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Systemic risk contribution of financial institutions in South Africa

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Abstract

The recent global financial crisis of 2007-2008 highlighted the necessity of measuring systemic risk amongst banks, insurance firms, and other systemically important institutions, as the failure of these organisations could have incalculable consequences on the financial sector and spillover to the real economy. An investigation into systemic risk is limited in emerging markets, including South Africa, thus maintaining financial stability can be challenging for regulators due to inadequate risk measurements being applied as well as insufficient monitoring of the vulnerable role-players within the financial system. This paper employs two systemic risk measures: the Conditional Value-at-Risk measure referred to as CoVaR pioneered by Adrian and Brunnermeier (2011) and Granger causality tests proposed by Billio *et al*. (2012). CoVaR is used to determine the systemic risk contribution of individual institutions and Granger causality tests depict the interconnectedness within the financial system that leads to risk spillover to other institutions. The study analyses 22 financial firms within the banking, insurance, and financial services sectors for the period 2005-2017. The results suggest that spillovers increase during distressed periods and that banks and insurance firms are the highest contributors to systemic risk.

Keywords: Systemic Risk; South Africa; CoVaR; Granger causality network.

1. Introduction

Systemic risk, according to the European Central Bank (2009, p. 134), "refers to the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially". The 2008 global financial crisis (GFC) triggered by the collapse of the United States (US) banking system, propagated adverse shocks to other financial sectors, the real economy (Bernal, Gnabo & Guilmin, 2014) and in turn the international financial market. This spreading of financial distress gave way to an abundance of literature that investigates the factors contributing to systemic risk, and how systemic risk is appropriately measured. This is required in order to identify the risky role players in the financial system to aid regulators and policymakers in understanding the vulnerabilities of the system so that effective risk control can be applied (ECB, 2007). These studies have predominantly been carried out in the US and European markets, largely due to the sizeable impact of the global financial crisis on these markets as well as due to the 2010 sovereign debt crisis that originated in Europe. Research investigating the contributors to systemic risk in the emerging market context, specifically examining systemic risk in the South African (SA) financial system is limited.

One of the key contributors to systemic risk is the increased interconnectedness amongst financial institutions. This promotes the spread of distress amongst institutions and to the financial system as the linkages between institutes serves as conduits for the transfer of risk. The interconnectedness of financial institutions increases financial stress contagion.

Huang, Zhou and Zhu (2009) highlight the significance of banks in the economy by describing banks as being the most important financial intermediaries, and thus failure of the banking system would exert severe cost impacts on the real economy. Walters, Beyers, van Zyl and van den Heever (2018) also explain that the collapse of the banking system could critically damage the economy, as banks are central to a sound financial system. The South African banking system that comprises of local and foreign-controlled banks, local branches of foreign banks as well as mutual and cooperative banks plays an important role in the local economy. This sector provides employment, contributes significantly to corporate tax, facilitates transactions between stakeholders in the economy and plays an important role in the transmission of monetary policy (BASA, 2017). The banking system is profitable and has maintained capital adequacy ratios exceeding that required by regulation. The important functions that the SA banking system performs in the economy make it crucial to assess the stability of individual banks along with the financial system as a whole. Systemic risk measurements enable the soundness of a financial system to be assessed which drives macroprudential regulation.

Unlike banks, which are considered primary drivers of systemic risk (Society of Actuaries, 2017), systemic risk did not apply to “traditional” insurance firms due to their longer-term assets as well as being less interconnected with the financial system. Banks are the primary lenders to other banks, while insurance firms mainly interact with consumers with exposure to other insurance firms being limited to those firms that transact in reinsurance contracts. The increase in studies that examine the contribution of insurance firms to systemic risk is due to American International Group (AIG), a multinational insurance organisation, which was one of the major firms to play a part in the global financial crisis. Acharya and Richardson (2014) explain that the insurance sector is more interconnected with the financial system as they do not perform only traditional insurer activities but have ventured into insuring against macro wide events as well as offering products with non-diversifiable risk, thereby being a potential source of systemic risk.

The financial system not only comprises of banks and insurance firms but also includes other financial service institutes. Financial services have become highly interconnected with the banking system as they provide a source of lending to banks as well as invest in bank assets. The exposure of local financial intermediaries to the South African banking sector is one of the highest in the world (SARB, 2018). A growing interconnectedness of the financial system leads to shocks propagating not just within the sector but also throughout the financial system and the real economy (Bernal *et al*., 2014). The interconnectedness of today’s financial system motivates the need to investigate all financial firms due to the various forms of systemic risk (e.g. spillover risk, interbank risk, and counterparty risk) that can spread within the system.

An investigation into both banks and insurance firms, which are regarded as systemically important financial institutions, along with examining financial services firms will safeguard the financial stability of the South African economy and will enable an in-depth analysis into the inter-linkages that exist within the financial system. To the best of our knowledge, a study of this nature, which aims to identify the systemically important banks, insurance firms, and financial services firms as well as their interconnectedness, has not been sufficiently explored in South Africa. The limited studies carried out in South Africa include that by Foggit (2016) and Manguzvane (2016); however, both these papers focus specifically on the banking sector. For regulators to respond to emerging threats to retain financial stability and to prevent crisis spillovers to the real economy, accurate risk measurement is required (Sithole, Simo-Kenge, & Some, 2017).

Accordingly, this study empirically determines the contribution of individual financial institutions in South Africa to systemic risk, as well as depicts the interconnectedness that exists in the local financial market. This paper, therefore, fills several gaps in the literature by analysing the SA financial system for the period of March 2005 to December 2017, thereby assessing the period pre and post the global financial crisis. The key contributions of this paper are that it identifies the systemically important financial institutions, not just within the banking sector but in the insurance and financial services sectors too, as all three sectors play an important role in the financial system. Secondly, this study explores the interconnectedness of the financial system by identifying the spillover effects of individual institutions. Adrian and Brunnermeier's (2011) Conditional Value-at-Risk is commonly known as the CoVaR method for measuring systemic risk is adopted, as well as Granger-causality tests proposed by Billio, Getmansky, Lo and Pelizzon (2012) for measuring the degree of interconnectedness amongst the financial institutions is applied. Understanding the contributors to systemic risk and the degree to which institutions are interconnected will assist macroprudential policymakers in maintaining financial stability as well as improve crisis management.

This rest of the paper is organised as follows: Section two presents the literature review, section three defines the methodology used to conduct this research, section four presents and discusses the results obtained and lastly, section five concludes the findings of the paper and provides recommendations for further research.

