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A network approach to interbank contagion risk in South Africa

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Abstract

We investigate the resilience of the South African banking system using a dynamic agent-based model and the DebtRank algorithm. This approach enables us to identify each bank's importance and vulnerability in the interbank network and is not limited to listed banks, as previous studies were. We find that larger banks are more systemically important, but a bank's interbank-lending-to-equity multiple is significantly correlated with its vulnerability. Our research offers policymakers a direct and practical indicator for improved monitoring of financial stability.

JEL classification

C63, G17, G21

Keywords

Systemic risk, interbank network, contagion risk, agent-based modelling, DebtRank

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1. Introduction

The stability of the South African banking system has attracted increasing attention from researchers (see Brink and Georg 2011, Foggit et al. 2017, Walters et al. 2018 and Havemann 2021) and policymakers (International Monetary Fund 2014, 2022) since the Asian financial crisis in 1997, when South Africa was the only country in sub-Saharan Africa to be significantly affected by the crisis through financial channels (Harris 1999). This attention is due to the distinct features of the South African banking system, including its high degree of concentration, accelerated growth in assets, and opaque and intricate interconnections, which are often challenging to fully comprehend (International Monetary Fund 2014, 2022).

In recent years, an increasing number of studies on systemic risk in South Africa have been conducted. Manguzvane and Mwamba (2019), Leukes and Mensah (2019), and Chatterjee and Sing (2021) have all examined systemic risk in the South African banking sector. However, these studies rely on market data for listed banks, which are restricted to the domestic systemically important banks (D-SIBs) and exclude unlisted small and medium-sized banks.

To comprehensively grasp the intricacies of systemic risk in the South African banking sector, it is imperative to incorporate small and medium-sized banks into the analysis. Over the past three decades, South Africa has experienced 23 bank failures and deregistrations in its banking sector (see Annexure 1 for a comprehensive list of these occurrences). Notably, most of these banking failures were attributed to institutions in the small and medium-sized category. The most severe episodes of banking failure in South Africa occurred in 2002 and 2003 (Havemann 2021), triggered by the collapse of Saambou Bank, the seventh-largest bank in South Africa, in February 2002. Saambou's failure quickly spread to small and medium-sized banks through contagion, resulting in an immediate run on seven banks. As a result, half the country's banks had been deregistered by the end of 2003, triggering a banking crisis (Havemann 2021). This highlights the importance of investigating D-SIBs and small to medium-sized banks. The potential failures of small and medium-sized banks can also lead to substantial, often unanticipated, financial burdens for individuals, governments and society. In addition, the adoption of a risk-based supervision approach by the South African Reserve Bank (SARB) supports a more inclusive supervision process. This approach aims to identify the most critical risks and vulnerabilities faced by individual banks in a financial system, regardless of their size.

We used a network approach to study systemic risk in the South African interbank market for three reasons. First, our approach relies on banks' balance sheet data, which allows us to include smaller banks in our analysis. These banks are often excluded from studies of systemic risk because they are unlisted, but a bank's failure can significantly threaten the financial stability of the country's banking sector regardless of the bank's size. Second, the history of bank failures demonstrates both the importance and vulnerability of banks, especially the latter, as vulnerable banks are more likely to fail. This leads to our third reason: to identify the factors that contribute to a bank's systemic importance and its vulnerability and to make suggestions for policymakers.

This paper builds on the work of Lin and Zhang (2022) by combining the agent-based modelling (ABM) approach (Liu et al. 2020) to model the dynamic interbank network and the DebtRank algorithm (Battiston et al. 2012 and Bardoscia et al. 2015) to analyse the contagion risk and identify the important and vulnerable banks in the South African banking system. More importantly, we extend Lin and Zhang's work (2022) by conducting a panel data analysis to investigate the business factors that impact a bank's importance and vulnerability.

The novelty of this paper is its finding on banks' vulnerability and its suggestions for policymakers. We found insufficient evidence that a bank's size contributes to its vulnerability, which indicates that larger banks are not necessarily less vulnerable. In other words, policymakers should not rely on size to monitor a bank's vulnerability. Our results also show that increasing the capital ratio can substantially decrease vulnerability, but this effort will be considerably undermined if a bank has a higher interbank lending ratio. Due to the offsetting effect of these two ratios, we introduced the interbank-lending-to-equity multiple to measure a bank's excess interbank lending in relation to its capital. Our results show that this multiple is positively and significantly correlated with vulnerability. This provides a direct and useful indicator for monitoring vulnerability and suggests that policymakers should pay closer attention to banks with high interbank-lending-to-equity multiples.

This paper makes two contributions. First, we extend the systemic risk analysis in the South African banking sector by including unlisted banks. This provides a more comprehensive overview of the risk landscape, in line with the risk-based supervision requirements of the SARB. Second, most of the literature on systemic risk focuses only on banks' influences or impacts on the financial system, while less attention is paid to banks' vulnerability. Our research sheds light on banks' vulnerability, offering valuable insights to regulators.

The rest of this paper is structured as follows: Section 2 discusses the relevant literature, data are presented in Section 3, the methodology is described in Section 4, Section 5 presents the results, and we conclude in Section 6.

2. Literature review

Section 2.1 of this paper discusses the growing body of literature on systemic risk in the South African financial landscape. We note, however, that many of these studies employ methodologies that rely predominantly on market data, excluding small and unlisted banks. The resulting analysis is consequently incomplete and warrants further exploration. This limitation can be overcome by using a network approach, which for systemic risk modelling requires two steps. The first step is to reconstruct an interbank network, discussed in Section 2.2. The second step is to consider how contagion risk is propagated through the network, discussed in Section 2.3. Section 2.4 discusses the driving factors that contribute to systemic risk in terms of systemic importance and vulnerability.

2.1 Systemic risk

Given the advances on the regulatory and supervisory fronts, the literature about systemic risk in South Africa is evolving (see Foggitt et al. 2017, Manguzvane and Mwamba 2019, Chatterjee and Sing 2021, and Havemann 2021). These studies identify risk characteristics in South Africa and serve as the basis for understanding systemic risk in the country. For instance, Manguzvane and Mwamba (2019) found that the risk of systemic failure in the South African banking system increased during the global financial crisis (GFC), identifying African Bank, which became insolvent in 2014, as the riskiest bank in the country. Chatterjee and Sing (2021) note that although the D-SIBs are not ‘global’ enough, the high concentration in the banking sector could significantly impact financial stability if any of these banks were to experience distress. However, these studies suffer from two inherent limitations.

First, their reliance on conventional approaches ($\Delta CoVaR$, systemic risk index (SRISK) and marginal expected shortfall) limits their focus to large banks only, as these methods are based on market data and thus exclude unlisted banks. Second, these studies focus on banks’ importance per the D-SIBs classification and lack analysis of their vulnerability. In reality, a highly vulnerable bank of any size can pose a significant threat to financial stability. As mentioned above, the collapse of Saambou Bank caused widespread small bank failures and triggered a banking crisis in 2002–2003. Thus, an analysis of the country’s systemic risk must include small and medium-sized banks to be comprehensive.

Banks are interconnected as a result of various factors that stem from the nature of their operations and the financial system and because they carry out complex interbank transactions. From a methodological standpoint, the conventional approach to systemic risk thus tends to ignore the source of risk and the mechanism of risk propagation. These limitations can be circumvented through the network approach, which has several advantages over the conventional approach to systemic risk. First, the network approach allows for a more detailed analysis of the sources of risk, because each interbank claim can be established as an edge in the network. Second, it allows for a more detailed analysis of the mechanisms because the channels of propagation can be identified. Third, it can be used to identify the banks most vulnerable to systemic risk. A large body of literature is focused on the network approach to model systemic risk (see Gai and Kapadia 2010; Battiston et al. 2012; Hałaj and Kok 2013; Bluhm, Faia and Krahnen 2014; Elliott, Golub and Jackson 2014; Acemoglu, Ozdaglar and Tahbaz-Salehi 2015; Anand, Craig and von Peter 2015; and Langfield and Soramäki 2016).

Research on the South African interbank network is limited. Brink and Georg (2011) propose a Network Systemic Importance Index to evaluate the systemic importance of South African banks. This index evaluates the size, interdependence and substitutability of each bank, but it does not indicate the default probability of individual banks and must thus be supplemented with other macroprudential tools to provide a complete picture of systemic risk. Walters et al. (2018) present a network-based framework to model systemic risk that considers the propagation of shocks in a banking system. Using data from South African bank balance sheets, they show how one bank's liquidity issues and default might contribute to market frictions, such as a loss of trust in the financial wellness of other banks.

However, their research adopts the assumption of randomised edges when examining various network structures, thus incorporating potential structures that may not represent realistic networks. Among the network structures investigated are Erdős–Rényi, disassortative and core-periphery networks. The Erdős–Rényi network is characterised by equal probabilities of connection among all node pairs, neglecting the influence of network structure on systemic risk. The disassortative network, in contrast, displays a tendency for high-degree nodes to connect with low-degree nodes, a condition that could cause substantial impacts on smaller, heavily dependent banks if a major bank were to fail. Lastly, the core-periphery network is delineated into two discrete groups: a highly connected 'core' and a 'periphery' only connected to core nodes. The inherent structure of this network might foster rapid propagation of a shock from the core to the periphery, thereby accelerating systemic crisis. However, to truly understand systemic risk in the absence of real interbank transactional data, we need a method for interbank network formation, which is discussed in the following subsection.

2.2 Interbank network formation

Maximum entropy (ME) is one of the leading methods for network formation, with many studies on interbank systemic risk based on this approach (see Upper and Worms 2004, Wells 2004, Van Lelyveld and Liedorp 2006, Degryse and Nguyen 2007 and Mistrulli 2011). The ME method redistributes the links in a network by spreading the exposures as evenly as possible, subject to the constraints corresponding to the interbank assets and liabilities for each bank. However, this approach has been criticised for generating too many links, which can undervalue the extent of contagion (Mistrulli 2011).

To address the shortcoming of generating too many links, Anand, Craig and von Peter (2015) developed the minimum density (MD) method. Based on the economic rationale that interbank linkages are costly to add and maintain, minimum density assumes that banks would like to minimise the necessary number of links. Anand, Craig and von Peter (2015) used the balance sheet data of 1 800 German banks to construct the interbank networks with ME and MD. By comparing these estimated networks with the true one, they found that the true network lies between ME and MD, and that MD preserves some of the true network's structural features better than ME. Furthermore, their findings suggest that ME tends to underestimate (and MD tends to overestimate) contagion risk, which results in the real network being somewhere between the networks generated by ME and MD.

This leads to the ABM approach used by Liu et al. (2020) to simulate the interbank network based on the banks' decisions and behaviours. In this model, each bank sets its targets for interbank lending-borrowing ratios and evaluates other borrowers with a score that combines size and relationship. Using the balance sheet data of 6 600 United States banks between 2001 to 2014, Liu et al. (2020) reconstructed the interbank networks based on banks' decision rules and behaviours, showing that ABM produces a network structure that is well-bounded by the ME and MD and possesses many features close to the real one.

2.3 Interbank contagion

The network architecture established with ABM forms the basis for the subsequent phase of analysis to understand the propagation of default risk within the network. A pioneering work for risk propagation is the Eisenberg and Noe (2001, henceforth EN) model. The EN model shows how to compute a set of payments that clear the network and identifies which nodes default as a result of an initial shock to the system. The clearing process is governed by certain assumptions, such as the limited liabilities of banks, the prioritisation of interbank liabilities and proportionate repayment to creditor banks. Using an iteration algorithm, EN can always find a fixed-point-of-payment vector for clearing payments among the banks. Thus, EN is also characterised as a deterministic method. This methodology allows for the calculation of default cascades, the reallocation of funds and systemic effects when dealing with a network of contracts (Caccioli et al. 2018).

One major drawback of EN is that a loss is triggered only by actual insolvency, even though losses can occur in the absence of default because of credit quality deterioration (Caccioli et al. 2018). In other words, EN fails to capture a bank's loss when it is only in distress. The DebtRank distress propagation model, as delineated by Battiston et al. (2012) and Bardoscia et al. (2015), successfully addresses this shortcoming. Within the DebtRank framework, the incursion of a shock upon a bank elevates the associated probability of default. Consequently, the anticipated cash flow linked to exposures to the distressed bank diminishes. Were interbank assets subject to market valuation, the implication would be a diminishment in the valuation of interbank assets pertaining to banks interconnected with the distressed bank. DebtRank operates as a discrete-time mapping function delineating the temporal evolution of banks' equity subsequent to the initial system shock (Caccioli et al. 2018). It uses the relative equity loss of a bank to assess its impact, that is, its contribution to the propagation of distress, and its vulnerability, that is, its susceptibility to distress (Lin and Zhang 2022).

Lin and Zhang (2022) used EN and DebtRank to assess the contagion risks of Chinese banks and found that EN underestimates contagion risk because it fails to capture the distress propagation. However, they were able to calculate each bank's vulnerability score using the DebtRank algorithm. Their results revealed a level of systemic risk among lower-tiered banks. This differs from previous studies in the Chinese interbank market, where no systemic risk was detected (see Cao et al. 2017 and Sun 2020).

