crisis, particularly after the end of September 2008. Becher *et al* (2008) examine the broad network topology of interbank payments in the United Kingdom and show that the UK financial system exhibits a tiered structure, making it distinctly different from the United States' financial system. They use data from the Clearing House Automated Payment System (CHAPS) 2003 data survey, which includes intraday data for 5 days in February 2003.

Chang *et al* (2008) analyze the market structure and degree of completeness and heterogeneity in order to assess the financial fragility of the Brazilian financial system. They apply the Hirschman-Herfindahl index (HHI) which was used by Nissan (2004) and Geldos and Roldos (2004) to evaluate the concentration of banking systems in developing countries, as well as the dual HHI that was analyzed by Tabak *et al* (2009). They analyze the concentration, heterogeneity and completeness of the Brazilian banking system. Cajueiro and Tabak (2007) analyze the topology of the Brazilian interbank market. They introduce different measures, such as (weighted) degree, (weighted) efficiency, domination and the minimal spanning tree to analyze the topology of the interbank network. They could show that the Brazilian interbank market employs a scale-free toplogy and is characterized by money-center banks. Manna and Iazzetta (2009) use network theory to analyze monthly data on deposit exchanged by banks on the Italian interbank market from 1990 to 2008. They find that there is no direct connection between interconnectedness and volume of banks, leading to the question which of the three by IMF/BIS/FSB (2009) proposed criteria (volume, interconnectedness, and substitutability) gives the largest contribution to systemic risk.

We follow the second strand of literature and use actual exposures of banks obtained from the South African Multiple Option Settlement (SAMOS) system. Unlike Europe and the United States, the majority of interbank payments in South Africa are made via the SAMOS system, giving a uniquely accurate overview of the actual payments between banks. In total, there were nearly 13 million transactions taken into account over the period March 2005 to June 2010. Interbank loans were identified by a matching algorithm[6] where for each transaction from Bank A to Bank B, the algorithm searches for a matching transaction in the opposite direction. We focussed on interbank loans that are overnight, as these loans are the most prominent type of interbank loans and also represent the most rapid contagion channel for interbank systemic risk. We further required the loans to be larger than 10 Million Rand in order to enhance the probability that a transaction is indeed an interbank loan and not a retail transaction. The data set used in this analysis is one of the most extensive ones ever used to assess the stability of an interbank system on the basis of actual exposures. The analysis therefore can contribute to strengthening the trust in the long-term stability of the South African interbank system.

3.4 Network Measures

To analyze the structure of the South African interbank system, we make extensive use of tools and notions from network theory. We therefore give a brief overview of network and graph theory to introduce the necessary measures. We follow the notation by Manna and Iazzetta (2009) and start by defining what a graph is.

Definition. *A (un)directed graph* $G(V,E)$ *consists of a nonempty set* V *of vertices and a set of (un)ordered pairs of vertices* E *called edges. If i and j are vertices of* G *, then the pair* $i{:}j$ *is said to join* i *and* j *.*

For every graph one can construct a matrix of bilateral exposures which describes the exposure of bank i to bank j .

Definition. The matrix of bilateral exposures $W(G) = [w_{ij}]$ of an interbank market G with n banks is the $n \times n$ -matrix whose entries w_{ij} denote the bank i 's exposure to bank j . The assets a_i and liabilities l_i of bank i are given by:

[6] The matching algorithm was originally introduced by Furfine (1999)

$$a_i = \sum_{j=1}^{n} \mathbf{w_{ij}} \quad l_i = \sum_{j=1}^{n} \mathbf{w_{ji}}$$

Another important matrix is the adjacency matrix that describes the structure of the network without referring to the details of the exposures.

Definition. The entries a_{ij} of the adjacency matrix $A(G)$ are one if there is an exposure between i and j and zero otherwise.

A useful measure is the in- and out-degree of a node i. It is a measure for the connectedness of a node in the network and defined as follows.

Definition. The node in- and out-degree is defined as:

$$d_{in} = \sum_{j=1}^{n} \mathbf{a_{ji}} \quad , \qquad \mathbf{d_{out}} = \sum_{j=1}^{n} \mathbf{a_{ij}}$$

Following Mueller (2003) we define the value in-degree and value out-degree of a node $\mathbf{i}$ as the weighted in and out degree:

Definition. The weighted in- and out-degree of a node is defined as:

$$\mathbf{vdc_{in}} = \frac{\sum_{j=1}^{n} \mathbf{w_{ji}}}{\sum_{k=1}^{n} \sum_{j=1}^{n} \mathbf{w_{kj}}} \in [0, 1]$$

$$\mathbf{vdc_{out}} = \frac{\sum_{j=1}^{n} \mathbf{w_{ij}}}{\sum_{k=1}^{n} \sum_{j=1}^{n} \mathbf{w_{kj}}} \in [0, 1]$$

The value in-degree is the fraction of bank i 's credits of the total credit volume. It can therefore be interpreted as a measure for the size of bank i in the interbank market. Another important quantity is the betweenness of a node. It is a centrality measure that is defined by the number of shortest paths that pass through a given vertex. Nodes that occur on many shortest paths have a higher betweenness than nodes that occur on fewer shortest paths.

Definition. The betweenness $b(i)$ of a node is defined as:

$$b(i) = \sum_{j \neq i \neq k \in V} \frac{\sigma_{jk}(i)}{\sigma_{jk}}$$

where j and k are vertices of $G(E,V)$. σ_{jk} is the total number of shortest paths between j and k and $\sigma_{jk}(i)$ the number of shortest paths between j and k that pass through i .