2. Literature review

2.1. The South African financial system

The South African financial system is well functioning and well regulated, encompassing a developed banking sector as well as a developed stock market. The Banking Association South Africa in their 2017 report on financial transformation specify that there are 37 licensed banks in South Africa; however, the sector is dominated by its five retail banks. The Herfindahl Hirschman Index (H-index) is an indication of the degree of concentration of the banking sector.

An H-index below 0.1 indicates there is no concentration, a measurement between 0.1 – 0.18 shows there is medium concentration and above 0.18 indicates there is high concentration. The H-index of the local banking sector measures 0.18 (SARB, 2018), thus depicting a concentrated banking sector in which there is limited competition resulting in a high-interest rate spread. The South African Reserve Bank (SARB) governs the banking sector. Under the newly implemented "Twin Peaks" model, which was signed into law in 2017, the SARB now regulates all financial institutions. The Johannesburg Stock Exchange (JSE) is the largest stock exchange in Africa and ranked amongst the top 20 stock exchanges in the world. The 2016 stock market capitalisation to gross domestic product (GDP) ratio measured 323% (Trading Economics, 2016) indicating a highly developed stock market as per world standards. The ratio of domestic credit to the private sector as a percentage of GDP was estimated at 147% (The World Bank, 2017) for 2017, which is a development indicator of the financial depth of the finance sector.

2.2. Systemic risk

Systemic risk broadly refers to the risk of collapse of a financial institute that could potentially lead to the collapse of the financial system or the real economy. The spread of negative shocks within the financial system is predominantly due to linkages amongst financial institutions or common exposures (BIS, 2010). A systemic event emerges when a crisis escalates from a micro level to a macro level. There is no consensus on a formal definition of systemic risk in literature, possibly because systemic risk is still a developing field of study (Silva *et al*., 2017). Adrian and Brunnermeier (2011) explain that the spread of losses increase during a financial crisis as the co-movement of financial institutes is higher than during normal times. This measure of increased co-movement is systemic risk. Mensah and Premaratne (2017) depict systemic risk as the failure of financial institutions that lead to the disruption of the economy. Billio *et al*. (2012) describe systemic risk as the propagation of illiquidity, insolvency, and losses within the system during financial distress. Bisias, Flood, Lo and Valavris (2012) further report some of the various ways that systemic risk has been defined; risk to economic growth and welfare, impact on the real economy and contagion. Vauhkonen (2008) maintains that systemic risk is contagion. Porter Stewart's (1964) definition of pornography has also been widely used in describing systemic risk: "hard to define but we think we know it when we see it."

Although there may be no agreement on the definition of systemic risk, there is no debate around the importance of reliable measurement techniques to maintain financial stability. Harrington (2009) explains that systemic risk can arise from shocks to a financial institute resulting in assets being sold at depressed prices and in turn lessening the prices of similar assets at other institutions. Financial institutes who do not honour their obligations resulting in spillovers to other markets is also a source of systemic risk as well as the unwillingness to continue with business at certain institutes due to financial concerns at other similar institutes which leads to the withdrawal of funds.

The 2007 financial crisis and the 2008 Eurozone sovereign debt crisis have shown how vulnerable the financial system is (Silva *et al*., 2017). The "Flash Crash" of 2010 and the collapse of Long Term Capital Management (LTCM) hedge fund also had severe impacts on the greater market and are termed systemic events due to this. These recent systemic events have led to an increased prominence in systemic risk research due to the impact of these events on their respective economies as well as their far-reaching spillovers. Published papers prior to 2007 pointed out the growing concerns around systemic risk. These concerns were a result of the increased number of intricate financial institutions, increased market integration, and the inefficient method of microprudential regulation in monitoring systemic risk as only the risk of individual institutions were considered. Vauhkonen (2008) further substantiates the value of adequate risk measurements by highlighting the importance of investigating methods that can equip authorities in assessing the impact of a financial crisis on the real economy. As the popular management adage states, "one cannot manage what one does not measure".

Silva *et al*. (2017) affirm the primary driver for the financial sector being the most supervised and most regulated is due to the significant risk that it poses on the economy. In light of the financial sector being regarded as systemically risky, Vauhkonen (2008) identifies banks, insurance companies, and hedge funds as systemically important due to the costs such institutions could inflict on the macroeconomy when in a crisis. Systemically important financial institutions (SIFI) are often characterised as such due to their size, complexity, and interconnectivity, with interconnectivity being more of a factor than size (Silva *et al*., 2017). Vauhkonen (2008) agrees with interconnectedness on the size versus interconnectedness debate, by pointing out that size is not a good representation of a bank's systemic importance. A smaller bank could be more systemically important than a larger bank if it has more links with the financial system than the larger bank.

Although Silva *et al*. (2017) consider hedge funds as systemically important; Billio *et al*. (2012) view banks and insurance firms to be more central to systemic risk due to the nature of their operations. The basis for this is that banks offer credit to other financial firms, both banks and insurers have increased their operations in non-traditional finance, as well as being more highly regulated than hedge funds are all possible causes for their spillovers to other institutions. Banking groups that also operate in multiple regions further threaten the financial stability of several countries.

Banks are considered to be at the centre of the financial system, and in turn, operational disruption of a particular bank can disrupt the operations of other institutions and lead to the weakening of capital adequacy and liquidity (Adams, Fuss & Gropp, 2012). A distressed bank influences investment consumption due to its reduced credit supply to the non-financial sector (Bernal *et al*., 2014). Studies have shown that banking crises can amount to tens of percent of an economy's annual gross domestic product (GDP) (Vauhkonen, 2008) and negatively impacts unemployment and government deficits (Rodriguez-Moreno & Pena, 2010).

This was clearly seen post the global financial crisis in the European Union (EU) and the US. In the EU, between January 2007 to November 2009, GDP growth decreased from 3.09% to 4.09%, unemployment increased from 7.8% to 9.4% and government deficits grew from 0.8% to 6.7%. Similarly, in the US between January 2007 to November 2009, GDP growth decreased from 2.14% to 2.45%, unemployment increased from 4.6% to 10% and government deficits went from 1.14% to 9.9%. The decreased liquidity experienced by banks during the GFC that was caused by subprime mortgages resulted in banks offering less finance to firms thereby lowering investment. Lower investment and lower investor confidence which reduced consumer spending resulted in demand deficient unemployment and declined GDP growth. Increased government spending in an effort to restore financial stability through bank recapitalisation and depositor guarantees increased government deficits.

Mensah & Premaratne (2017) have recognised that due to regulators' lack of understanding regarding systemic risk, the failure of pivotal institutions during the financial crisis could not be addressed as well as identifying which institutions are systemically risky. Determining the contribution of different sectors to systemic risk (Adrian & Brunnermeier, 2011) and identifying the risks to financial stability will enable the early detection of crises by regulators as well as the management thereof. The International Monetary Fund (IMF)

Global Financial Stability report of 2009 stresses the importance of detecting systemic risk such that crises can be managed.