While Lin and Zhang (2022) show that a bank is more important if it is larger in size and has greater financial connectivity, the banks' sizes were not correlated with their vulnerability. It is thus crucial to prioritise factors such as a bank's interbank lending ratio and financial connectivity when assessing vulnerability. The interbank lending ratio, which measures the liquidity of the interbank market, is calculated by dividing the total amount of interbank lending by a bank's total assets. Similarly, the interbank borrowing ratio represents the total amount of interbank borrowing divided by a bank's total liabilities. These indicators offer valuable insights into a bank's vulnerability and warrant increased attention in vulnerability assessments.

2.4 Driving factors for systemic risk

Based on the identified systemic risk, another area of literature focuses on exploring its explanatory factors. According to Glasserman and Young (2015, 2016), a bank's importance is associated with its asset size, external leverage and financial connectivity. Laeven, Ratnovski and Tong (2016) investigated the determinants of systemic risk, considering various factors, such as bank size, capital ratio, funding structure and market-based activity. The capital ratio measures a bank's buffer against liquidity shock, while funding structure examines thea bank's reliance on deposit funding, captured as the ratio of retail deposits to total assets. Market-based activity is measured as the ratio of loans to total assets to capture the bank's involvement in market-based lending activities. Using $\Delta CoVaR$ and SRISK as measures for a bank's risk, they found significant evidence that systemic risk increases with a bank's size, but also that systemic risk is lower for better-capitalised banks. In addition, Lin and Zhang (2022) found the interbank lending ratio to be positively correlated with a bank's vulnerability.

Most studies in the field are devoted to explaining a bank's systemic importance, while less attention has been paid to vulnerability; more studies are necessary to explore the driving factors for both importance and vulnerability. Following Lin and Zhang (2022), we used ABM and DebtRank to evaluate the importance and vulnerability of South African banks. We used a panel data analysis to explore their risk characteristics and assess the macroprudential implications.

3. Data

The South African banking sector comprises 31 banks, with the six largest ones classified as D-SIBs. The D-SIBs held 93.4% of the banking sector's assets as of December 2021. The BA 100 returns from the SARB, which are representative of the regulated monthly balance sheet statistics of banks in South Africa, were utilised. The data cover the period from January 2008 to December 2022. The current investigation omits seven banks due to inadequate data availability across the entire temporal spectrum. The excluded banks are African Bank, BNP Paribas, Discovery Bank, BoCom Ltd, Tyme Bank, Goldman Sachs and ICICI Bank. Collectively, these entities represent a marginal 1.1% of the aggregate assets in the banking system, so our analysis nevertheless encompasses an extensive sample, representing almost 99% of the banking sector. Table 1 presents pertinent details regarding the key balance sheet components for the banks included in this study.

Table 1: Key balance sheet data

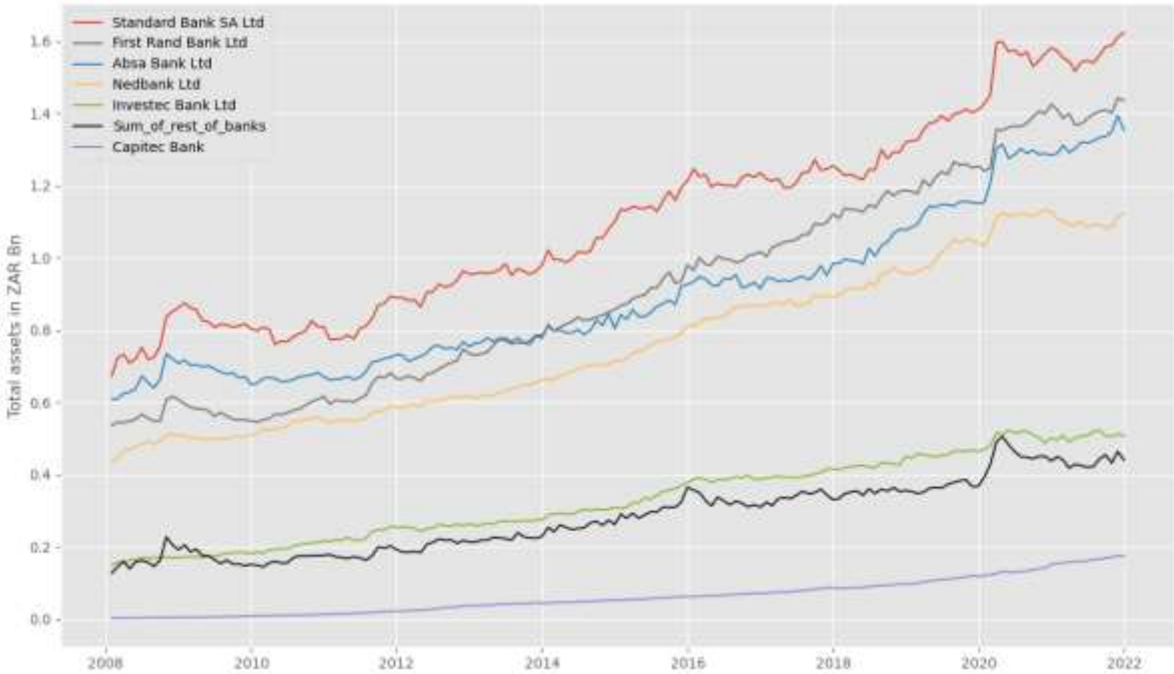
No.	Banks	Total assets	Total liabilities	Total equities	Interbank lending	Interbank borrowing
Panel (A): Balance sheet data						
1	Standard Bank SA Ltd	1 622.73	1 505.69	117.04	153.08	116.47
2	FirstRand Ltd	1 435.44	1 327.34	108.10	78.37	46.49
3	Absa Bank Ltd	1 352.94	1 253.29	99.65	79.58	150.42
4	Nedbank Ltd	1 123.14	1 036.33	86.81	54.83	49.10
5	Investec Bank Ltd	507.44	465.83	41.61	46.67	20.65
6	Capitec Bank Ltd	174.36	142.72	31.64	20.84	0.23
7	Citibank NA	85.32	75.63	9.69	25.98	4.29
8	HSBC Bank Plc (Johannesburg branch)	70.43	64.86	5.56	24.88	5.00
9	JPMorgan Chase bank, N.A. (Johannesburg branch)	65.23	51.48	13.76	20.82	7.16
10	Standard Chartered Bank	43.31	38.46	4.85	10.42	1.46
11	China Construction Bank Corporation (Johannesburg branch)	41.78	35.99	5.79	19.92	14.60
12	Bank of China Limited (Johannesburg branch)	40.08	30.20	9.88	5.32	16.60
13	Deutsche Bank AG	17.45	15.87	1.58	5.14	4.16
14	Grindrod Bank	13.72	12.03	1.69	0.77	0.03
15	Bidvest Bank	11.16	8.89	2.27	2.31	0.36
16	Sasfin Bank	10.19	9.04	1.15	1.66	0.03
17	State Bank of India	9.50	7.58	1.92	6.18	7.01
18	Albaraka Bank Limited	8.60	7.77	0.83	2.07	0.00
19	HBZ Bank Limited	7.91	7.33	0.59	1.60	0.10
20	Ubank	5.32	4.90	0.42	0.20	0.00
21	Access Bank	4.57	4.21	0.36	0.85	1.65
22	Ithala Bank Ltd	3.15	2.76	0.39	0.58	0.00
23	Bank of Taiwan Ltd	1.76	1.38	0.38	0.72	1.10
24	Habib Bank	1.11	1.01	0.10	0.51	0.01
Panel (B): Data statistics						
	Mean	277.36	254.61	22.75	23.47	18.62
	Std. dev.	521.28	483.30	38.25	36.50	38.18
	Min.	1.11	1.01	0.10	0.20	0.00
	Max.	1 622.73	1 505.69	117.04	153.08	150.42

Note: This table reports the key financial data of the 24 banks studied in this paper based on the result as of 31 December 2021. The data are sorted in descending order by total assets in millions of ZAR. Panel (A) shows the values of the balance sheet items and Panel (B) shows the column-wise corresponding statistics.

Source: Prudential Authorithy, SARB

Figure 1 shows the evolution of the banking sector in terms of total assets. This figure shows six D-SIBs, while the remaining small and medium-sized banks are shown in aggregate (the black line). The rest of the small banks are close in size to Investec Bank but are smaller than Standard Bank, FirstRand Bank, Absa Bank and Nedbank, illustrating the concentration of the banking sector.

Figure 1: The progression of total assets for the South African banking sector from January 2008 to December 2021



Note: The chart shows the trend for six D-SIBs, with the other 25 banks shown in aggregate (the black line).
Source: Prudential Authority, SARB

The interbank market also grows quickly with the development of the banking sector. Figure 2a shows that the aggregate of interbank lending and borrowing roughly double their sizes for the observed period. Figure 2b indicates the imbalance of interbank lending-borrowing ratios among the banks. The D-SIBs (large dots) generally have lower interbank lending ratios (<0.1) and lower interbank borrowing ratios (<0.2); small banks typically have higher ratios for both.

Figure 2a: Aggregate of interbank lending-borrowing

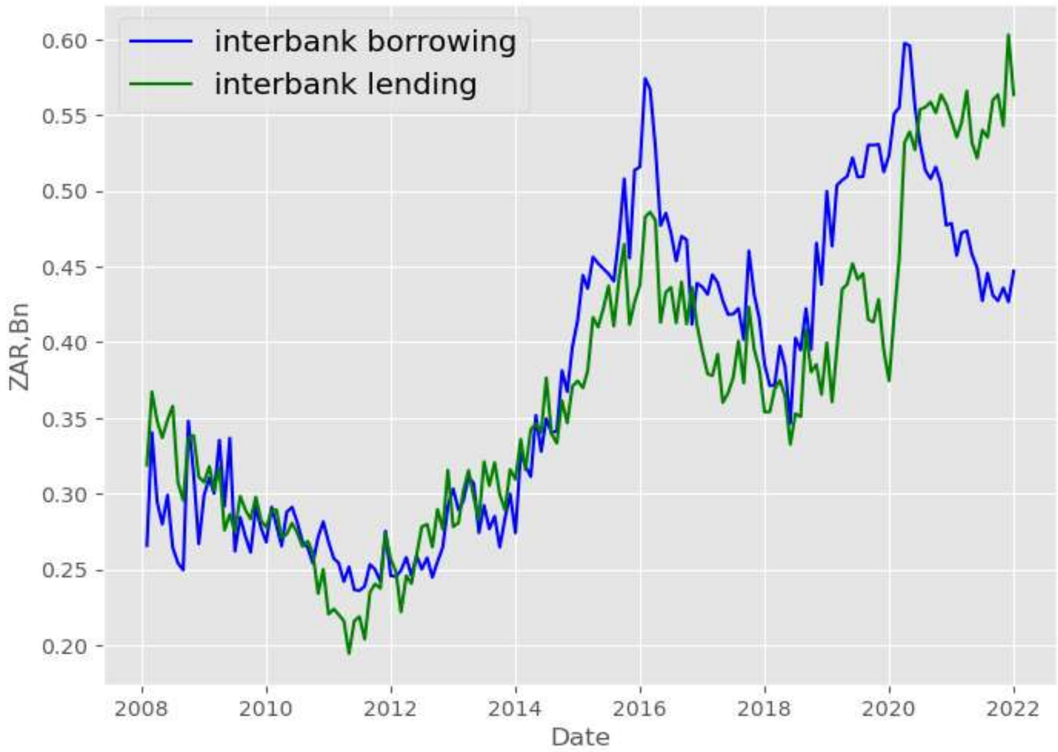
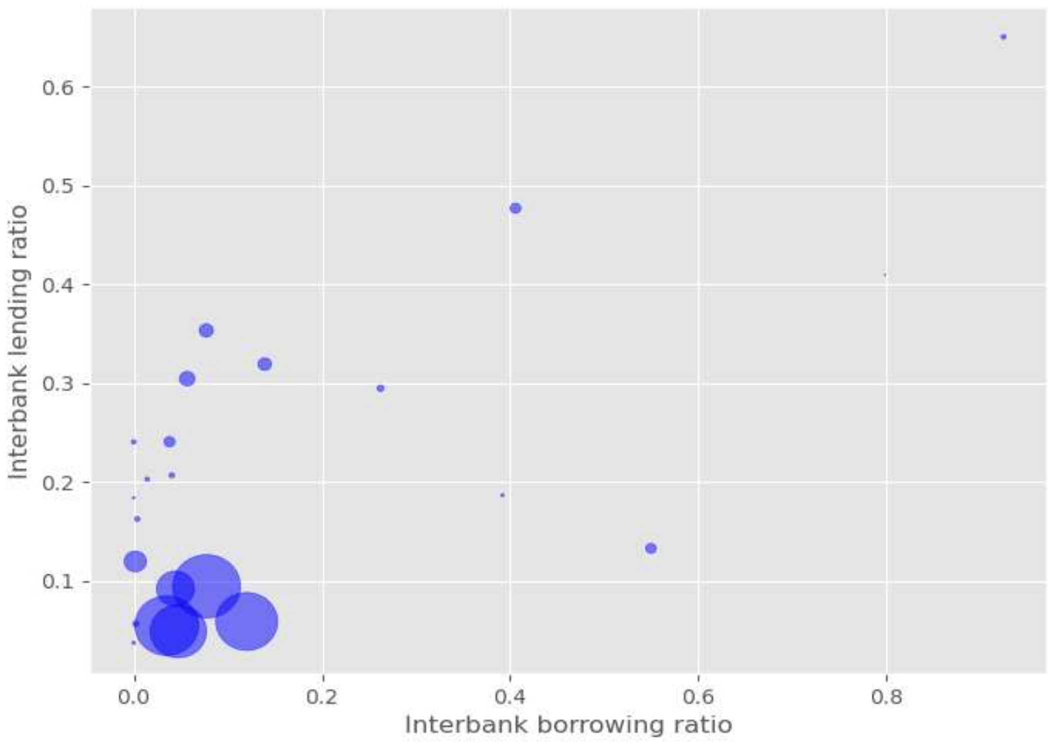


Figure 2b: Interbank lending-borrowing ratio



Note: Figure 2a shows the aggregate of interbank lending and borrowing (in billion ZAR). Figure 2b is a scatterplot that illustrates the interbank borrowing ratio (along the x-axis) vs the interbank lending ratio (along the y-axis) as of December 2021. The bank's total assets is represented by the dot size.