Since every shortest path between two nodes represents a flow of interbank funds, the betweenness of a node i can be interpreted as a measure for the substitutability of that node. A node that lies on many shortest paths will be harder to substitute than a node that lies only on very few shortest paths.

So far we have investigated three different network measures that assess the importance of a node in the network. One commonly used quantity to describe the topology of a network is the clustering coefficient, introduced by Watts and Strogatz (1998). Given three nodes i , j and k , with i lending to j and j lending to k , then the clustering coefficient can be interpreted as the probability that i lends to k as well. For $i \in V$, we define the number of opposite edges of i as

$$m(i) \equiv |\{j,k\} \in E: \{i,j\} \in E \ \wedge \ \{i,k\} \in E|$$

and the number of potential opposite edges of i as

$$t(i) \equiv d(i)(d(i) - 1)$$

Where $d(i) = d_{in}(i) + d_{out}(i)$ is the degree of the vertex i .

Definition. The clustering coefficient $c(i)$ of a node i is given as:

$$c(i) \equiv \frac{m(i)}{t(i)}$$

and the clustering coefficient $C(G)$ of the whole network $G = (V,E)$ is defined as:

$$C(G) \equiv \frac{1}{|V'|} \sum_{i \in V'} c(i)$$

where V' is the set of nodes i with $d(i) \geq 2$.

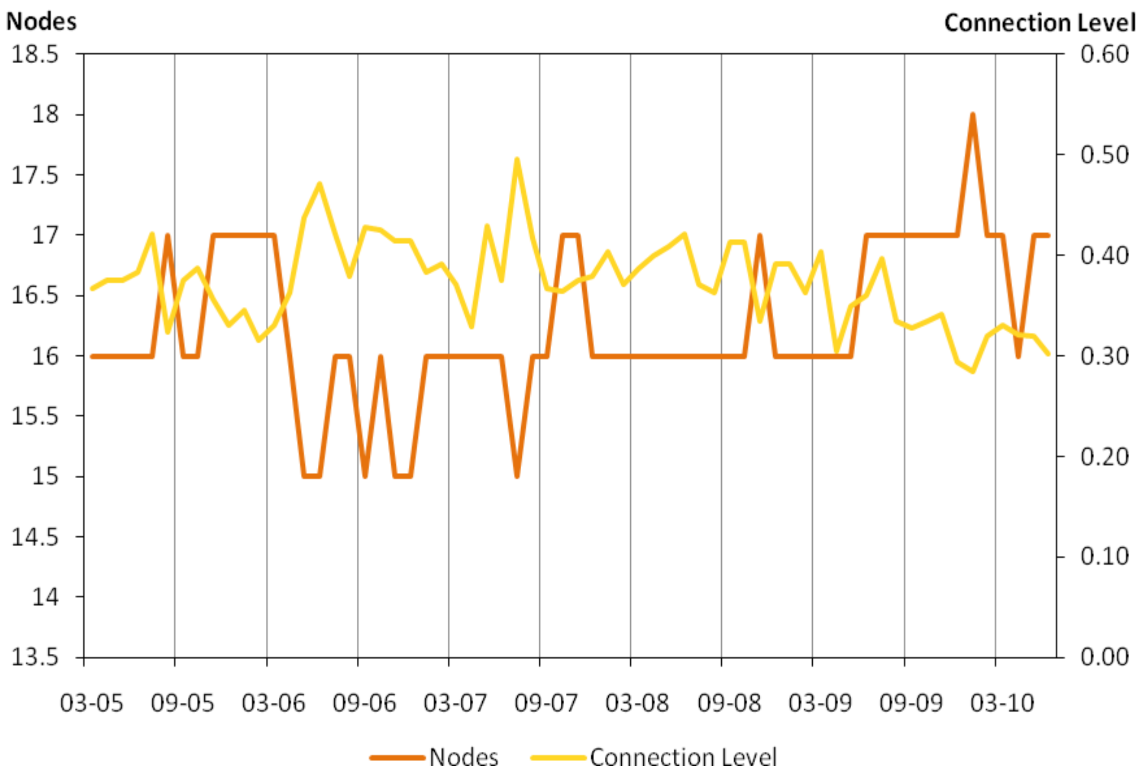
The clustering coefficient can be used to identify small-world networks which have a high clustering coefficient and low average path length. These networks are possibly more prone to contagion effects than scale-free networks and therefore need special attention when assessing systemic risk.

4 Network Measures of the South African Interbank System

In order to describe the network topology of the South African interbank system, one can resort to measures from network theory. Four properties were used to describe a network in this note. The first one is the size of the network, given by the number of nodes in the network and shown in Figure 1 on the left axis. The second measure is the connectivity of the interbank market. This is defined as the fraction of actual edges to possible edges between nodes and called the connection level. It can range from 0 (no interconnections) to 1 (every bank is connected to every other bank) and shown in Figure 1 on the right axis. In normal times a high connection level will lead to a more stable system as banks can access liquidity from more sources.

In the South African system, the number of banks (nodes) that participate in interbank lending varied between 15 and 18, while the connection level varied between 0,33 and 0,50. It can be seen that the system is largely stable both by looking at the fairly stable number of banks that participate in interbank lending and the relatively high level of connections between the banks.