In the event of a financial crisis, a bailout of key institutions or institutions regarded as "too big to fail" may be required to prevent the collapse of the financial sector and the economy (Mensah & Premaratne, 2017). One of the primary aims of the 2010 US Dodd-Frank Act, which focuses on financial stability, is to promote market discipline by reducing institutions expectations of government bailout (Adams *et al*., 2012). Government bailout is not a favourable act, as it often results in reduced market discipline and moral hazard (Harrington, 2009). Early identification of the contributors to systemic risk as well as identifying the factors that cause systemic risk would be beneficial to regulators. Reliable systemic risk measurements will further enable a timely response to threats by regulators before government bailout is inevitable.

As the financial system has become increasingly integrated, assessing its sub-sectors is important for financial regulation (Drakos & Koureta, 2014). Measuring systemic risk and interconnectivity amongst financial institutions is important for macroprudential policy. The CoVaR method by Adrian & Brunnermeier (2011) is the most widely used measure of systemic risk and Granger-causality tests are important in capturing the degree of interconnectedness and the causal relationships that exist in the financial network. Several studies in the United States and Europe have been carried out to investigate the factors contributing to systemic risk; however, these studies are limited elsewhere. Size, complexity, and interconnectedness are key determinants of systemically risky financial institutions, although, the interconnectedness of a firm is more of a factor. Banks and insurance firms are considered central to the financial system and are thus systemically important institutes to monitor. The focus of this paper is on banks, insurance firms, as well as financial services, which is motivated by the view of Bernal *et al*. (2014) and Roengpitya and Rungcharoenkitkul (2011). Institutes in these sectors of various sizes are investigated to confirm if interconnectivity outweighs size.

3. Methodology

This study investigates the systemically risky banks, insurance firms, and financial services firms in the South African financial sector by adopting the CoVaR methodology (Adrian & Brunnermeier, 2011). The use of the CoVaR approach is encouraged by it being the most popular measure of systemic risk, having been used or mentioned in more than 23 articles (Silva *et al.*, 2017). The investigation into the abovementioned three sub-sectors is motivated by their systemically important nature and the impact their failure could pose on the real economy. The CoVaR estimates indicate which institutions are systemically risky and ΔCoVaR specifies the institution's marginal contribution to systemic risk. The causal relationships that exist within the South African financial system are determined using linear Granger causality tests. This study seeks to assist regulators and policymakers in being able to monitor the vulnerable players of the system such that financial stability can be ensured. This study appears to be the first that investigates the systemic risk contribution of banks, insurance companies, and financial services firms in South Africa. The research follows the methodology outlined by Mensah and Premaratne (2017).

3.1. Definition of CoVaR

Adrian and Brunnermeier's (2011) definition of CoVaR stems from the Value-at-Risk concept commonly used in financial risk management. Equation (1) illustrates the VaRiq definition, where the return losses of an institution *i* is less than or equal to a predetermined VaR at the specified *q*% probability

$$\Pr\left(X^i \leq VaR_q^i\right) = q \tag{1}$$

Equation (2) represents the $CoVaR^i_q$ definition. The VaR of the financial system (institution j) conditional on the return losses of an individual firm (institution *i*) being at its VaR^i_q at its q^{th} percentile distribution.

$$\Pr\left(X^j \leq CoVaR_q^{j|i} \middle| X^i = VaR_q^i\right) = q \tag{2}$$

Δ $CoVaR_q^{j|i}$ is institution i's contribution to j as shown below:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i} \tag{3}$$

Equation (3) represents an institution's contribution to systemic risk by calculating the difference between the CoVaR of the system when the institution is distressed (fifth percentile) and the difference when the institution is at its normal state (50th percentile). This allows for the losses to the financial system to be computed conditional on a specific institution. The return losses of the financial system are given by the growth rate of the market valued total financial assets.

The computation of delta CoVaR (ΔCoVaR) is outlined in a three-step procedure.

Step 1

The market valued total financial assets (MVTFA) for each financial institution is constructed using accounting data. The market valued total financial assets

(MVTFA) for institute *i* is represented by A_t^i .

$$A_t^i = BA_t^i\left(ME_t^i/BE_t^i\right) = ME_t^i . LEV_t^i \tag{4}$$

where BA_t^i is the book value of total assets for institute i, ME_t^i is the market value of total equity for institute *i* and BE_t^i is the book-valued total equity for institute i. LEV_t^i is the ratio of total assets to total book equity. The book value of total assets is calculated as follows:

$$BA_t^i = TA_t^i - \left(TL_t^i - TIA_t^i\right) \tag{5}$$

where TA_t^i is the total assets of institution i, TL_t^i is the total liabilities of institution *i* and TIA_t^i is the total intangible assets of institution *i*. The growth rate of MVTFA is given by:

$$X_t^i = \frac{ME_t^i.LEV_t^i - ME_{t-1}^i.LEV_{t-1}^i}{ME_{t-1}^i.LEV_{t-1}^i} = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i} \tag{6}$$

The returns of the financial system as required by Equation (10) is calculated excluding institution *i* under investigation. These returns are a cross-sectional summation of the weighted asset returns of each institution excluding institution *i*.

$$X_t^{s,i} = \sum_{j=1,j\neq i}^{n} w_{j,t} X_t^j \tag{7}$$

where the weighted asset returns are calculated as follows:

$$w_{j,t} = A_{t-1}^j\left(\sum_{j=1,j\neq i}^{n} A_{t-1}^j\right)^{-1} \tag{8}$$

Step 2

To estimate the coefficients in Equation (9) and (10), a regression analysis is used based on cross-sectional daily return data of each financial institution X_t^i, as well as of the system, X_t^{system} and lagged state variables represented by M_{t-1}. Lagged state variables allow for the estimation of a time-varying CoVaR and VaR. The use of systematic state variables required in the CoVaR methodology uses data from the United States due to limited local data availability. This is justified by the fact that the US is considered a "global leader" (Mensah & Premaratne, 2017, p. 20).

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{9}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i} \tag{10}$$

The error term is assumed to be independent and identically distributed (iid) with zero mean and variance. The approach followed by Adrian and Brunnermeier (2011) is used in the selection of state variables.