4. Model and methodology

As mentioned earlier, three key methods are involved in this study. We use ABM (see Section 4.1) for network formation and DebtRank (see Section 4.2) to analyse contagion, including to identify important and vulnerable banks. Lastly, the $\Delta CoVaR$ approach (see Section 4.3) is used as a robustness check for systemic risk against DebtRank.

4.1 Agent-based modelling

A significant challenge in the literature on network contagion is the population of networks with incomplete information, specifically the estimation of bilateral exposures given marginal or aggregate information. To address this challenge, we use ABM to simulate financial network dynamics by taking into account the decisions made by each agent and striving to create a 1:1 representation of all the banks that constitute the South African financial system.

We derive a network of bilateral exposures for short-term interbank borrowing by incorporating bank lending and borrowing behaviours based on individual bank balance sheet statistics. In ABM, each bank sets its target for interbank lending and borrowing ratios and acts as an agent to borrow and lend in the market. The borrowing requests are made to other banks at random. The lending banks make their lending decision based on an evaluation score of the borrowing bank's size and relationship (see Section 4.1.2).

We assume that a new cycle begins every month. During each cycle, all banks (or agents) in the system are required to complete three tasks: pay off outstanding debts, settle new obligations and update financial statements. Before taking on any new loans at the beginning of period t, banks must first pay all their overdue obligations from the period $t-1$ (see Section 4.1.1). Participating banks will begin to settle new debts (in accordance with the processes indicated in Section 4.1.2) as soon as all payments linked to debts have been cleared. Once this process is complete, banks in the system will revise their financial statements for the period t to accurately represent the interbank assets and liabilities established (see Section 4.1.3). These processes go on into the subsequent cycle at time $t+1$, and so forth. This recursive process is illustrated in Figure 3.

Figure 3: ABM flow chart

Note: The ABM is a recursive flow comprised of three processes: paying outstanding debts for the previous period $t-1$, starting to settle new obligations for the current period t, and updating financial data for the new lending-borrowing positions and getting ready for the next step, $t+1$.

4.1.1 Paying outstanding debts

The South African interbank market is predominantly an overnight market. These typically take the form of bank call accounts and increasingly secured interbank transactions, predominantly in the triparty repo arrangement.[1] Considering the objectives of this research, it is stipulated that the secured interbank is of marginal significance. Call accounts are typical senior unsecured creditors and would thus rank similarly to other senior creditors of the bank. Consequently, the lending and borrowing conducted on the interbank market cannot be prioritised in the case of a default from a legal standpoint.

It is also presumed that at the beginning of each cycle, all agents are required to pay off any outstanding debts before they approach their counterparties with requests for additional borrowing. The payment of outstanding debts is handled using the clearing payment vector of EN. Should a bank be unable to fulfil its commitments, the equity loss of its creditors will be triggered. According to the payment vector, the repayment amount will be computed on a proportional basis. If the losses incurred exceed the bank's equity, the bank will default. Following Liu et al. (2020) and Lin and Zhang (2022), we developed an initial network by estimating the interbank network through ME. Subsequent interbank networks were then generated through the ABM approach.

[1] In a triparty repo arrangement, there are three parties involved: the borrower, the lender and the custodian. The borrower sells securities to the lender, who agrees to repurchase them later. The custodian holds the securities. This is a popular form of secured interbank transaction because it is safe and efficient.

4.1.2 Settling new debts

Each bank initially establishes interbank lending and borrowing target ratios. Depending on the ratios it has established, each bank can then determine the annual target amounts for its interbank lending and borrowing activities. Banks that have not attained their target borrowing ratios would initiate random borrowing requests with other banks. If a lender cannot fulfil a bank's request for borrowing, the borrowing bank will request another bank until the request is entirely satisfied. After going through all the lending banks in the system, the borrowing bank may end up with an unsatisfied funding gap if it does not match the lending requirements.

On the lending side, when a lending bank receives a borrowing request, it must decide whether to lend and, if so, how much. The lender will evaluate the borrower based on the nature of their relationship as well as the size of the borrower. The relationship as described above can be determined as follows:

$$S_{i,j}^{R}(t)=\begin{cases}\log(debts) & \text{if } i \text{ and } j \text{ have bilateral debts}\\ \eta\cdot S_{i,j}^{R}(t-1) & \text{if } t>0\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

where $S_{i,j}^{R}(t)$ is the relationship score of bank j (the borrower) evaluated by bank i (the lender) in period t. The debts examined in this paper are reciprocal, directed and bilateral debts between banks i and j. This indicates that debts may be owed by bank i to bank j as well as by bank j to bank i. The memory decaying factor parameter η is fixed at 0.9 by default (Liu et al. 2020 and Lin and Zhang 2022).

The size of the borrower is evaluated as:

$$S_{i,j}^{S}(t)=\log(A_j(t))-\frac{\sum_{k,k\neq i}\log(A_k(t-1))\prod_{i,k}(t-1)}{\sum_{k,k\neq i}\prod_{i,k}(t-1)} \tag{2}$$

where

$$\prod_{i,k}(t)=\begin{cases}1 & \text{if } i \text{ and } k \text{ have a relationship at period } t\\ 0 & \text{otherwise}\end{cases} \tag{3}$$

where $S^S_{i,j}(t)$ is the size score of bank j evaluated by bank i in period t, $A_j\,(t)$ is the total assets of bank j at time t, and $\prod_{i,k}(t)$ is a binary variable used to record prior debt obligations. Whether or not to lend is a problem of binary categorisation. A sigmoid function governs the lender's decision-making process. Combining the relationship and size scores determines a borrower's total score. The overall score is determined by the formula:

$$S^T_{i,j}(t) = \omega \times S^S_{i,j}(t) - (1-\omega) \times S^R_{i,j}(t) \tag{4}$$

where $S^T_{i,j}(t)$ is the total score that bank i assigns to bank j for period t. The total score is a weighted average of the relationship and size scores, with ω a weighting parameter. The probability of the lender extending credit to the borrower is determined by (5), derived from a sigmoid function and based on the borrower's overall score:

$$P\left[S^T_{i,j}(t)\right] = \frac{1}{1+\alpha \cdot \exp\left[\beta \cdot S^T_{i,j}(t)\right]} \tag{5}$$

where $P\left[S^T_{i,j}(t)\right]$ is the probability of bank i lending to bank j, which depends on the parameters α and β, which control the intercept and slope of the sigmoid function respectively. The cut-off threshold for the probability is set at 0.5, which means bank i will only lend to bank j if $P\left[S^T_{i,j}(t)\right] \geq 0.5$.

4.1.3 Updating financials

Each bank will have engaged in one interbank transaction or more with its counterparties once all banks' lending and borrowing processes have been completed, except for a few isolated banks that do not have interbank lending or borrowing balances. When assembling an interbank lending network, we obtain a complete list of all the transactions that could occur along its edges. Next, the total amount of interbank lending and borrowing for all banks is entered to update the stylised balance sheet's financial items for the same period. Total assets, liabilities and equity are derived from empirical data, as are external assets and external liabilities. Finally, the updated balance sheet and the interbank network serve as inputs to settle outstanding payments for the following period.

4.1.4 Parameter tuning

The purpose of the ABM is to redistribute the interbank connections determined by each bank's interbank lending and borrowing ratios. The model is therefore sensitive to the setting of parameters, including ω, α and β. ω is the weight for adjusting the relationship score and size score in determining the total score. α and β control the intercept and slope, respectively, of the sigmoid function in determining a bank's lending decision. Similar to the mean square error, the objective of parameter turning is to minimise the simulation error ∅, which is defined as follows:

$$\phi = \sqrt{\frac{1}{N}\sum_{i}^{N}\left(\frac{L_i - \hat{L}_i}{L_i}\right)^2 + \frac{1}{N}\sum_{i}^{N}\left(\frac{A_i - \hat{A}_i}{A_i}\right)^2} \qquad (6)$$

where $\hat{L}_i$ and $\hat{A}_i$ are the simulated interbank liability and asset for bank i. The combination of $\alpha = 1$ and $\beta = -1$ gives a probability of lending of 0.5 when the total score is zero. To minimise ϕ, we use a grid search method to identify the optimal parameters by varying α between [0.1, 1.9], β between [-1.9, -0.1] and ω between [0.05, 0.95], with a step size of 0.01 for each parameter. As a result, the optimal parameters are achieved with $\alpha = 1.11$, $\beta = -0.58$ and $\omega = 0.68$ and with the simulation error $\phi = 0.003$. The parameter $\omega = 0.68$ means that, when making a lending decision, the bank evaluates the borrower with a total score by placing more weight on the size (0.68) and less weight on the relationship (0.32). In contrast, the parameters $\alpha = 1.11$ and $\beta = -0.58$ specify the sigmoid function wherein a minimum total score of 0.185 is required to get a probability of lending equal to or greater than 0.5.

After determining the optimal parameters, the randomness of the model must be managed. As described in Section 4.1.2, because the transmission of contagion depends on the structure of the network, the random sequence in which lenders and borrowers settle new debts could alter this network structure. We thus run 100 rounds of simulations for the ABM to produce 100 networks, and we then draw conclusions based on the average performance of these networks to obtain a reliable result.

4.2 The DebtRank model

Nodes in a financial network cannot accurately estimate the actual risks associated with lending to other nodes in the network unless they have complete information on the riskiness of each other node. These risks can be evaluated by using network metrics such as the DebtRank model of the interbank liability network (Bardoscia et al. 2015).

DebtRank can be illustrated by denoting $A_i^e(t)$ as external assets, $L_i^e(t)$ as external liabilities, $A_{ij}(t)$ as the interbank assets of bank i from bank j, and $L_{ij}(t)$ as the interbank liabilities of bank i to bank j. Thus $A_i(t)$ and $L_i(t)$ are the interbank assets and interbank liabilities of bank i at time t. After a shock is applied to the system, DebtRank will generate a discrete-time map detailing how each bank's equity has evolved. Let $E_i(t)$ denote the equities of bank i at time t. DebtRank defines a bank as having defaulted if $E_i \leq 0$, where a bank's liabilities exceed its assets. Two states are possible in the DebtRank dynamic for banks: active and inactive. Let $\mathbb{R}(t)$ denote the set of active banks at time t, as follows:

$$\mathbb{R}(t) = \{i: E_i(t) > 0\} \tag{7}$$

The model considers a mark-to-market evaluation for interbank assets, while liabilities keep their face value. When bank j defaults, it defaults to all its interbank liabilities, meaning its creditors will not recover its lending to bank j, so $A_{ij} = 0$. Bank i's equities at time t thus read as follows:

$$E_i(t) = A_i^e(t) - L_i^e(t) + \sum_{j \in \mathrm{R}(t-1)} A_{ij}(t) - \sum_{j=1}^{N} L_{ij}(t) \tag{8}$$

The relative changes in the equity of borrowers are reflected in equal relative changes in the interbank assets of the lenders at the next time step:

$$A_{ij}(t+1) = \begin{cases} A_{ij}(t)\dfrac{E_j(t)}{E_j(t-1)} & \text{if } j \in \mathrm{R}(t-1) \\ A_{ij}(t) = 0 & \text{if } j \notin \mathrm{R}(t-1) \end{cases} \tag{9}$$

where the case $j \notin \mathbb{R}(t-1)$ ensures that when bank j defaults, the corresponding interbank assets A_{ij} of its creditors will remain zero for the rest of the evolution. By iterating the balance sheet identity (8) and shock propagation mechanism (9), the contagion dynamics can be cast in terms of relative cumulative equity loss of bank i: $h_i(t) = (E_i(0) - E_i(t))/E_i(0)$:

$$h_i(t+1) = \min\left\{1, h_i(t) + \sum_{j=1}^{N} \Lambda_{ij}(t) + \left[h_j(t) - h_j(t-1)\right]\right\} \tag{10}$$

where the interbank leverage matrix ∧ is defined as

$$\Lambda_{ij}(t) = \begin{cases} \dfrac{\mathrm{A}_{ij}(t)}{E_i(0)} & \text{if } j \in \mathrm{R}(t-1) \\ 0 & \text{if } j \notin \mathrm{R}(t-1) \end{cases} \tag{11}$$

We measure the response of each bank to the shock in terms of its contribution $H_i(t)$ to the relative equity loss of the system:

$$H_i(t) \equiv \frac{E_i(0) - E_i(t)}{\sum_i E_i(0)} = h_i(t)\frac{E_i(0)}{\sum_i E_i(0)} \tag{12}$$

Following Bardoscia et al. (2015), the relative equity loss of the system when bank i is shocked is used to measure the importance of bank i, namely DebtRank Impact (DI). Similarly, we estimate the vulnerability of bank i by the average relative equity loss of bank i due to a shock on other banks, namely DebtRank Vulnerability (DV).