Figure 1 Network Properties of the South African Overnight Interbank Market

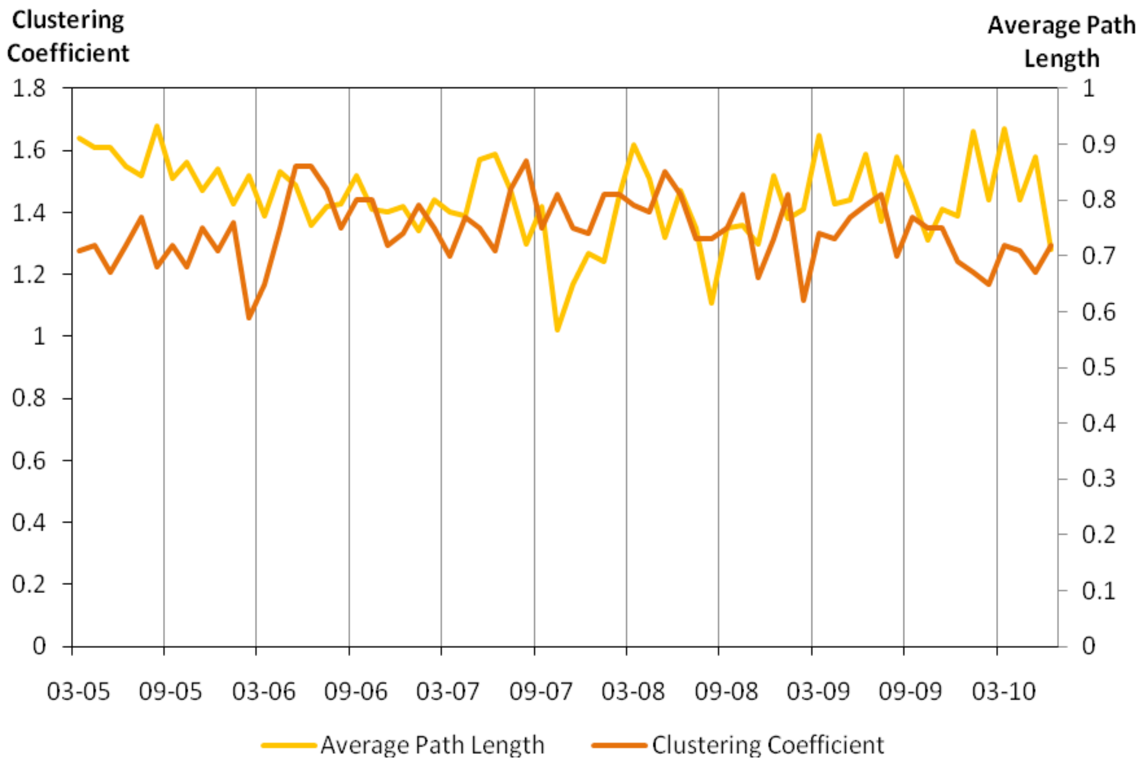


Source: South African Reserve Bank, SAMOS Data

The third quantity that is used to determine the structure of the interbank system is the average path length, which is defined as the average number of connections that is needed to transfer liquidity from one bank to another. In normal times a small average path length indicates a well connected system, where liquidity can easily be transferred from one bank to another. In times of crises, however, a short average path length also implies that contagion can spread faster through the system. Note that the average path length does not give any indication of the probability of an initial knock-on default but rather describes how such an exogenous event can spread in the system.

The fourth measure of the network topology is the clustering coefficient, which is defined as the probability of two banks being exposed to each other, if both of them are exposed to a common third bank. A high clustering coefficient, similar to the average path length, indicates a well connected interbank system where banks distribute liquidity widely in the system. In times of crises, however, a high clustering coefficient increases the risk of joint failure of banks. In Figure 2 the results for average path length (left axis) and clustering coefficient (right axis) are shown.

Figure 2 Clustering and Average Path Length of the South African Overnight Interbank market



Source: South African Reserve Bank, SAMOS Data

The short average path length and high clustering coefficient of the South African interbank system vary little over time, indicating a stable network structure even in times of distress such as the crisis on the international financial markets in September and October 2008. These results are in line with the findings of Brink (2009) stating that the direct impact of the financial crisis of 2007/08 on the South African interbank market were modest.

5 The systemic importance index for South African banks

While the results above are measures of the global network topology, a more detailed view of individual banks is needed in order to assess their individual systemic importance. The FSB proposes three key criteria to determine the systemic importance of markets and institutions namely *size* (the volume of financial services provided by the individual component of the financial system), *substitutability* (the extent to which other components of the system can provide the same services in the event of a failure) and *interconnectedness* (linkages with other components of the system).