- Volatility Index (VIX). This is supplied by the Chicago Board of Options Exchange (CBOE) and captures volatility in the equity market;
- Liquidity spread between the 3-month US Repo Rate and the 3-month US Treasury bill rate. The liquidity spread is to proxy short-term liquidity risk, an important trait of a healthy financial system (Mensah & Premaratne, 2017);
- The change in the 3-month treasury bill rate;
- Adrian and Brunnermeier (2011) apply the following two fixed income factors that are considered leading indicators to proxy the business cycle:
- The yield spread between the 10-year US treasury rate and the 3-month US Treasury bill rate;
- The difference between the US BAA-rated bonds and the 10-year US treasury rate with matching maturities;

Lastly, equity market returns are controlled for, so that the intrinsic risk of the financial system can be considered (Bernal *et al*., 2014). This is achieved by applying the following:

- The daily returns of the banking, insurance and financial services sectors for South Africa.

Step 3

The CoVaR of the system is determined using linear quantile regression analysis by Koenker and Basset (1978). Quantile regression is used in the CoVaR model instead of ordinary least squares (OLS) estimation as quantile regression does not demand the distributional assumptions as is required by OLS estimation (Adrian & Brunnermeier, 2011). The model is computed at q=5% and q=50%.

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-i} \tag{11}$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-i} \tag{12}$$

The contribution to systemic risk from institute i is then estimated from its CoVaR as follows:

$$\Delta CoVaR_t^i(5\%) = CoVaR_t^i(5\%) - CoVaR_t^i(50\%) = \beta\left[VaR_t^i(5\%) - VaR_t^i(50\%)\right] \tag{13}$$

3.2. Granger-causality measures

Granger-causality measures use linear regression to determine if previous values of X can forecast Y and vice versa. These measures are employed to establish the degree of interconnectedness amongst the individual firms. The methodology that is followed is guided by Billio *et al*. (2012) to depict the degree of spillover that exists amongst the role players in the financial system. The significance of coefficients b_j and c_j will indicate the direction of the causal relationships within the system. Daily stock market return data of banks, insurance firms, and financial services firms are used in computing the directionality and significance of the causal relationships.

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \tag{14}$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \omega_t \tag{15}$$

Daily return market data is also used to measure the level of interconnectedness amongst these institutes. The Dynamic Causality Index[1] (DCI) is measured for a 12-month rolling window period on a quarterly basis to illustrate the level of interconnectedness during different periods. Mensah and Premaratne (2017) and Billio *et al.* (2012) both adopt a 36-month rolling window, however, a 12-month approach similar to Zheng, Boris, Feng and Baowen (2012) is applied in order for pre and post-crisis periods to be represented. The DCI is computed as follows:

$$DCI_t = \frac{number\ of\ causal\ relationships\ in\ window}{total\ possible\ number\ of\ causal\ relationships}, \tag{16}$$

where a high and low DCI values indicates high and low levels of interconnectedness of the financial system, respectively.

3.3. Data

The study considers 22 publicly traded financial organisations of various sizes, which comprises of 7 banks, 5 insurance companies, and 10 financial services firms. These financial institutions are listed in Table 1. The initial sample was of 54 companies, but several were excluded due to insufficient data. The period under consideration is 1 March 2005 to 29 December 2017 to enable analysis pre and post the global financial crisis.

The estimation of ΔCoVaR requires accounting data on each institution and stock market data of each institution is required for the Granger-causality tests. This data and the state variable inputs is obtained using Bloomberg. Daily book value and market data are applied in the estimation methods to allow a highly reactive model to be generated. In the computation of ΔCoVaR, data on the total assets, total liabilities, total intangible assets and the ratio of market to book

[1] The total possible causal relationships for n financial institutions is computed as $n(n-1)$

value of shareholders' equity is collected for each firm. The Granger-causality relationships are adjusted for autocorrelation and heteroscedasticity using the HAC standard errors correction procedure. The HAC procedure is only valid in large samples and therefore further substantiates the use of daily observations.

Table 1: List of Financial Firms Investigated

Banks	Insurance	Financial services
ABSA GROUP (ABSA)	Discovery Ltd (DSY)	African Dawn Capital Ltd (ADW)
CAPITEC (CAP)	Liberty Holdings Ltd (LBH)	African Equity Empowerment Investments Ltd (SKJ)
FIRSTRAND LTD (FRS)	MMI Holdings Ltd (MMI)	AfroCentric Investment Corporation Ltd (ACT)
INVESTEC LTD (INVES)	Old Mutual PLC (OML)	Brimstone Investment Corporation Ltd (BRT)
NEDBANK GROUP (NED)	Santam Ltd (SNT)	Ecsponent Ltd (ECS)
SASFIN (SASFIN)		Remgro Ltd (REM)
STANDARD BANK (STD)		Stratcorp Ltd (STA)
		Investec PLC (INP)
		Nictus Ltd (NCS)
		PSG Group Ltd (PSG)

Note: The ticker of each firm is indicated in brackets.

3.4. Descriptive statistics

The descriptive statistics of the individual institution returns and of the identified state variables are represented in Tables 2, 3, and 4.

Table 2: Descriptive Statistics of Bank Returns

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Range	Minimum	Maximum
ABSA	0.001	0.000	0.021	46.341	1.994	0.611	-0.217	0.395
CAP	0.002	0.000	0.020	11.847	0.539	0.384	-0.143	0.241
FRS	0.001	0.000	0.020	4.418	-0.045	0.279	-0.148	0.130
INVES	0.001	0.000	0.025	72.563	3.101	0.749	-0.206	0.543
NED	0.001	0.000	0.021	61.390	1.846	0.709	-0.308	0.401
SASFIN	0.001	0.000	0.023	35.734	0.942	0.591	-0.292	0.299
STD	0.001	0.000	0.020	16.872	0.611	0.476	-0.202	0.273

The descriptive statistics of the bank returns show that the banks in the dataset have similar mean values and standard deviations. Capitec, First Rand Bank and Standard Bank are the least volatile banks as they have the lowest standard deviation. Capitec Bank also has the highest mean. The most volatile bank is Investec Ltd. The kurtosis estimates show that the returns of all the banks do not follow a normal distribution.

Table 3: Descriptive Statistics of Insurance Firm Returns

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Range	Minimum	Maximum
DSY	0.001	0.000	0.020	40.044	1.638	0.537	-0.222	0.315
LBH	0.001	0.000	0.025	445.240	10.534	1.311	-0.466	0.845
MMI	0.002	0.000	0.070	1890.309	39.993	4.151	-0.677	3.474
OML	0.000	0.000	0.030	308.015	-9.173	1.218	-0.942	0.276
SNT	0.001	0.000	0.019	22.714	0.391	0.399	-0.189	0.209

MMI Holdings Ltd has the highest mean and is the most volatile as shown by its standard deviation. Santam Ltd is the least volatile insurance firm in the dataset. The return data of the insurance firms does not follow a normal distribution.