4.3 $\Delta \boldsymbol{CoVaR}$ for systemic risk measurement

For the robustness check of our measure on the bank's importance (DI), we use another well-known measure, $\Delta CoVaR$. In our case it can only be applied to listed banks, the D-SIBs. As our dataset contains 168 periods, we can make a time series comparison between two measures for each D-SIB.

The systemic risk measure of $\Delta CoVaR$ by Adrian and Brunnermeier (2016) is based on value at risk, denoted VaR. VaR_q^i is the worst loss over a target horizon that will not be exceeded with a given level of confidence 1 – q. Statistically, the VaR_q^i defined for a confidence level 1 – q corresponds to the q-quantile of the projected distribution of gains and losses over the target horizon (Bernal, Gnabo and Guilmin 2014). The VaR_q^i of bank i, with tail level q, is defined as:

$$\Pr(R^i \leq VaR_q^i) = q \quad (13)$$

where R^i is the (return or) loss of bank i for which the VaR_q^i is defined.

$CoVaR_q^{s|i}$ is the VaR_q^s of the financial system conditional on an event $C(R^i)$ affecting a bank i.This event is materialised when the return for this bank (R^i) is equal to its VaR for a q^{th} quantile of the conditional probability distribution of returns of s:

$$\Pr(R^s \mid C(R^i) \leq CoVaR_q^{s|C(R^i)}) = q \quad (14)$$

$\Delta CoVaR$ is defined as the difference between the $CoVaR$ of the financial system s when a given bank i is in distress – that is, when it reaches an adverse level of VaR (e.g. 5%) – and the $CoVaR$ of the same financial system conditional on the normal state of the same bank, that is, when bank i is at its median state (i.e. 50%):

$$\Delta CoVaR_q^i = CoVaR_q^{s|R^i = VaR_q^i} - CoVaR_q^{s|R^i = VaR_{50\%}^i} \quad (15)$$

This measure captures the change in $CoVaR$ when the conditioning event is shifted from the median return of bank i to the adverse VaR_q^s.

Here we follow a factor-based quantile regression method to estimate $\Delta CoVaR$ (Bernal et al. 2014, Adrian and Brunnermeier 2016, and Bianchi and Sorrentino 2020). This method captures time variation in the joint distribution of R^s and R^i, and estimates $VaRs$ and $CoVaR^s$ as a function of state variables, allowing us to model the evolution of the joint distributions over time. The method indicates time-varying $VaR_q^i(t)$ and $CoVaR_q^i(t)$ and estimates the time variation conditional on a vector of lagged state variables $M(t-1)$. To match our study, we estimate the quantile regression on monthly data:

$$R^i(t) = d_q^i + \Upsilon_q^i M(t-1) + \varepsilon_q^i(t) \tag{16}$$

where d_q^i and Υ_q^i are the coefficients, $\varepsilon_q^i(t)$ is the error term, and

$$R^{s|i}(t) = d_q^{s|i} + \Upsilon_q^{s|i} M(t-1) + \beta_q^{s|i} R^i(t) + \varepsilon_q^{s|i}(t) \tag{17}$$

where $d_q^{s|i}$, $\Upsilon_q^{s|i}$ and $\beta_q^{s|i}$ are the respective coefficients and $\varepsilon_q^{s|i}(t)$ is the estimation error term. We then use the predicted values from these regressions to obtain

$$VaR_q^i(t) = \hat{d}_q^i + \hat{\Upsilon}_q^i M(t-1) \tag{18}$$

and

$$CoVaR_q^i(t) = \hat{d}_q^{s|i} + \hat{\Upsilon}_q^{s|i} M(t-1) + \beta_q^{s|i} VaR_q^i(t) \tag{19}$$

Finally, we compute $\Delta CoVaR_q^i(t)$. For each bank:

$$\Delta CoVaR_q^i(t) = CoVaR_q^i(t) - CoVaR_{50\%}^i(t) \tag{20}$$

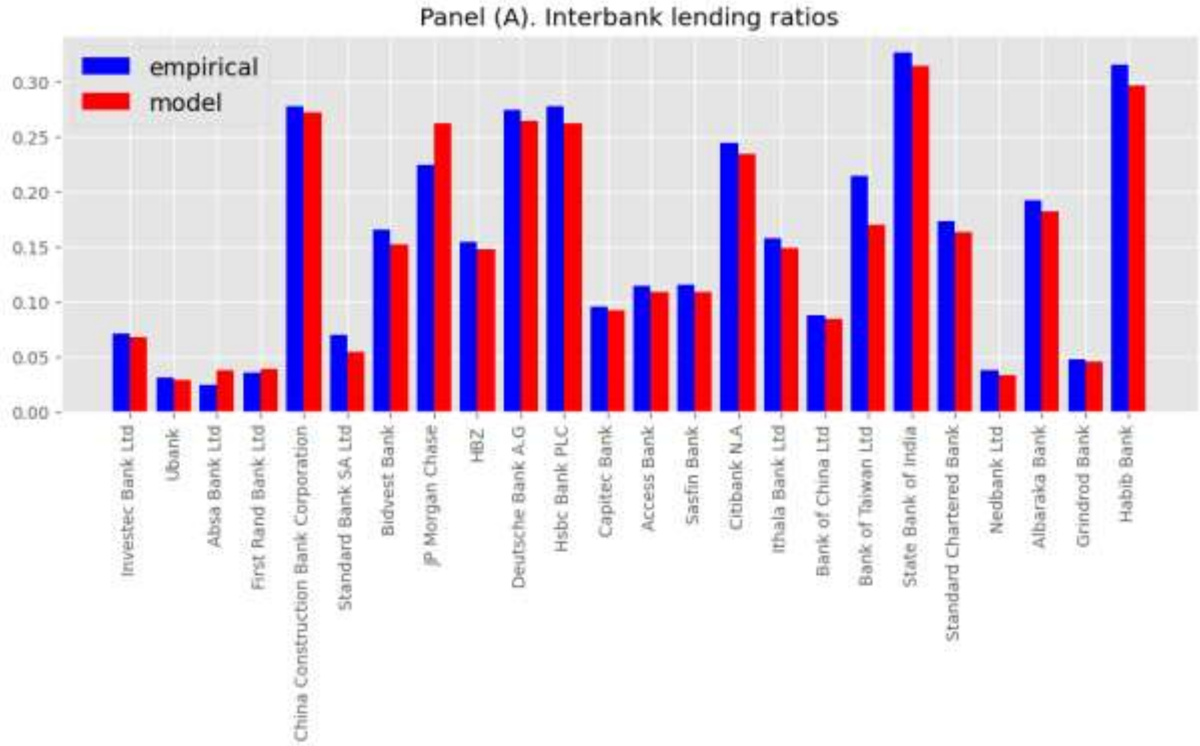
5. Results

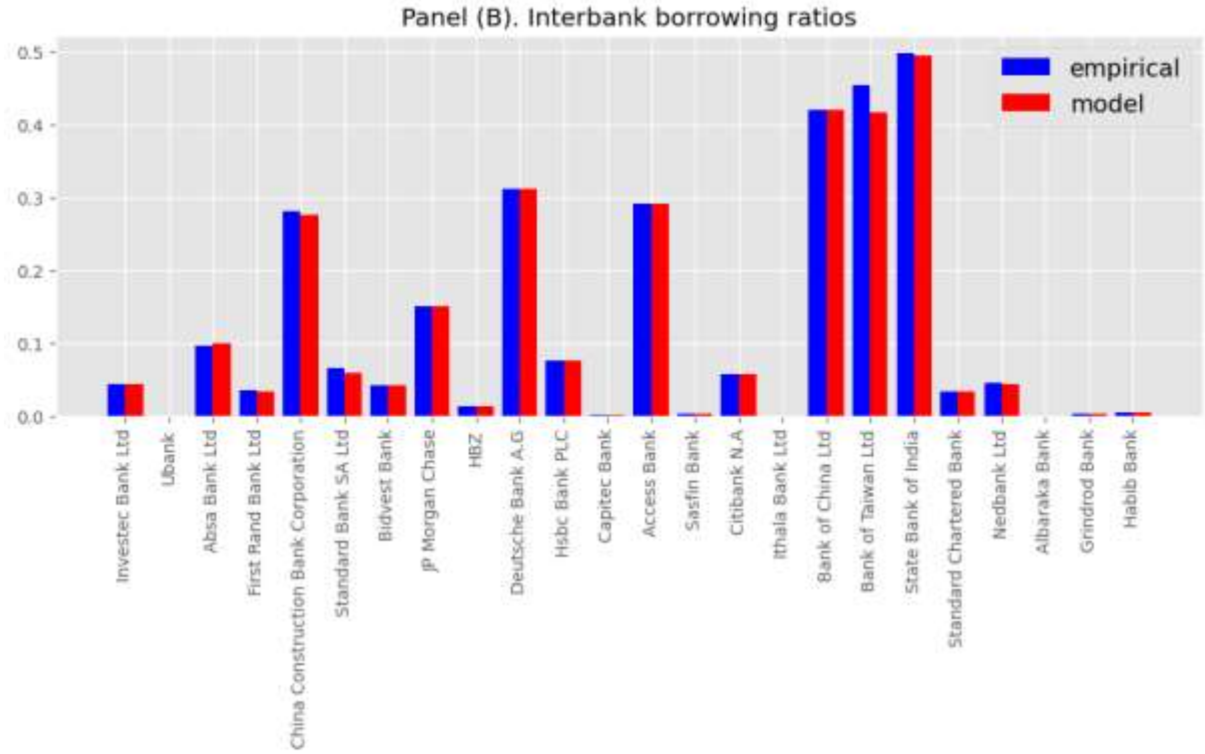
Section 5.1 validates the ABM network formation from a comparison of the target interbank lending-borrowing ratio between the model and the empirical data and from a comparison of network density. Based on the ABM network, the interbank contagion results using DebtRank are presented in Section 5.2 and are followed by a robustness check using $\Delta CoVaR$ in Section 5.3. Section 5.4 explores the determinants for both DI and DV using a panel data analysis, and a conclusion is drawn according to the findings.

5.1 Validation of ABM network formation

ABM aims to redistribute each bank's interbank lending and borrowing with counterparties based on the target ratios. Thus, one way to validate the model is to compare the interbank lending-borrowing ratios between the simulated and the empirical data. The comparison (Figure 4) is based on the average result of the 100 simulated networks. The empirical and simulated ratios for interbank lending (in Panel (A)) and interbank borrowing (in Panel (B)) for each bank indicate the low simulation error of the ABM.

Figure 4: Comparison between empirical and simulated interbank lending and borrowing ratios



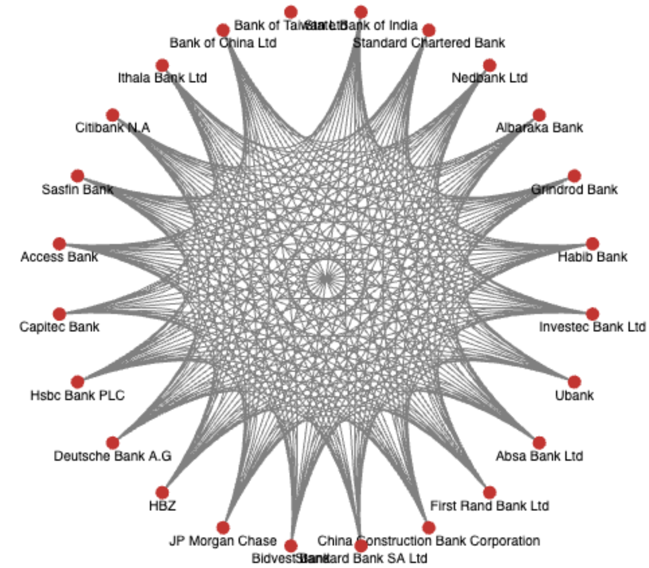


Note: The simulated results are based on the average of 100 simulations. The comparison between the empirical and simulated ratios indicates a low simulation error.