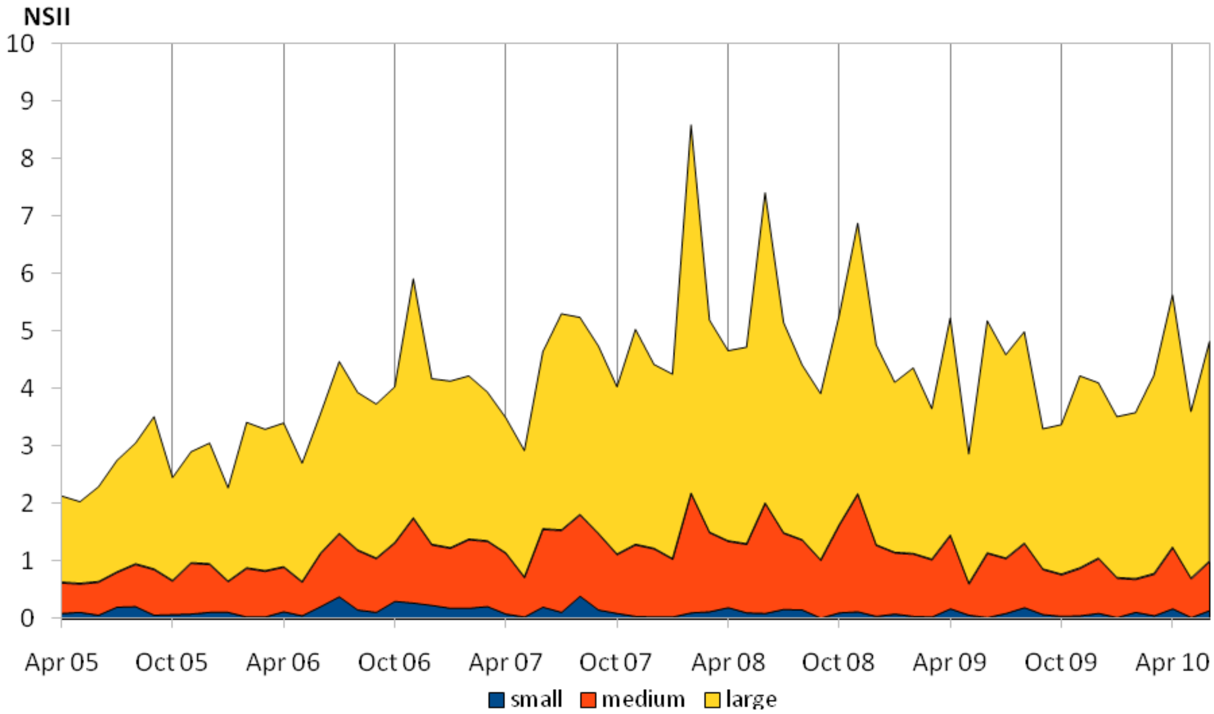
These measures can be translated into measures from network theory. To assess the systemic risk that is associated with a given bank, one has to look at the impact that a default of this bank would have on the rest of the system. In case of insolvency it will be the bank's liabilities that determine its size for the purpose of this note. The impact of a shock that originates from this bank will increase the larger its interbank liabilities. The second variable to assess the systemic risk associated with a given bank is its interconnectedness. As in the case for interbank liabilities, the impact of a shock will be larger if the bank is more connected to the rest of the system. In terms of a network measure it is therefore the number of edges that originate from somewhere in the system and end at the given bank that depict its systemic importance. In network theory this is referred to as the node in-degree of the bank. The third and most complicated measure is a bank's substitutability. A bank will be difficult to substitute if it receives and originates a lot of interbank funding. It will therefore be harder to substitute if it is in the middle of many interbank payment flows and its systemic importance will increase the harder it is to substitute. The network measure that can be associated with this property is a node's "betweenness". It measures the number of shortest paths between any other two nodes in the network, which pass through the node in question. The higher the number of 'shortest paths' that pass through a given node, the more interbank funding flows through this bank and the harder it will be to substitute.

In order to construct the systemic importance index from these three measures, every measure was normalized to be between zero and one. This normalisation was done by taking each variable and dividing it by the maximal variable in the network. The network systemic importance index (NSII) of any given bank is then the sum of the three submeasures. To account for the fact that the total interbank volume changes over time, the NSII was multiplied with the actual volume of interbank exposures and normalized by the total exposures for the first measurement point, which is March 2005. The NSII will thus measure the systemic importance of individual banks for every month from March 2005 to June 2010. Note, however, that it is a relative measure and will only give the systemic importance of one bank in comparision to other banks in the system.

The results for the NSII of three groups of South African banks are shown in Figure 3. The first group consists of *"large"* banks, comprising all banks that had a network systemic importance index of $NSII \geq 2$ in June 2010. The groups of *"medium"* banks consists of all banks with $0.5 \leq NSII < 2$. All other banks are defined to be *"small"*. The NSII shown in Figure 3 is normalized by the number of banks in each of the three groups.