Table 4: Descriptive Statistics of Financial Services Returns

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Range	Minimum	Maximum
ADW	0.007	0.000	0.145	289.904	11.406	5.248	-0.832	4.416
SKJ	0.001	0.000	0.045	21.564	-0.098	1.064	-0.671	0.394
ACT	0.134	0.000	7.250	3326.952	57.598	420.769	-1.949	418.820
BRT	0.002	0.000	0.044	507.281	15.176	2.117	-0.627	1.490
ECS	0.011	0.000	0.327	1056.083	21.164	19.784	-5.785	13.998
REM	0.001	0.000	0.020	351.838	-10.194	0.842	-0.671	0.171
STA	0.016	0.000	0.301	550.020	19.421	12.457	-2.453	10.004
INP	0.001	0.000	0.023	9.427	0.109	0.411	-0.206	0.204
NCS	0.001	0.000	0.054	231.856	7.973	2.196	-0.659	1.538
PSG	0.002	0.000	0.039	604.502	16.667	1.995	-0.613	1.382

AfroCentric Investment Corporation Ltd has the highest mean and highest standard deviation amongst the financial service firms, while Remgro Ltd is the least volatile. The return data of the financial services firms does not follow a normal distribution.

TABLE 5: DESCRIPTIVE STATISTICS OF THE STATE VARIABLES

	Mean	Median	Standard Deviation	Kurtosis	Skewness	Range	Minimum	Maximum
Volatility Index	0.003	-0.002	0.073	7.197	1.394	0.938	-0.296	0.642
Liquidity Spread	-0.026	0.000	0.321	141.321	-8.667	8.881	-6.764	2.117
Change in 3-month Tbill	0.000	0.000	0.465	73.624	1.688	13.774	-6.143	7.631
Yield Spread	-0.015	0.000	0.539	126.807	3.326	17.595	-6.595	11.000
Diff BAA-rated bond and 10 year treasury rate	-0.012	0.000	0.440	241.950	-9.524	16.948	-10.973	5.975
Banking Sector Returns	0.001	0.000	0.017	3.780	0.042	0.225	-0.135	0.090
Insurance Sector Returns	0.000	0.000	0.015	4.381	-0.090	0.185	-0.091	0.094
Financial Services Sector Returns	0.001	0.000	0.012	3.992	-0.057	0.155	-0.081	0.075

The yield spread is the most volatile state variable, whilst the financial services sector returns is the least volatile. All the state variables have fat tails expect for the banking and financial services sector returns who both have a kurtosis estimate close to three.

4. Results

This section applies the methodology described in section three in which historical accounting and market data is used to analyse the banking, insurance, and financial services sectors' of South Africa. Section 4.1 describes the results from the implementation of the CoVaR method and Section 4.2 explains the outcomes of the linear Granger-causality tests. The DCI estimates are described in Section 4.3.

4.1. Delta CoVaR

The ΔCoVaR of the 22 firms is calculated for the full sample period of 2005-2017 and the three sub-periods: 2005-2006 (pre-crisis), 2007-2008 (GFC crisis) and 2009-2017 (post-crisis). As ΔCoVaR measures downside risk, it is calculated as a negative value, however, the convention is to report risk measures as absolute values, and thus the highest absolute measurement of ΔCoVaR implies the highest contributor to systemic risk.

Table 6 reports the ΔCoVaR estimates at the 5% significance level for the full sample period. The companies are ranked according to their ΔCoVaR estimates in order to portray the systemically important financial institutions. The top four contributors to systemic risk are SA's "big four" banks: FirstRand (1.83%), Absa (1.66%), Standard Bank (1.58%) and Nedbank (1.49%). This could be attributed to the fact that the SA banking sector is very concentrated, with these four retail banks along with Investec representing more than 90% of the total assets within the banking sector (IMF, 2018). The bottom three are financial services firms namely, AfroCentric Investment Corporation Ltd, Nictus Ltd, and Ecsponent Ltd. AfroCentric Ltd does not contribute to systemic risk indicated by its zero ΔCoVaR value. Nictus Ltd (0.01%) and Ecsponent Ltd (-0.03%) provide stability to the financial system due to their ΔCoVaR estimates being negative, possibly due to their engagement in less risky and less complex business activities. On the right-hand side of Table 6, the firms' VaR estimates are indicated along with their VaR ranking. It is evident that ranking according to the ΔCoVaR estimate and VaR estimate do not yield the same outcome. The VaR estimate of the four banks with the highest ΔCoVaR is 9, 11, 13 and 14 respectively. African Dawn Capital Ltd, which has the highest VaR estimate of 11.42%, is only ranked 18 in terms of its contribution to systemic risk. This implies that there is a weak correlation between VaR and ΔCoVaR, substantiating that VaR is an inadequate risk measure as it measures idiosyncratic risk, which is not suitable for macroprudential regulation (Adrian & Brunnermeier, 2011).

Table 7 presents the ΔCoVaR estimate for 2005-2006 which is the window leading up to the financial crisis. Banks are still the highest contributors to systemic risk. Absa Bank is ranked number one with a ΔCoVaR of 1.87% followed by Standard Bank (1.79%) and FirstRand Bank (1.68%). Apart from banks, insurance companies are also predominant in the top 10 contributors to systemic risk. MMI Holdings Ltd is ranked fourth with a ΔCoVaR of 1.14%, Discovery Ltd (0.76%) is ranked eighth, Santam (0.75%) is ranked ninth and Liberty Holdings Ltd (6.55%) is tenth. Financial services firms are still the bottom three indicating a favourable contribution to financial stability, possibly due to the role financial services play in social and economic transformation.

Table 6: ΔCoVaR and VaR Ranking for Mar 2005 – Dec 2017

Institute	ΔCoVaR Ranking	ΔCoVaR	VaR	VaR Ranking
FRS	1	1.83	3.40	9
ABSA	2	1.66	3.16	11
STD	3	1.58	3.11	13
NED	4	1.49	3.03	14
OML	5	1.16	3.98	6
INP	6	1.05	3.59	7
INVES	7	1.01	3.58	8
REM	8	0.99	2.60	19
DSY	9	0.99	2.74	18
SNT	10	0.48	2.57	20
CAP	11	0.47	3.17	10
LBH	12	0.38	2.40	21
SASFIN	13	0.33	3.14	12
BRT	14	0.14	2.80	16
PSG	15	0.09	2.98	15
MMI	16	0.07	2.77	17
SKJ	17	0.06	6.69	4
ADW	18	0.05	11.42	1
STA	19	0.01	11.24	2
ACT	20	0.00	4.40	5
NCS	21	-0.01	2.08	22
ECS	22	-0.03	9.51	3

Note: The table reports the 5% ΔCoVaR and 5%VaR for 22 firms for the full sample period March 2005 – December 2017. The ΔCoVaR and VaR estimates are reported as percentages.