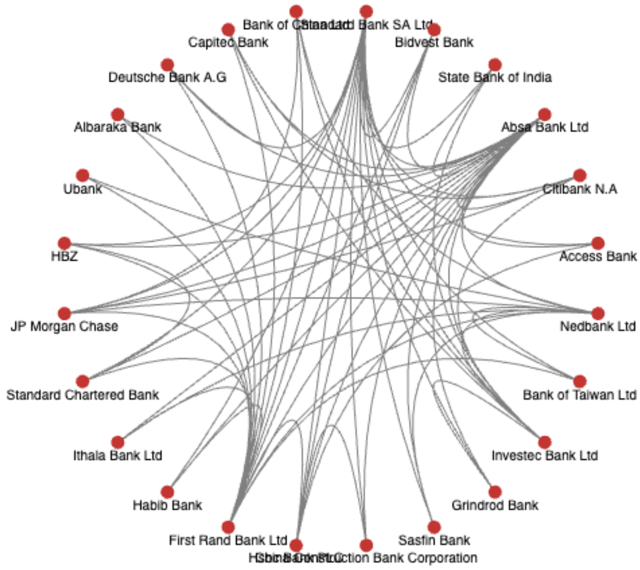
Figure 5 compares the network generated by ME and ABM. The initial network generated using ME has a high density of 0.757, as shown in Panel (A). Higher density implies that banks generally maintain more borrowing and lending relationships with counterparties. The density of 0.757 means that each bank maintains an average of 34.8 relationships (including lending and borrowing) with 24 banks. This seems unrealistic, as it is costly to maintain too many relationships (Liu et al. 2020). As shown in Panel (B), our ABM network has a density of only 0.139. This density corresponds to the total degree of 6.4, which implies that each bank maintains an average of three borrowing and three lending relationships. This is considered more realistic in practice for a banking system with only 24 banks.

Figure 5: Networks by ME and ABM

Panel (A): ME network



Panel (B): ABM network

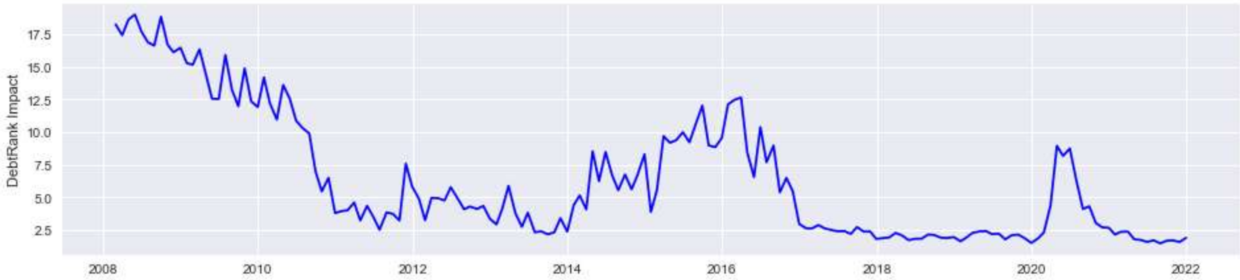


Note: Panel (A) shows the initial network generated by ME, and the network density =0.757, while Panel (B) shows the ABM network for the final period, density =0.139.

5.2 Contagion results with DebtRank

Our monthly balance sheet data allow us to perform a time-varying analysis of the banks' systemic risk. We use the first period of the balance sheet (January 2008) to estimate an initial network by ME and subsequently generate 167 monthly ABM networks from February 2008 to December 2021. We repeat this procedure 100 times to draw a conclusion based on the average results. Figure 6 depicts an overview of the systemic risk in the banking sector by the monthly aggregate DI (ADI), $ADI_t = \sum_i^n DI_{i,t}$. In general, three upsurges can be identified: between 2008 and 2009, between 2014 and 2016, and in 2020.

Figure 6: Monthly ADI from 2008 to 2021



Note: $\boldsymbol{ADI_t} = \sum_i^n \boldsymbol{DI_{i,t}}$. The results show upsurges in 2008–09, 2014–2016, and 2020.

The first upsurge took place between 2008 and 2009, which coincided with the global financial crisis. Although the South African banking system remained relatively stable during the GFC, there was an inevitable dip in commercial banks' profitability amid rising bad debts, curtailed credit extensions and a progressive decline in domestic demands (Chatterjee and Sing 2021). The second upsurge occurred in 2014–2016, when a number of significant events negatively affected the market. In August 2014, African Bank collapsed and was placed under curatorship. Its failure shocked the market and introduced significant systemic risk to the financial system (Sanderson, Maré and De Jongh 2017). In December 2015, the Minister of Finance was unexpectedly and controversially replaced, causing the local financial market to react negatively, significant currency depreciation (Walters et al. 2018) and significant losses in both equity and bond markets (Chatterjee and Sing 2021). In 2016, South Africa was beset by several negative factors, including currency depreciation, a weak economic outlook and an imminent credit review by Standard & Poor's to decide whether to downgrade South Africa's sovereign rating to junk status (Walters et al. 2018). The third upsurge occurred in early 2020 as a result of the COVID-19 pandemic, which caused significant turbulence in global financial markets.

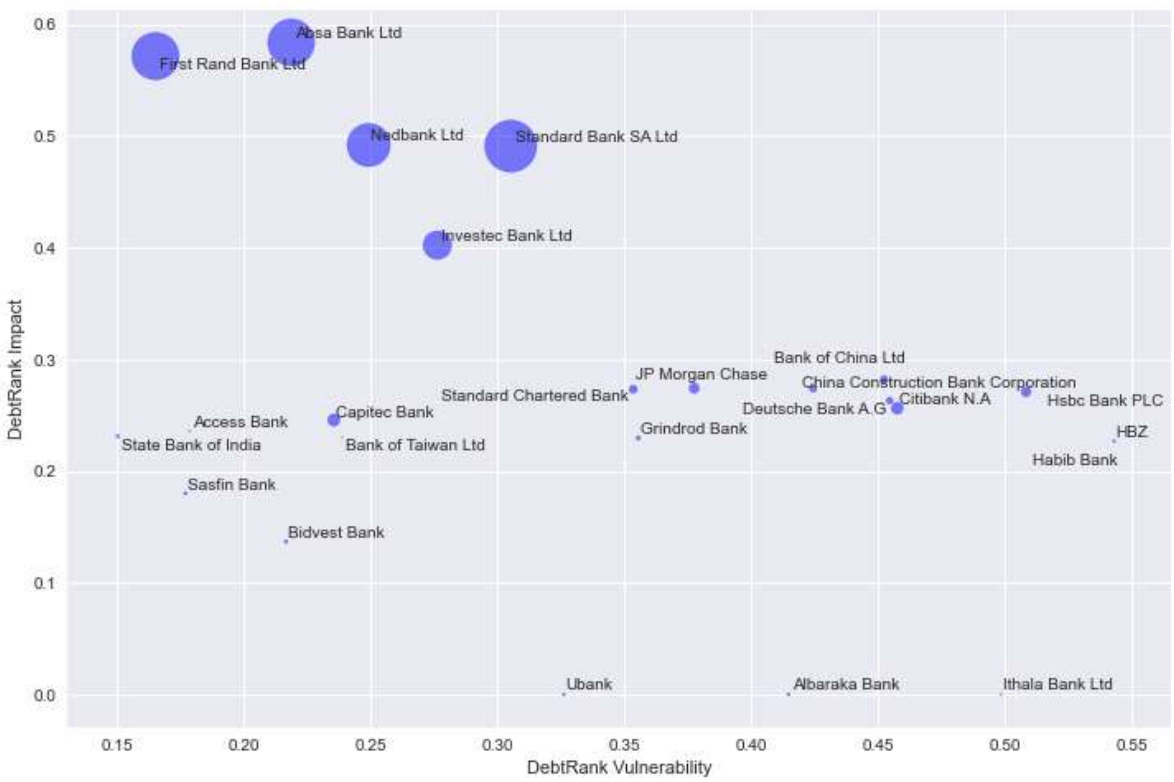
Figure 7 provides an overview of the position of each bank in terms of DI and DV, with the size of the dots proportional to the size of the banks. Panel (A) shows a high-level overview of the observed period, with DI and DV based on the average result of

167 periods. Panel (B) shows a snapshot as of December 2021. Three observations can be summarised. First, the values for DI and DV in Panel (A) are generally higher than those in Panel (B) due to the upsurges during the period. Second, five D-SIBs (excluding Capitec) occupy the high-impact area in both panels. Third, it can be inferred that a failure of any of these banks could cause significant damage to the system, leading to system-wide equity loss of between 40% and 60%, as shown in Panel (A), which may imply that larger banks are more impactful.

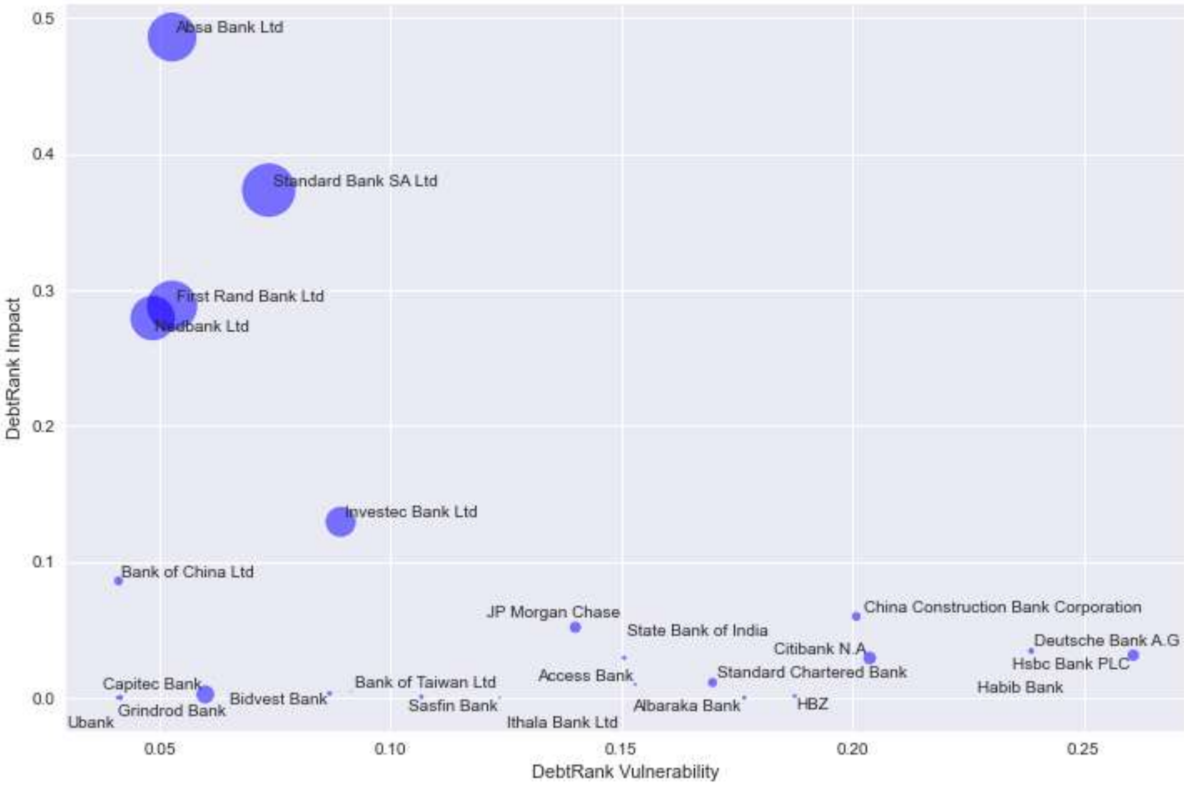
In terms of vulnerability, both panels show that D-SIBs and some smaller banks are in the low-vulnerability area, which suggests that a bank's size does not affect its vulnerability. Despite being a D-SIB, Capitec Bank's DI deviates from the other five D-SIBs. Capitec is located at the medium level in Panel (A) and at the lower level in Panel (B), suggesting it is not as systemically important as the other five D-SIBs. Chatterjee and Sing (2021) similarly conclude that Capitec has the lowest systemic importance based on other systemic risk measures (such as $\Delta CoVaR$, SRISK and marginal expected shortfall). It is therefore proposed that Capitec Bank be treated as an exception from the list of D-SIBs.