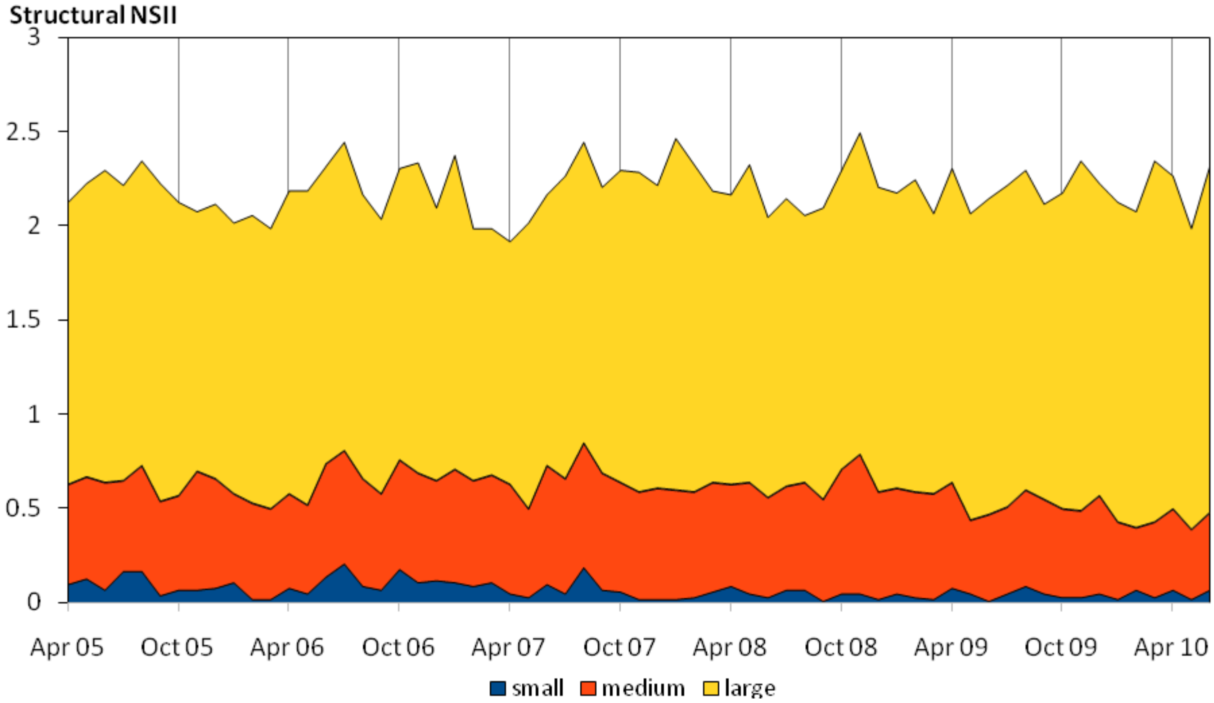
As can be seen in Figure 3, the main contribution to systemic importance comes from large banks, while almost no contribution comes from small banks. It is illustrative to look at the structural component of the network systemic importance index, as an increase in the total NSII of a group of banks can also stem from an increase in total market volume. In Figure 4 this structural component of the NSII for the South African banks is shown.

Figure 3 Network Systemic Importance Index (NSII) for South African banks



Source: South African Reserve Bank, SAMOS Data

Figure 4 Structural component of the NSII for South African banks

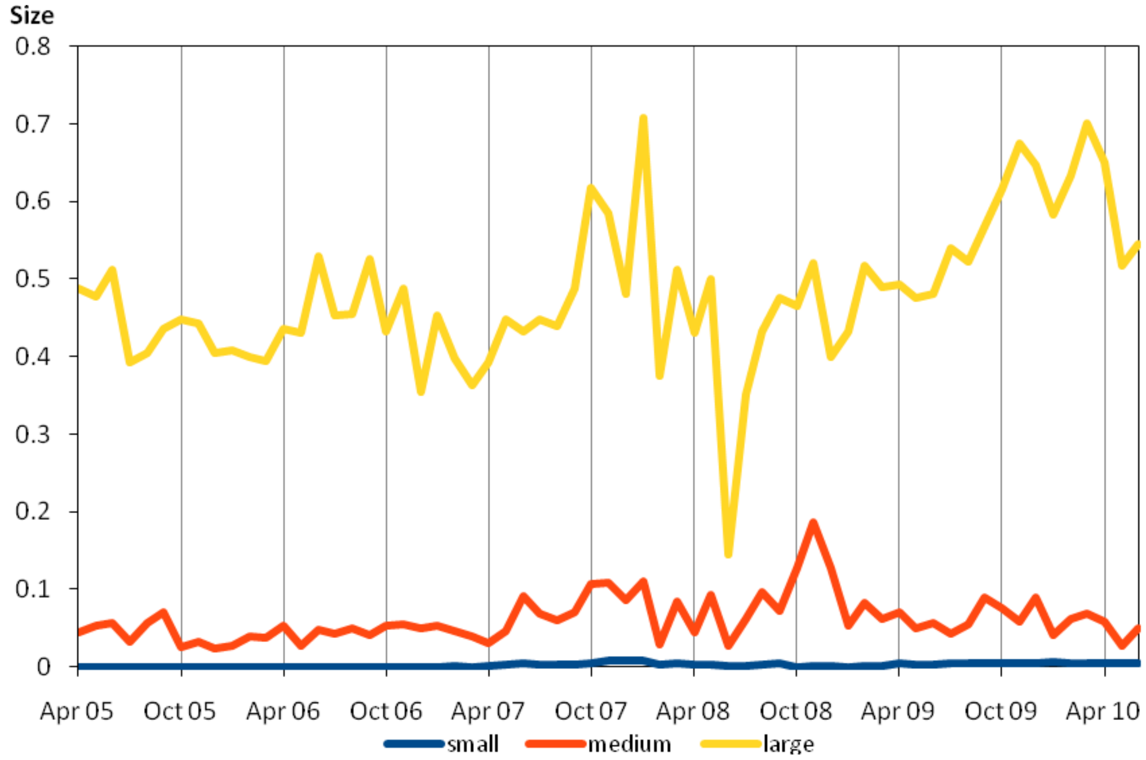


Source: South African Reserve Bank, SAMOS Data

It can be seen, that the structural NSII has remained approximately constant over the period under investigation. This indicates a stable network structure during the whole period where the large banks contribute about two third to overall network systemic importance.

In order to properly assess systemic risk of the three groups of banks, one has to analyse which of the three criteria (size, interconnectedness and substitutability) contributes most to the overall NSII of each group. In Figures 5-7 the results for the individual measures are shown for all three groups. They all range from 0 to 1 as they were normalized by first calculating each measure for every individual bank, then dividing them by the maximum value and finally adding them and dividing them by the number of banks in the respective group.