TABLE 7: ΔCOVAR AND VAR RANKING FOR MAR 2005 – DEC 2006

Institute	ΔCoVaR Ranking	ΔCoVaR	ΔVaR	VaR Ranking
ABSA	1	1.87	3.13	12
STD	2	1.79	3.20	11
FRS	3	1.68	3.67	7
MMI	4	1.14	3.09	14
NED	5	0.81	2.69	16
INP	6	0.81	2.81	15
DSY	7	0.76	2.22	20
SNT	8	0.75	1.99	21
REM	9	0.69	2.42	18
LBH	10	0.65	2.38	19
SASFIN	11	0.54	3.34	9
OML	12	0.28	2.66	17
BRT	13	0.25	4.14	6
SKJ	14	0.19	7.23	3
INVES	15	0.15	3.11	13
ADW	16	0.10	5.18	5
CAP	17	0.08	3.27	10
ACT	18	0.03	5.72	4
NCS	19	0.00	0.00	22
STA	20	-0.03	8.63	2
PSG	21	-0.05	3.46	8
ECS	22	-0.16	32.09	1

Note: The table reports the 5% ΔCoVaR and 5%VaR for 22 firms for the pre-crisis period March 2005 – December 2006. The ΔCoVaR and VaR estimates are reported as percentages.

For the period 2007-2009, which depicts the financial crisis, it can be seen from Table 8 that the ΔCoVaR estimates of the top contributors are higher than that of the pre-crisis period. The highest ΔCoVaR estimate for 2005-2006 is 1.87% compared to 2.16% during the global financial crisis. Banks are still the main contributors to systemic risk with FirstRand (2.16%), and Absa Bank (2.04%) ranked first and second. Banks and insurance companies make up the highest ten contributors to systemic risk with the exception of Remgro Ltd, a financial services firm, which is ranked eighth with a ΔCoVaR of 1.26%. The results shown in Table 6, Table 7 and Table 8 highlight the systemic importance of banks and insurance firms in the South African financial sector. The weak correlation between ΔCoVaR and VaR is observed in all three sub-periods.

TABLE 8: ΔCOVAR AND VAR RANKING FOR JAN 2007 – DEC 2009

Institute	ΔCoVaR Ranking	ΔCoVaR	ΔVaR	VaR Ranking
FRS	1	2.16	4.04	11
ABSA	2	2.04	4.50	7
OML	3	1.98	7.21	2
NED	4	1.91	3.85	13
STD	5	1.69	3.92	12
INVES	6	1.53	6.34	5
INP	7	1.53	6.34	4
REM	8	1.26	3.14	19
DSY	9	1.14	3.63	14
MMI	10	0.89	2.77	21
SNT	11	0.73	3.24	18
ADW	12	0.52	6.74	3
SASFIN	13	0.42	3.37	17
BRT	14	0.30	2.84	20
CAP	15	0.23	3.43	16
PSG	16	0.10	3.56	15
LBH	17	0.09	4.37	9
SKJ	18	0.01	4.44	8
ECS	19	0.01	4.29	10
ACT	20	0.00	7.98	1
NCS	21	0.00	0.00	22
STA	22	-0.18	5.77	6

Note: The table reports the 5% ΔCoVaR and 5%VaR for 22 firms for the crisis period January 2007 – December 2009. The ΔCoVaR and VaR estimates are reported as percentages.

Table 9 presents the ΔCoVaR estimates for 2010-2017, which is post-financial crisis. The highest ΔCoVaR estimate is lower than the previous two sub-periods possibly due to financial recovery from the global financial crisis. The American economy has seen recovery with its higher employment rates and improved stock market performance. Once again, banking and insurance firms are the systemically important financial institutes due to these firms being the leading contributors to systemic risk.

The SARB in their 2018 Financial Stability Report describes banks as being “potentially systemically important by nature” (p. 1). The ΔCoVaR results presented above confirm this; as the “big four” retail banks dominate the top rankings in terms of potential systemic risk contribution. Considering that banks

Table 9: ΔCoVaR and VaR ranking for Jan 2010 – Dec 2017

Institute	ΔCoVaR Ranking	ΔCoVaR	ΔVaR	VaR Ranking
FRS	1	1.53	2.74	12
ABSA	2	1.50	2.89	8
NED	3	1.49	2.69	14
STD	4	1.49	2.70	13
OML	5	1.23	3.21	6
INP	6	1.04	2.75	10
INVES	7	1.04	2.75	11
REM	8	0.96	2.33	20
LBH	9	0.96	2.05	21
DSY	10	0.94	2.52	16
CAP	11	0.84	2.54	15
PSG	12	0.68	3.03	7
SNT	13	0.43	2.44	19
SASFIN	14	0.12	2.81	9
ACT	15	0.11	3.52	5
BRT	16	0.10	2.48	18
SKJ	17	0.06	6.78	3
MMI	18	0.06	2.48	17
STA	19	0.00	0.00	22
ADW	20	-0.01	14.44	1
ECS	21	-0.04	9.21	2
NCS	22	-0.05	4.78	4

are interconnected with other banks on the interbank lending market, and are interconnected with other financial intermediaries as banks are highly leveraged deposit-taking institutions explains their high ranking with regards to systemic risk contribution. Liquidity shortages in banks usually arise from default on loans or a decrease in asset value. Negative feedback loops often occur when a bank begins to sell its assets causing the assets of other banks to decrease. Asset fire sales lead to banks defaulting due to capital shortages (Gauthier, Lehar & Souissi, 2012). The four retail banks are the key institutes responsible for providing essential financial services, and thus if these banks can no longer offer credit, productive investment activities would not be possible in turn negatively affecting economic growth. Shocks to the key players in the banking system will likely lead to a systemic event. To prevent a financial crisis, governments usually intervene by offering bailouts to systemically important institutes. The four largest banks do contribute the most to systemic risk, suggesting that firm size does have a bearing on a firms systemic risk contribution. However, concerning total assets, Standard Bank is the biggest retail bank in South Africa but is not the most significant contributor to systemic risk. This observation highlights that size alone is not the only characteristic of systemically important firms, but other contributing factors such as complexity and connectivity are also determinants of a firms' contribution to systemic risk.

4.2. Granger-causality

The Granger-causal relationships, for the three sub-periods, are estimated at the 5% significance level and are presented in Table 10. There are 106 significant Granger-causal relationships in the pre-crisis period of 2005-2006 with this number increasing to 123 during the crisis. The significant causal relationships indicate that there are spillover effects in the South African financial sector, which increases during times of crisis. For the pre-crisis period, the major firms causing spillovers are from the financial services and insurance sectors. Discovery Ltd and Liberty Holdings Ltd insurance firms were each responsible for ten causal relationships, while in the financial services sector the highest number of causal relationships were due to PSG Group Ltd (10) and African Dawn Capital Ltd (9). For the period 2007-2009, the banking sector was the main trigger of spillover effects.