Figure 7: DebtRank Impact (DI) and DebtRank Vulnerability (DV)

Panel (A): DebtRank based on average result



Panel (B): DebtRank based on December 2021



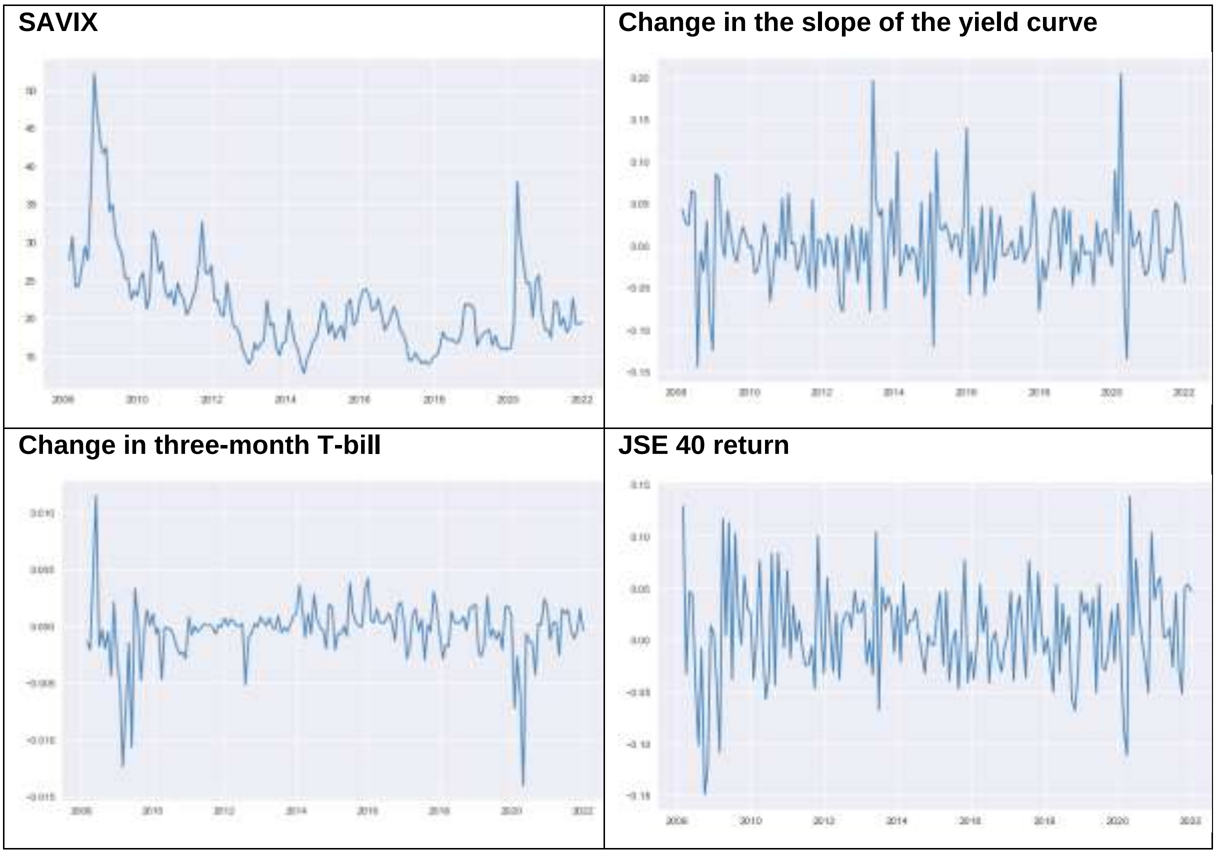
Note: In Panel (A), the values for DI and DV are calculated on the average result of 167 periods between February 2008 and December 2021. Panel (B) shows a snapshot as of December 2021. Node size is based on total assets using the min-max scaling method.

5.3 Robustness check

As mentioned in the literature review, before analysing the factors that explain DI and DV, it is necessary to conduct a robustness check on the outcome of the variables generated from the DebtRank algorithm. To validate DI as an effective measure of a bank's systemic importance, we compare it with other measures that are based on different approaches, such as $\Delta CoVaR$, which is based on market data.

We use the quantile regression method to estimate the $\Delta CoVaR$. The state variables include the change in the three-month Treasury bill, yield curve slope, volatility and the equity market return (Manguzvane and Mwamba 2019; Chatterjee and Sing 2021). The change in the three-month Treasury bill is the difference between the three-month Treasury bill rate at time t and $t-1$. The yield curve represents the changes in interest rates over time, specifically from the 10-year government bond and three-month Treasury bill rates. Market volatility is measured by the JSE SA Volatility Index (SAVIX). Lastly, the JSE Top 40 Index measures equity return. All variables are monthly to align with the time interval of our analysis. Figure 8 depicts the state variables' time series, and Table 2 summarises statistics. All variables are confirmed stationary using the Augmented Dickey-Fuller test.

Figure 8: State variable movements used to conduct the $\Delta CoVaR$



Note: Top left panel: SAVIX: JSE SA Volatility Index. Top right panel: Change in the slope of the yield curve: the difference between the 10-year government bond rate and the three-month T-bill rate. Bottom left panel: Change in three-month T-bill: the difference between the three-month T-bill rate at time t and $t-1$. Bottom right panel: JSE 40 return: the return of the JSE Top 40 Index.

Table 2: Description of state variables for ∆CoVaR

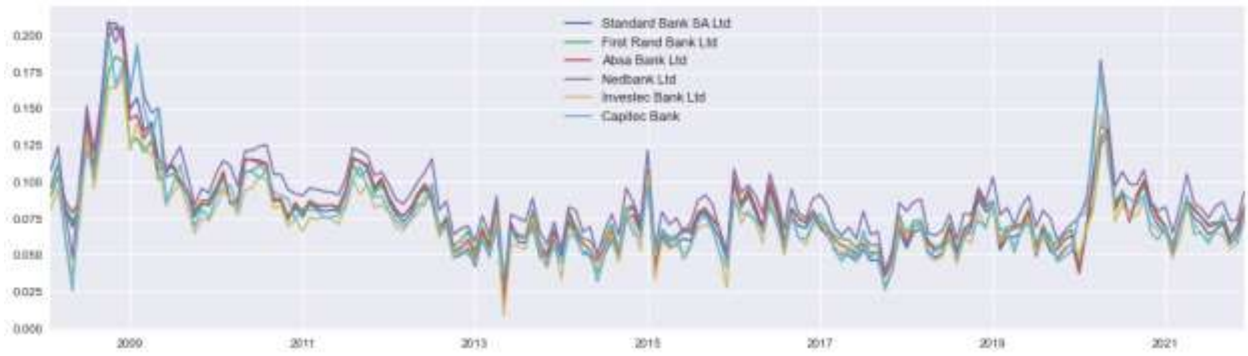
	Mean	Std. dev.	Min.	Max.
Yield curve slope	0.0017	0.0485	-0.1436	0.2050
T-bill change	-0.0004	0.0027	-0.0141	0.0115
SAVIX	21.5680	6.4225	12.7000	52.1400
JSE 40 return	0.0070	0.0474	-0.1491	0.1377

Note: This table reports the descriptive statistics for the state variables estimating the ∆CoVaR. The yield curve slope indicates the change in slope of the yield curve represented by the 10-year government bond rate and the three-month T-bill rate of South Africa. The T-bill change is the difference between the three-month T-bill rate at time t and $t-1$. The market volatility is measured by the SAVIX. JSE 40 return is the return for the JSE Top 40 Index for $N = 167$ observations.

Source: Bloomberg

Figure 9 shows the time-varying $\Delta CoVaR$s for large banks. The values are presented in absolute values to be consistent with the direction of DI. This indicates that the greater the $\Delta CoVaR$, the greater the level of systemic risk. As highlighted, two time periods are associated with significant levels of systemic risk: the fourth quarter of 2008, which corresponds to the onset of the GFC, and the first quarter of 2020, which corresponds to the onset of the COVID-19 pandemic.

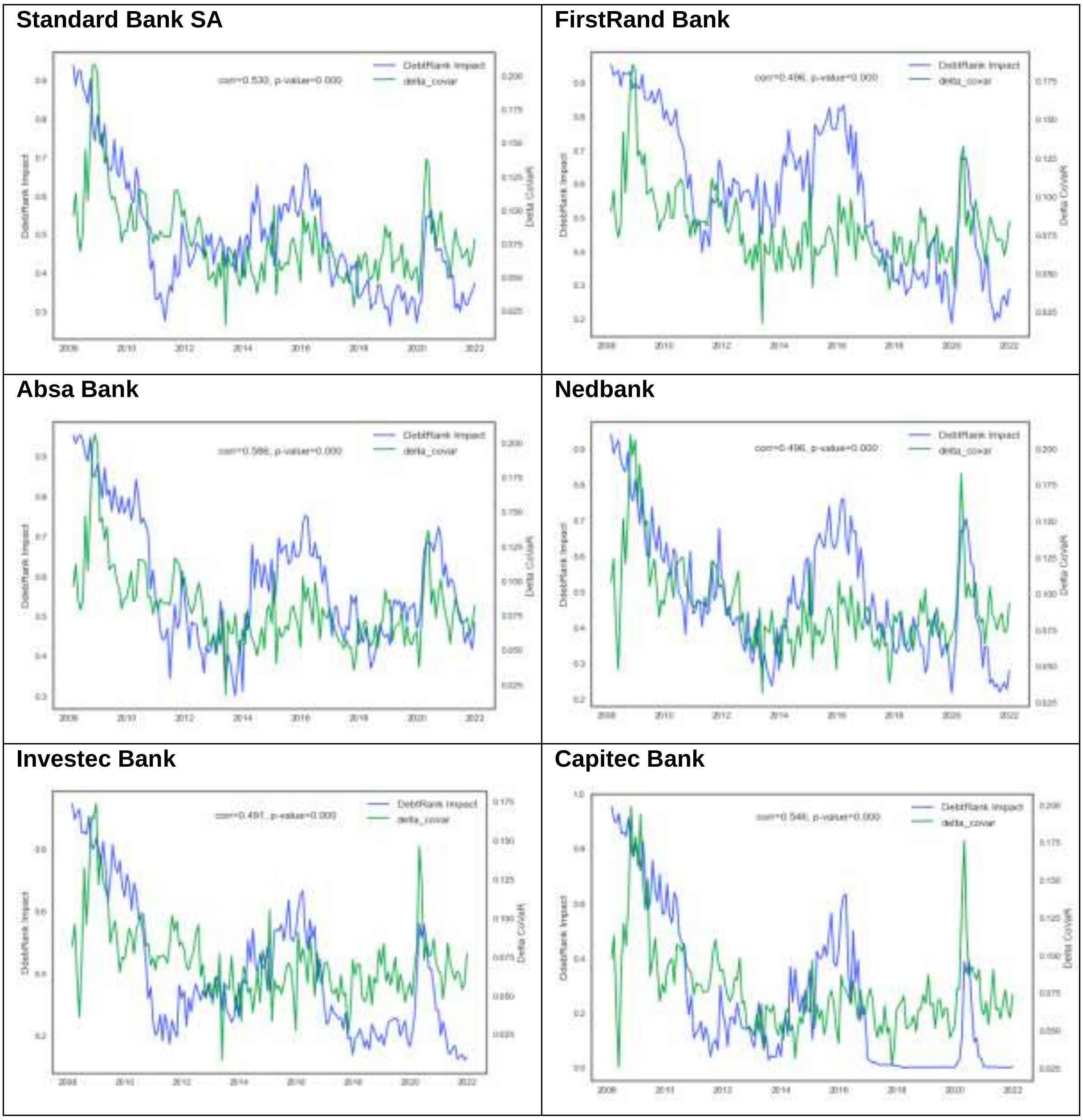
Figure 9: Δ*CoVaR* of the large banks from 2008 to 2021



Note: The values for Δ*CoVaR* are positive to be consistent with our DI measure – the greater the value of Δ*CoVaR,* the higher the systemic risk. Two periods with higher systemic risks are also shown: the outbreak of the global financial crisis in 2008 and the outbreak of the COVID-19 pandemic in 2020.

In comparing the DI with $\Delta\mathrm{CoVaR}$ for each large bank, Figure 10 shows the moving trends of these two measures and their respective correlations. These two measures are significantly correlated for all the large banks, with correlation coefficients ranging from 0.49 to 0.59. Although the two measures are based on different approaches ($\Delta CoVaR$ is based on market data and our framework is based on the balance sheet), both capture the banks' risk characteristics.

Figure 10: Comparison of DI and $\Delta CoVaR$ for six large banks from February 2008 to December 2021



Note: The correlations for the DI and $\Delta CoVaR$ for each bank are all significant at 1% (coefficients range from 0.49 to 0.59).

5.4 Panel data analysis for the importance and vulnerability of banks

To formulate relevant macroprudential policies for financial stability, it is important to identify the factors that contribute to a bank's importance and vulnerability. To this end, we conduct a panel data analysis using banks' balance sheet data to identify the underlying factors that impact these measures.