Figure 5 Size of South African Banks in the interbank market by bank groups

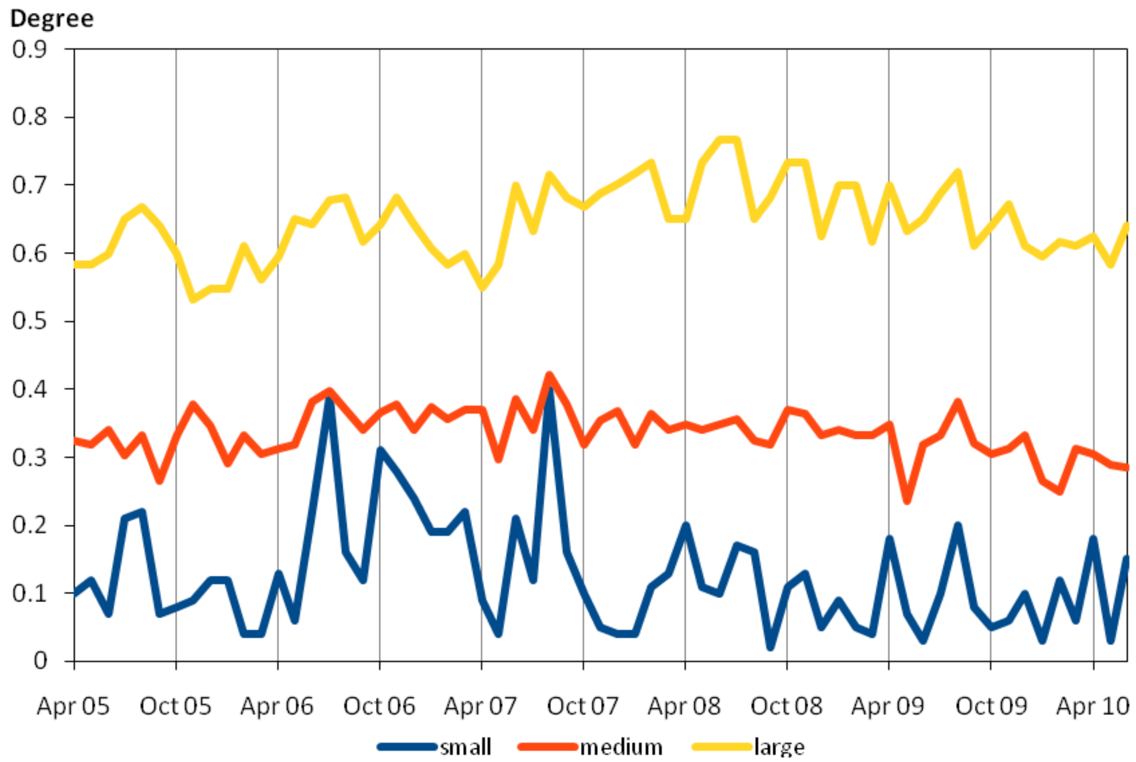


Source: South African Reserve Bank, SAMOS Data

It can be seen from Figure 5 that the contribution of size to overall network systemic importance is the largest for large banks, while there is almost no contribution for small banks. The results also indicate that size is a key factor that accounts for the large difference in the systemic importance of large and medium banks and that size is a key difference between medium and small banks.

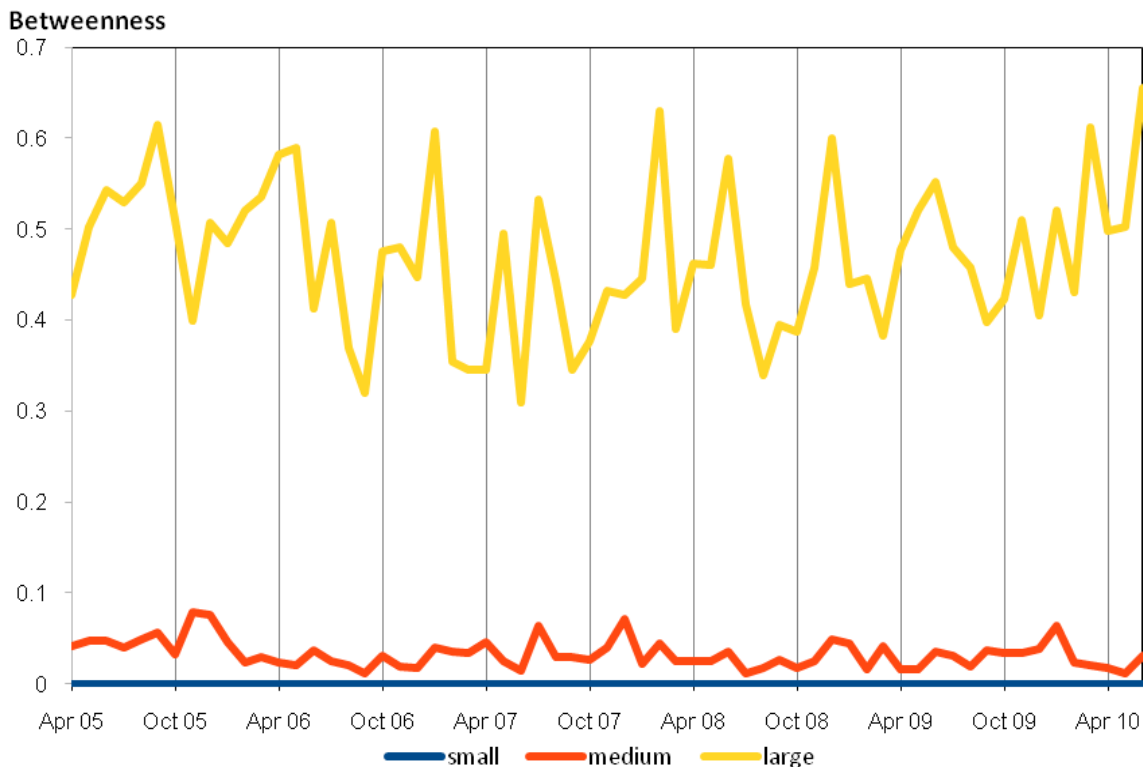
In Figure 6 the connectedness of South African banks in the interbank market is plotted for the three groups of banks. One can see that for all banks a large part of their overall systemic importance stems from their interconnectedness. This holds true for small banks, as their interconnectedness is the only quantity that contributes to their systemic importance on a relevant level. The medium banks have a contribution from interconnectedness which is significantly larger than for the small banks. The results show that the high interbank transaction volume of large banks goes hand in hand with a large interconnectedness, making them the central hubs of funding flows.