The major contributors in the banking sector are Sasfin bank who is responsible for 14 Granger-causal relationships, followed by Capitec bank, which has 11 Granger-causal relationships. The number of significant causal relationships post the financial crisis decreases to 116, once again indicating that there are fewer spillover effects outside of a financial crisis; however, this is still higher than the pre-crisis period thus indicating there is increased interconnectedness in the financial system. Although the number of significant relationships is not as high as during the financial crisis, there is an increase in the number of causal relationships of individual institutions. AfroCentric Investment Corporation Ltd, a financial services firm, has 13 causal relationships. Within the insurance sector Liberty Holdings Ltd, MMI Holdings Ltd, and Santam produce 13, 12 and 11 causal relationships respectively. Sasfin Bank initiates 16 spillovers within the financial system, this being the highest spillover of an individual firm across all three sub-periods. Table 10 also indicates each firm's causal relationships as a percent of the total significant causal relationships in the sample window.

TABLE 10: NUMBER OF GRANGER-CAUSAL RELATIONSHIPS FROM INDIVIDUAL INSTITUTIONS

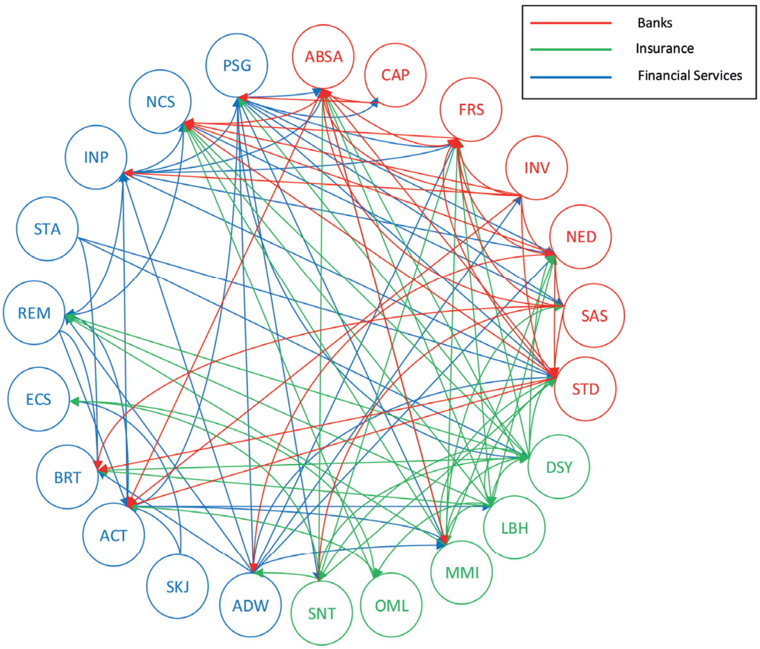
Financial Services	2005-2006		2007-2009		2010-2017	
	No.	% of Total	No.	% of Total	No.	% of Total
African Dawn Capital	9	8.49%	10	8.13%	1	0.86%
African Equity Empowerment Investments Ltd	2	1.89%	5	4.07%	5	4.31%
AfroCentric Investment Corporation	4	3.77%	2	1.63%	13	11.21%
Brimstone Investment Corporation Ltd	0	0.00%	6	4.88%	1	0.86%
Ecsponent Ltd	0	0.00%	0	0.00%	3	2.59%
Remgro Ltd	3	2.83%	6	4.88%	8	6.90%
Stratcorp Ltd	3	2.83%	4	3.25%	0	0.00%
Investec PLC	7	6.60%	6	4.88%	1	0.86%
Nictus Ltd	1	0.94%	0	0.00%	1	0.86%
PSG Group Ltd	10	9.43%	11	8.94%	7	6.03%
Insurance						
Discovery Ltd	10	9.43%	7	5.69%	3	2.59%
Liberty Holdings Ltd	10	9.43%	5	4.07%	13	11.21%
MMI Holdings Ltd	8	7.55%	10	8.13%	12	10.34%
Old Mutual PLC	3	2.83%	3	2.44%	0	0.00%
Santam Ltd	6	5.66%	3	2.44%	11	9.48%
Banks						
Absa Group	5	4.72%	3	2.44%	2	1.72%
Capitec	2	1.89%	11	8.94%	5	4.31%
FirstRand Ltd	1	0.94%	4	3.25%	1	0.86%
Investec Ltd	7	6.60%	6	4.88%	2	1.72%
Nedbank Group	5	4.72%	4	3.25%	5	4.31%
Sasfin	6	5.66%	14	11.38%	16	13.79%
Standard Bank	4	3.77%	3	2.44%	6	5.17%

4.3. Granger-causal network diagrams

The total Granger-causal relationships at the 5% significance level for each sub-period are illustrated in the network diagrams presented in Figures 1, 2 and 3. This shows the degree of interconnectedness and the direction of spillovers in the South African financial system. Causal relationships stemming from banks are indicated in red; those from insurance firms are indicated in green and financial services are depicted in blue.

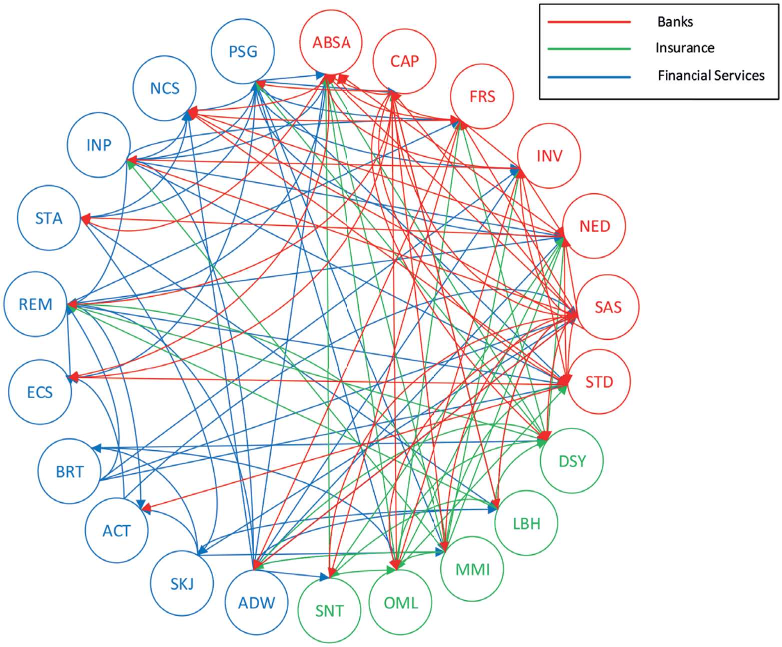
The spillovers depicted in Figure 1 (pre-crisis) is largely due to the financial services sector followed by the insurance sector. Figure 2, which represents the financial crisis period, once again illustrates that the majority of spillovers originates from financial services firms, closely followed by banks. Insurance firms seem to contribute the least to spillover effects during a crisis, and the significant causal relationships from insurance firms surprisingly decrease when compared to the significant relationships in the pre-crisis period. Financial services still maintain being the main contributor to spillover effects for the post-crisis period, which is depicted in Figure 3. Insurance firms are the second highest contributor to spillovers and have more significant causal relationships than identified during the crisis. The least number of spillovers is from the banking sector. The banking sector appears to contribute the least to spillovers within the financial system during tranquil periods.