Our dataset has a time series of 167 periods ($t = 167$) for 24 banks ($n = 24$), which makes it possible to conduct a panel data analysis to investigate the characteristics that explain a bank's importance (DI) and vulnerability (DV). We select the explanatory factors according to Glasserman and Young (2015, 2016), Laeven, Ratnovski and Tong (2016), and Lin and Zhang (2022). Table 3 provides a description of the data (Annexure 2 provides a table for the key variables for the most recent period, December 2021).

Table 3: Panel data description

	Definition	Mean	Std. dev.	Min.	Max.
DI	Model	0.2646	0.2736	0.0000	0.9546
DV	Model	0.3384	0.2502	0.0000	0.9044
Size	Natural log of total assets	16.8230	2.1962	12.7176	21.2074
Financial connectivity	Interbank liabilities to total liabilities	0.1440	0.1968	-0.0005	0.9327
External leverage	Outside liabilities to equities	8.0261	3.9865	0.2990	29.7813
Interbank lending ratio	Interbank lending to total assets	0.2213	0.1569	0.0000	0.7010
Capital ratio	Equities to total assets	0.1217	0.0733	0.0266	0.4779
Activity	Loans to total assets	0.4848	0.2147	0.0000	0.9436
Funding	Retail deposits to total assets	0.2452	0.2736	0.0000	0.9157

Note: This table reports the description of the panel data for 24 banks ($n = 24$) in South Africa from February 2008 to December 2021 ($t = 167$). There are 4 008 observations ($N = 4\ 008$) for each bank. DI and DV are obtained from our model described in this paper. Other variables are derived from the balance sheets of the banks.

We continue the analysis with a fixed-effects panel regression based on the test results. The results of the tests to determine the use of the fixed-effects model are provided in Annexure 3. Our models are as follows:

$$DI_{i,t} = \beta^I X_{i,t} + u_i^I + e_{i,t}^I \tag{21}$$

and

$$DV_{i,t} = \beta^V X_{i,t} + u_i^V + e_{i,t}^V \tag{22}$$

where $i = 1, \dots, N, t = 1, \dots, T$. $DI_{i,t}$ and $DV_{i,t}$ are the DebtRank Impact and DebtRank Vulnerability, respectively, for bank i at time t. $X_{i,t}$ are the *K* explanatory variables. β represents the *K* regression coefficients. u_i is the panel-specific, time-invariant fixed effect. $e_{i,t}$ is the idiosyncratic error term. The superscripts for β, u and e are to distinguish them between *DI* (I) and *DV* (V) models.

We conduct the analysis using the ordinary least square (OLS) as a basis model for comparison; the adjusted R^2 is 0.2420 for DI and 0.4420 for DV (more detailed results can be found in Annexure 4). In contrast, our results with the fixed-effects model show the adjusted R^2 is 0.5249 for DI and 0.7533 for DV. The improved results, relative to the OLS model, suggest that the fixed-effects model is important. The estimation results[2] are summarised in Table 4.

Table 4: Panel data regression estimation results

	DI	***p*-value**	**DV**	***p*-value**
Size	0.0533***	<0.0001	-0.0013	0.1163
Capital ratio	0.1698**	0.0180	-1.0357***	<0.0001
Financial connectivity	0.2587***	<0.0001	-0.1511***	<0.0001
External leverage	0.0061***	<0.0001	0.0024***	0.0037
Interbank lending ratio	-0.1699***	<0.0001	0.8859***	<0.0001
Activity	0.1213***	<0.0001	-0.0729***	<0.0001
Liquidity	-0.0642	0.3275	0.0778	0.0618
Funding	-0.0048	0.7987	-0.0881***	<0.0001
$Adj-R^2$	0.5249		0.7533	

****p*-value < 1%, ***p*-value < 5%

Note: This table reports the estimation result for the dependent variables of DI and DV based on the fixed-effects model. The coefficients and their *p*-values for respective regressors are reported.

Size has a significantly positive impact on DI (0.0533) at the 1% level, whereas there is no statistical proof that size affects DV. While our findings align with the traditional wisdom that large banks are more systemically important, they also suggest that large banks are not necessarily more vulnerable. Similar results in the Chinese interbank market (Lin and Zhang 2022) show no significant correlation between size and vulnerability.

Bank capital acts as a loss-absorbing buffer. Regulators use a bank's capital ratio as a key measure to assess the bank's financial strength: banks with high capital ratios are likely to be more resilient to shocks and therefore less vulnerable. This is confirmed by our results, which show that capital ratio has a substantially negative impact on DV

[2] To conduct the multicollinearity test, we compute the variance inflation factor for every regressor. The results indicate that there is multicollinearity between the selected variables, namely size, activity and funding. We execute the fixed-effects model excluding size, activity and funding. The results indicate that the direction and significance of the coefficients for other regressors remain unchanged. The R^2 for DI is 0.3149 and for DV is 0.7361. Multicollinearity only introduces type II errors, so it has no effect on our findings about the explanatory significance of the regressors.

(-1.0357), suggesting that increasing the capital ratio can substantially reduce vulnerability. Our results also show that an increase in capital ratio is associated with a small but significant (p-value < 5%) increase in DI (0.1698). There are multiple possible reasons for this complex relationship, but one reason may be that banks with higher capital ratios are more trusted and thus take on a greater role within the financial network.

Financial connectivity, also known as the interbank borrowing ratio, measures the extent to which banks are connected through borrowing. A higher interbank borrowing ratio indicates that banks are more interconnected. A shock to one bank is more likely to propagate to other banks, thus making the bank more important. Our results for financial connectivity add nuance to the finding, which has a significantly positive impact on DI (0.2587). Determining whether an increase in connectivity would cause a decrease or increase in the bank's vulnerability is not straightforward.

From a diversification standpoint, increasing connectivity allows risk-sharing among banks, which can help banks be less susceptible to failure when subject to a shock. This is supported by our results showing that financial connectivity negatively impacts DV (-0.1511). However, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) argue that greater connectivity could amplify (or dampen) the contagion risk when the magnitude of the shock is above (or below) a certain threshold. A similar result is found in Nier et al. (2007), where the authors conclude that increasing connectivity increases shock transmission and absorption, with the first effect dominating at low connectivity and the second at higher connectivity. These findings suggest that policymakers cannot simply rely on increasing financial connectivity to reduce a bank's vulnerability. Other factors must also be considered, such as the shock's size and the bank's connectivity level.

The interbank lending ratio has a small negative impact on DI (-0.1699), but its effect on DV (0.8859) is rather substantial. A greater interbank lending ratio indicates that a bank is more exposed to the interbank market, meaning it is vulnerable to failure if its interbank borrowers fail to meet their obligations. It is thus more vulnerable to shocks from other banks. The impact of the interbank lending ratio on DV is almost 10 times that on DI. This provides valuable insight for regulators, who can use this information to identify which banks might need more stringent oversight or regulatory intervention.

It is therefore suggested that regulators not focus solely on a bank's DI, as such a bank may receive less attention even when its vulnerability score has significantly increased.

External leverage has a significant positive impact on DI (0.0061) and DV (0.0024), because higher leveraged banks are more prone to failure and are thus more vulnerable (Glasserman and Young 2015), and their failure has systemic consequences. However, the magnitude of both measures is economically small.

The market-based lending activity is significantly positive for DI (0.1213) and negative for DV (-0.0729), which suggests that increasing market-based lending activities could increase a bank's importance and reduce its vulnerability in the interbank market.

Lastly, our results do not indicate a significant impact of funding on DI; Laeven, Ratnovski and Tong (2016) had similar results using $\Delta CoVaR$ or SRISK. However, funding negatively impacts (-0.0881) at 1% confidence level. This result is comparable to Havemann's (2021) observation that failing banks in South Africa between 2002 and 2003 were typically characterised by a high degree of short-term wholesale funding withdrawal. Havemann also concludes that the run of wholesale funding as opposed to retail funding caused the failure of small banks.

In summary, our analysis reveals that a bank is more influential if it is more connected to the financial system (0.2587), better capitalised (0.1698), has more market-based lending activities (0.1213) and is larger in size (0.0533). These results align with the existing understanding of the bank's importance (Glasserman and Young 2015; Lin and Zhang 2022). However, more interesting results were found regarding the bank's vulnerability. Our results show a bank's vulnerability is not about its size but its capital (-1.0357) and interbank lending (0.8859). Increasing the capital ratio substantially reduces a bank's vulnerability, but excessive interbank lending will considerably undermine the effect of capital ratio requirements and make a bank more vulnerable.

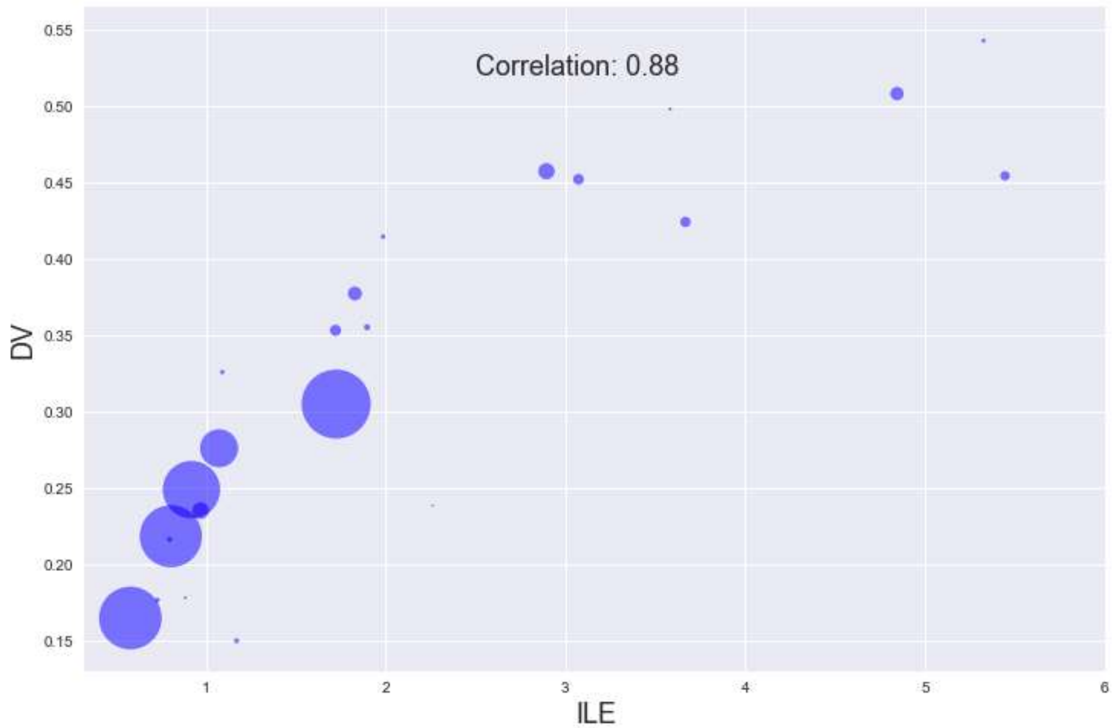
As the interbank lending ratio and capital ratio have an offsetting effect on the vulnerability measure, we introduce the interbank-lending-to-equity (ILE) multiple to examine their joint effect. This is defined as:

$$ILE_i(t) = \frac{A_i(t)}{E_i(t)} = \underbrace{\frac{A_i(t)}{TA_i(t)}}_{\text{Interbank borrowing ratio}} \times \underbrace{\frac{TA_i(t)}{E_i(t)}}_{\text{Inverse of capital ratio}} \tag{23}$$

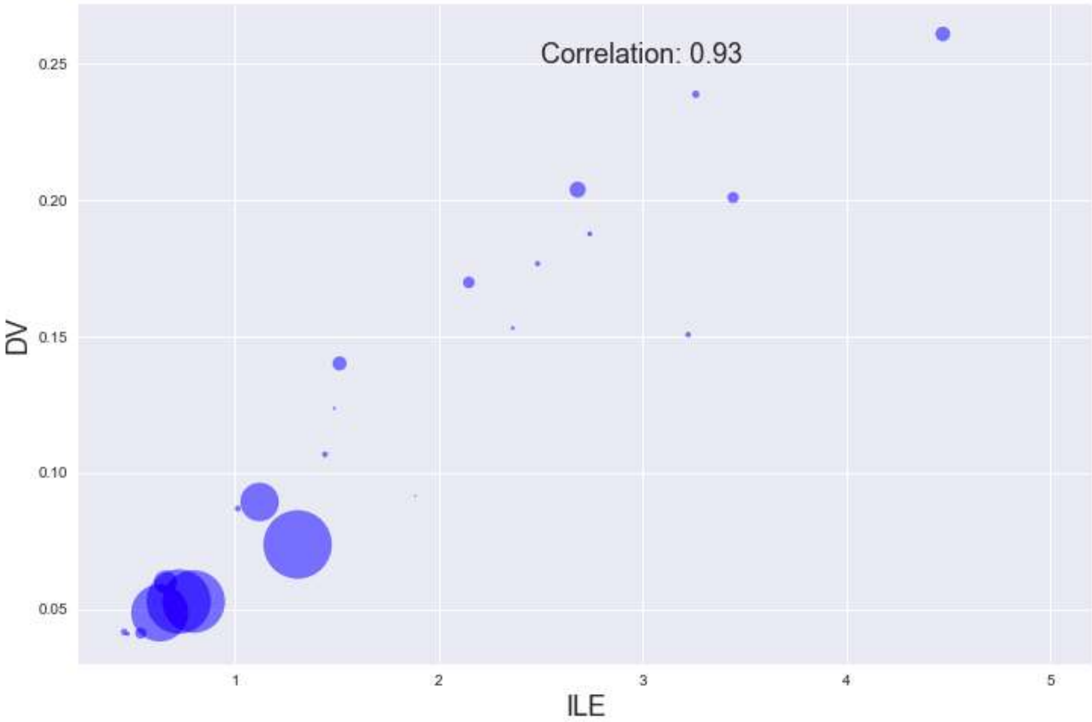
where $TA_i(t)$ is the total assets of bank i at time t. ILE can be regarded as a bank's interbank lending per unit of capital. A higher ILE can be interpreted as more aggressive interbank lending activity in relation to its capital. Figure 11 plots the relationship between ILE and DV. The left panel shows an overview of the relationship based on the average of 167 periods. The right panel shows the relationship for the most recent result as of December 2021. In both panels, two measures are positively and highly correlated, with a coefficient of 0.88 for the left panel and 0.93 for the right panel. In other words, banks with a higher ILE are more vulnerable. Figure 11 also shows that D-SIBs, represented by the large dots, typically have lower vulnerability. This is direct evidence that focusing only on D-SIBs is insufficient to assess South Africa's financial stability.