Figure 6 Connectedness of South African banks in the interbank market by bank groups



Source: South African Reserve Bank, SAMOS Data

Figure 7 Betweenness of SA banks in the interbank market by bank groups



Source: South African Reserve Bank, SAMOS Data

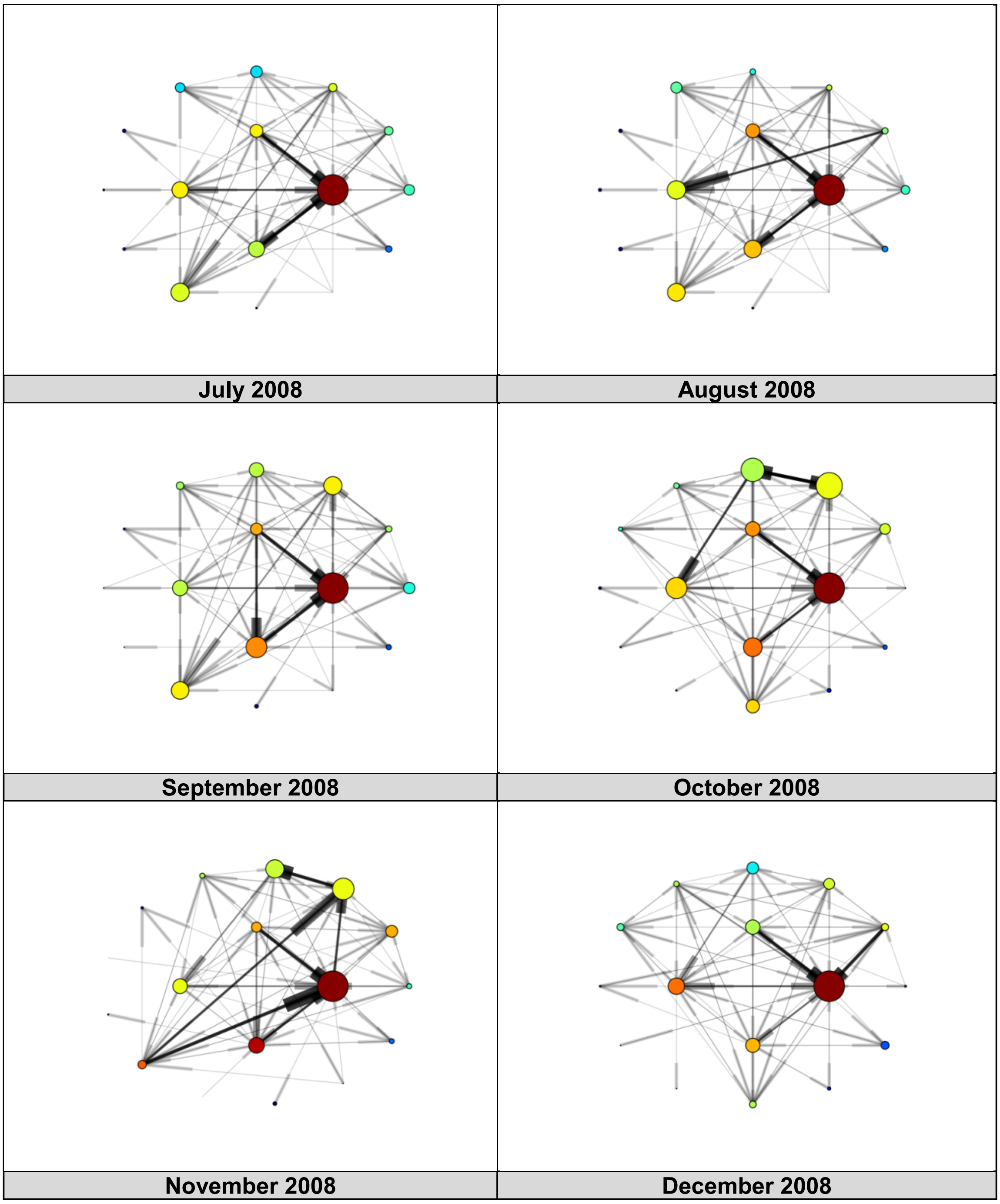
In Figure 7 the betweenness of the three groups of banks is shown and it can be seen that the small banks have virtually no betweenness. The betweenness is the quantity that ultimately distinguishes medium from large banks.