Figure 11: ILE ratio vs DV

Panel (A): Relationship-based on average result



Panel (B): Relationship as of December 2021



Note: Panel (A) shows the overview of the relationship for the observed period. Both measures are calculated based on their respective average of 167 periods from February 2008 to December 2021. Panel (B) is based on December 2021. Two measures are correlated, with a coefficient of 0.88 for Panel (A) and 0.93 for Panel (B), p-value < 0.0001 for both panels. Node sizes are proportional to total assets.

6. Conclusion

This paper employed an ABM method with the DebtRank algorithm to examine contagion risks in the South African banking sector. The analysis is based on a unique dataset of 168 monthly balance sheets from 24 banks, including listed and unlisted ones. Our sample covers nearly 99% of the South African banking system. The systemic importance of a bank and its vulnerability can be determined using the DI and DV indicators, respectively. A panel data analysis on DI and DV was performed to investigate some explanatory factors.

The main findings of the study are that a bank is more influential if it is more connected to the financial system, better capitalised, larger in size and has more market-based lending activities. Our findings also offer valuable insights into understanding a bank's vulnerability. We did not find compelling evidence that a bank's size contributes to its vulnerability, but our results show that increasing the bank's capital ratio can substantially decrease its vulnerability. This effect is undermined if the bank has a higher interbank lending ratio. Finally, our results reveal a strong and positive correlation between the interbank-lending-to-equity ratio and vulnerability.

Our research provides a comprehensive risk analysis for both listed and unlisted banks in South Africa by assessing their systemic risks from the perspectives of importance and vulnerability. From a regulatory point of view, such an approach aligns with the risk-based supervision requirements for a more inclusive, risk-based and data-centric method.

Our proposed approach has two limitations. The first relates to ABM, as we assume that a bank's lending decision is based on an evaluation of its relationship with the borrowing bank and the borrower's size. In practice, more factors should be considered, such as the cost, return, tenor and timing of lending. These factors could be added to improve the model. The second limitation is that our network only considers interbank lending and borrowing. More interbank transactions, such as over-the-counter derivatives, security financing transactions and repurchase agreements, could affect the interbank market. All these areas could pave the way for future research.

Annexure 1: Bank failures in South Africa

Table A1: Overview of bank failures in South Africa

Bank	Year of curatorship	Reasons
Alpha Bank	1990	Fraud
Cape Investment Bank	1991	Fraud
Pretoria Bank	1991	Bad management
Alpha Bank	1993	Liquidated
Sechold Bank	1994	Liquidity problems
Prima Bank	1994	Liquidity problems
African Bank	1995	Bad management and liquidity problems
Community Mutual Bank	1996	Liquidity problems
Islamic Bank	1997	Bad management
FBC Fidelity Bank	1999	Bad management and liquidity problems
Cashbank Mutual Bank	2001	Acquired by BOE Bank Limited
TA Bank of South Africa Limited	2002	Bank run
Merrill Lynch Capital Markets Bank Limited	2002	Bank run
Cadiz Investment Bank Limited	2002	Bank run
FirstCorp Merchant Bank Limited	2002	Bank run
PSG Investment Bank Limited	2002	Bank run
Regal Treasury Bank	2002	Improper financial statements; bank run
New Republic Bank	2002	Bad management and liquidity problems
Saambou Bank	2002	Bad management and liquidity problems
BOE Bank Limited	2003	Assets and liabilities transferred to Nedbank Ltd
Internationale Nederlanden Bank NV	2003	Bank run
African Bank	2014	Liquidity problems
VBS Mutual Bank	2018	Bad management and liquidity problems

Note: Small and medium-sized banks account for most bank failures.

Source: SARB

Annexure 2: Key data for the banks' characteristics

Table A2: Key data for the banks' characteristics based on December 2021 results

No.	Bank	DI	DV	ILR	FC	CAR	Size	EL	Liquidity	Activity	Funding
1	Absa Bank Ltd	0.4861	0.0527	0.0588	0.1200	0.0737	21.0255	11.0676	0.0259	0.6838	0.2417
2	Standard Bank SA Ltd	0.3734	0.0736	0.0943	0.0774	0.0721	21.2074	11.8696	0.0231	0.6090	0.1897
3	FirstRand Ltd	0.2883	0.0527	0.0546	0.0350	0.0753	21.0847	11.8487	0.0250	0.5783	0.2376
4	Nedbank Ltd	0.2793	0.0485	0.0488	0.0474	0.0773	20.8394	11.3722	0.0244	0.6599	0.2118
5	Investec Bank Ltd	0.1294	0.0892	0.0920	0.0443	0.0820	20.0449	10.6983	0.0223	0.6020	0.2178
6	Bank of China Ltd	0.0859	0.0411	0.1328	0.5497	0.2464	17.5063	1.3771	0.0197	0.4668	0.0080
7	China Construction Bank Corporation	0.0598	0.2008	0.4769	0.4057	0.1385	17.5479	3.6971	0.0416	0.2895	0.0016
8	JP Morgan Chase Bank	0.0518	0.1400	0.3192	0.1392	0.2109	17.9935	3.2213	0.0051	0.1308	0.0000
9	Deutsche Bank AG	0.0344	0.2387	0.2948	0.2623	0.0904	16.6747	7.4223	0.0076	0.0928	0.0000
10	HSBC Bank PLC	0.0313	0.2608	0.3533	0.0770	0.0790	18.0701	10.7598	0.0469	0.2126	0.0000
11	State Bank of India	0.0293	0.1506	0.6503	0.9244	0.2018	16.0665	0.2990	0.0136	0.3174	0.0322
12	Citibank NA	0.0292	0.2037	0.3044	0.0567	0.1136	18.2619	7.3633	0.0318	0.2597	0.0000
13	Standard Chartered Bank	0.0112	0.1697	0.2407	0.0380	0.1121	17.5839	7.6218	0.0187	0.2551	0.0000
14	Access Bank	0.0097	0.1530	0.1866	0.3918	0.0790	15.3361	7.0917	0.0264	0.7065	0.3791
15	Bank of Taiwan Ltd	0.0048	0.0915	0.4095	0.7984	0.2173	14.3800	0.7262	0.0087	0.2647	0.0377
16	Bidvest Bank	0.0032	0.0868	0.2067	0.0405	0.2037	16.2281	3.7508	0.0585	0.3220	0.4008
17	Capitec Bank	0.0025	0.0599	0.1195	0.0016	0.1814	18.9766	4.5040	0.0473	0.3866	0.7356
18	HBZ Bank Ltd	0.0012	0.1875	0.2028	0.0143	0.0740	15.8837	12.3359	0.0156	0.3096	0.3688
19	Sasfin Bank	0.0006	0.1067	0.1625	0.0036	0.1127	16.1372	7.8454	0.0367	0.4636	0.2047
20	Grindrod Bank	0.0002	0.0415	0.0564	0.0021	0.1232	16.4347	7.1037	0.0246	0.6398	0.0624
21	Habib Bank	0.0000	0.2267	0.4593	0.0054	0.0922	13.9185	9.7939	0.0332	0.3431	0.5659
22	Ubank	0.0000	0.0408	0.0372	0.0000	0.0784	15.4863	11.7630	0.0471	0.0806	0.8673
23	Ithala Bank Ltd	0.0000	0.1236	0.1839	0.0000	0.1236	14.9624	7.0936	0.0418	0.6374	0.5413
24	Al Baraka Bank	0.0000	0.1766	0.2406	0.0000	0.0968	15.9675	9.3279	0.0297	0.7154	0.5002

Note: The table is sorted in descending order by the DI. ILR: interbank lending ratio; FC: financial connectivity; CAR: capital ratio; Size: log total assets; EL: external leverage; Liquidity: cash to total assets; Activity: lending activity, measured by loan to total assets; Funding: retail deposit to total assets.

Annexure 3: Statistical tests for panel data analysis

We first conduct a unit root test for the panel data using the Levin, Lin and Chu (2002) test. The results shown in Table A3 confirm the stationarity of the data. Then, following Siebenbrunner, Sigmund and Kerbl (2017), we perform various tests to determine an appropriate model for the panel data analysis. Table A4 summarises the test results. We first test the importance of individual effects through the Breusch-Pagan Lagrangian multiplier test (Breusch and Pagan 1980). The rejections of the Breusch-Pagan test (*p*-value = <0.01 for both DI and DV) indicate that individual effects are important. We then use Honda (1985) and the standard F-test to compare the pooled model with the individual effects alternatives. The rejections of these tests again confirm the importance of individual effects for both DI and DV. Finally, the Hausman (2015) test is used to decide between fixed and random effects. The rejections of the Hausman test (*p*-value $=< 0.01$ for both DI and DV) indicate that the fixed-effects model is consistent.

Table A3: Unit root test for panel data

Variables	z-score	*p*-value	Result
DI	-5.86	<0.01	Stationary
DV	-4.70	<0.01	Stationary
Size	-9.53	<0.01	Stationary
Financial connectivity	-8.35	<0.01	Stationary
External leverage	-5.44	<0.01	Stationary
Interbank lending ratio	-7.82	<0.01	Stationary
Capital ratio	-5.45	<0.01	Stationary
Activity	-7.40	<0.01	Stationary
Funding	-9.06	<0.01	Stationary

Note: This table reports the unit root test based on the Levin, Lin & Chu test. The null hypothesis: the variable is non-stationary. The z-scores and *p*-values are reported. Based on the results, all variables are stationary.

Table A4: Statistical tests for panel data analysis

		DI		DV	
Null hypothesis	**Method**	**Stats**	***p*-value**	**Stats**	***p*-value**
Individual effect is not important	Breusch-Pagan	4659.6	<0.01	25240	<0.01
Individual effect is not important	Honda	140.94	<0.01	144.89	<0.01
Individual effect is not important	F-test	157.67	<0.01	394.24	<0.01
The preferred model is random effects – no significant correlation between the errors and the regressors	Hausman	2565.4	<0.01	1580.8	<0.01

Note: This table reports the testing results with different methods for the dependent variables DI and DV against the regressors. We test the importance of individual effect with the Breusch-Pagan, Honda test and standard F-test; the results are significant at 1%, indicating the importance of the individual effect. In addition, the Hausman test result is significant, which rejects the null hypothesis and suggests that only the fixed-effects model is consistent. Number of entities: n = 24; number of periods: t = 167; number of observations: N = 4 008.

Annexure 4: Results of the OLS model

Table A5: Panel data regression using the OLS model

	DI	*p*-value	DV	*p*-value
Intercept	-06775***	<0.0001	0.5152***	<0.0001
Size	0.0193***	<0.0001	-0.0291***	<0.0001
Capital ratio	1.4751 **	<0.0001	-0.0482	0.525
Financial connectivity	0.5860***	<0.0001	-0.1046***	<0.0001
External leverage	0.0444***	<0.0001	0.0329***	0.0010
Interbank lending ratio	-0.3520***	<0.0001	0.7279***	<0.0001
Activity	0.1679***	<0.0001	0.0097	0.624
Liquidity	0.0518	0.402	0.1027	0.288
Funding	-0.0627	0.126	-0.1727***	<0.0001
$Adj - R^2$	0.242		0.441	

***p-value < 1%, **p-value < 5%

Note：This table reports the estimation result for the dependent variables of DebtRank Impact (DI) and DebtRank Vulnerability (DV) based on the OLS model with clustered standard errors method.

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