While the large banks are high in size, interconnectedness and betweenness, the medium banks are moderate in size, moderate in interconnectedness and low in betweenness. Small banks are low in size and betweenness and moderate in interconnectedness. These structural differences between large, medium and small banks should be taken into account when prudential requirements are proposed.

The overall network systemic importance index is a very volatile quantity that changes on a real-time basis. To interpret this index, one has to look at how the interbank network changes over time. The network structure for overnight and longer-term interbank loans is a structure that is fixed every morning and varies from day to day. This volatile nature of the interbank system does not in itself threaten the stability of the financial system as it indicates a well-functioning interbank system where liquidity is readily distributed amongst its participants.

It is illustrative to display the interbank network structure in order to get a better understanding what a low/high network systemic importance means. The structure of the interbank market is displayed for the period of August 2008 (top left) to January 2009 (bottom right) when the turmoil on the international financial markets was at its highest. The size of each node in the network corresponds to the size of the node in terms of interbank exposure. In the centre of the graph are the largest node (in terms of interbank exposure) and all nodes that are at least half it's size, while all other nodes are grouped on the outside. The colour of the nodes is an indication for their interconnectedness and ranges from blue (little interconnectedness) to red (highly interconnected). The size of the edges is a measure for the exposure between two banks, a thicker line indicates higher exposure. The thick end of an edge is an indicator for the direction of the edge. Edges go from the small end to the thick end.

Figure 8 Network topology of the South African interbank system



Source: South African Reserve Bank, SAMOS Data

It can be seen that during the whole period there was one bank that had a significantly high systemic importance in terms of size, interconnectedness and betweenness. However, during the whole crisis period there was a well connected interbank system with large liquidity flows inside the system are a signal of trust amongst the South African banks as well as a signal of mistrust of South African banks to foreign banks. This situation is not alarming since the systemic importance of a bank itself is not related to the default probability of this bank. It is nonetheless desirable to have a situation with a low network systemic importance index since this situation will be even more resilient should a shock hit the South African interbank market.

6 Moral Hazard

One of the main concerns of attributing systemic importance to individual banks is related to moral hazard and implicit bail-out guarantees. A bank that knows that it will be bailed out, should it default, will be more likely to take on excess risks. The issuance of implicit or explicit bail-out guarantees therefore might increase the risk that the guarantees could actually be needed. While insolvencies are an important part of any healthy market economy, the insolvency of a bank might lead to a breakdown of the financial system as a whole and can have devastating effects on the real economy. These effects can be even more severe in a developing country with a relatively concentrated banking system, like South Africa. It is therefore necessary to keep moral hazard issues in mind when constructing measures for the systemic importance of a bank.

The network NSII is an index that does not solely depend on the properties of an individual bank. It rather depends on the properties of all banks in the interbank system. Even if a bank knows its network systemic importance index at a given point in time, its importance could change very quickly due to the interactions of the other banks. Every bank knows that it can increase its systemic importance by taking on larger risks and more connections in the interbank market. Banks can, however, not be sure that other banks are not doing the same. Since the network systemic importance index is a relative index, there are no guarantees for a bank that increasing exposures will lead to higher systemic importance. It is precisely that relative nature of the NSII that makes it less vulnerable to moral hazard.

In some countries the systemic importance of financial institutions is assessed in a discretionary manner by the central bank, the banking supervision authority and the government. Such a discretionary assessment, however, fails to take the volatile nature of systemic risk into account. And even worse, it creates major moral hazard problems. Banks that are deemed to be systemically relevant according to the discretionary assessment might correctly guess that they are and are therefore directly affected by moral hazard. The implicit bail-out guarantee that has been issued for systemically relevant banks by bailing them out in the financial crisis of 2007/2008 creates incentives for those banks to take on excessive risk. The situation is even worse for banks that are not deemed to be systemically important but assume they are. Those banks also have the incentive to take on excessive risks, but are not covered by a bail-out guarantee. Their insolvency might lead to informational contagion and an increase in the refinancing cost of the remaining banks, which in turn can trigger further defaults. To prevent such a situation, it is strongly desirable to have a transparent measure for the systemic importance of individual financial institutions and markets.

7 Concluding Remarks

The NSII defined in this discussion paper gives valuable insight into the structure of the South African interbank system, thereby representing one of the measures with which to assess systemic significance. With the index it is possible to measure the systemic importance of individual banks on an ongoing, day-to-day, month-to-month or even longer basis. In combination with other measures of systemic significance, this information could be used to impose prudential requirements on firms commensurate with their systemic importance. However, one has to take into account that systemic importance of the different groups of banks is driven by different criteria. Banks in the group of large banks are usually high in size, interconnectedness and betweenness, while medium banks are moderate in size, moderate in interconnectedness and low in betweenness. Small banks are low in size and betweenness and moderate in interconnectedness. It is argued that these structural changes have to be taken into account when further prudential requirements for firms are discussed. The South African banking system has been shown to be stable in terms of structure and number of participants, even in times of high transactional volumes and great distress in the international financial markets.

It is argued that moral hazard is less pressing when the network systemic importance index is taken into account and therefore preferable in this regard to having a “secret list” of banks that are considered to be systemically important. Moral hazard is less pressing, since the systemic importance of each bank depends not only on its own behaviour, but also on the behaviour and structure of the rest of the banking system.

While the South African interbank system has been proven to be resilient to shocks in the international financial markets, a continuous monitoring of the interbank network structure can help alleviate future stress and provide a tool for cross-section analysis of systemic risk. The network systemic importance index can therefore contribute to further strengthen the stability of the South African financial system.

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