Figure 1: Network Diagram of Granger-causal Relations for Mar 2005- Dec 2006



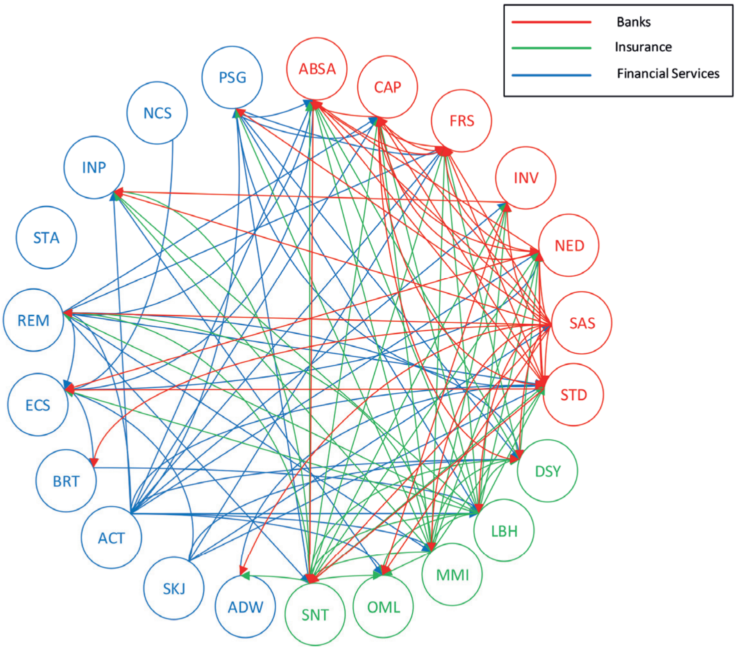
Note: The network diagram represents the Granger-causal relationships at the 5% significance level amongst 22 financial institutions. There are 106 significant Granger-causal relationships for the period.

FIGURE 2: NETWORK DIAGRAM OF GRANGER-CAUSAL RELATIONS FOR JAN 2006- DEC 2007



Note: The network diagram represents the Granger-causal relationships at the 5% significance level amongst 22 financial institutions. There are 123 significant Granger-causal relationships for the period.

FIGURE 3: NETWORK DIAGRAM OF GRANGER-CAUSAL RELATIONS FOR JAN 2010- DEC 2017

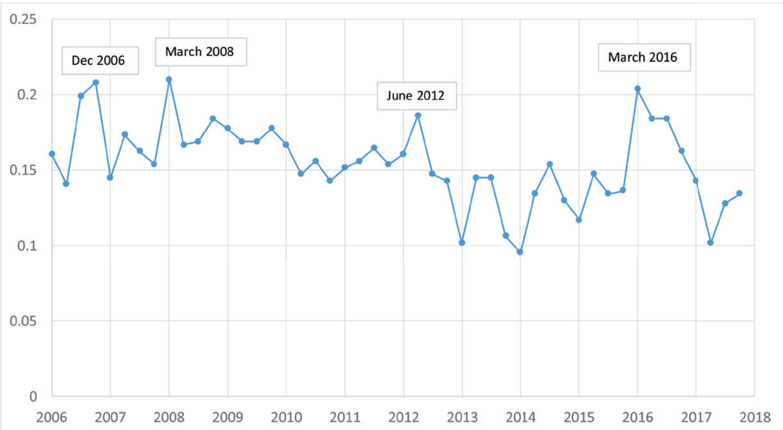


Note: The network diagram represents the Granger-causal relationships at the 5% significance level amongst 22 financial institutions. There are 123 significant Granger-causal relationships for the period.

4.4. Dynamic causality index

The dynamic causality index is constructed from data across the entire sample period using a 12-month rolling window estimate. Figure 4 presents the DCI estimates from March 2006 to December 2017. The DCI at the beginning of the sample period is approximately 0.16 and peaks at 0.21 due to spillover from the GFC. The DCI remains in the region of 0.17-0.18 until the last quarter of 2009. The increase in the level of interconnectedness depicted by peaks in the period preceding the GFC could be attributed to the US subprime mortgage crisis, which peaked in 2007, however foreclosure activity was predominant in 2006. The European debt crisis that began in 2009 had various points in 2010, 2011 and 2012 and was a risk to the global financial system. The increase in the number of causal links in the period of March 2016 was due to several factors; low investor confidence due to the run-up to the local government election causing strain on the financial market and spillover from China's stock market turbulence leading to contagion in emerging market economies. The signing of the referendum for the United Kingdom to leave the European Union also led to volatility in the domestic market (SARB, 2016).

Figure 4: Dynamic Causality Index for the SA Financial Sector



Note: The DCI represents the degree of interconnectedness amongst 22 South African financial institutions on a quarterly basis from March 2006 – December 2017 using the previous 12-month returns.

4.5. Summary

The results presented in this section considers the period before, during and post the global financial crisis. The application of systemic risk measures determines the main contributors to systemic risk as well as identifies the causal relationships that exist within the financial system. By using the CoVaR methodology, we confirm that banks and insurance firms are the systemically important financial institutes within the financial sector as they are the main contributors to systemic risk across all sub-periods that are assessed. The "big four" retail banks, in particular, should be closely monitored as they dominate in terms of ΔCoVaR ranking. Granger causal relationships, which are determined at the 5% significance level, increases during the period of financial crisis and are fewer during the tranquil periods. The DCI depicts the dynamic nature of the financial system by illustrating how the number of significant causal relationships in the financial system changes over time. Due to data availability, only 22 financial institutions were analysed, and thus the results are not a complete representation of the local financial system. Along with identifying the systemically important financial institutions and determining the interconnectedness of the financial system, it is also seen that size is not the only factor in determining if an institute is systemically important. In addition, the weak correlation between VaR and CoVaR highlights that microprudential regulation ignores systemic risk and therefore macroprudential regulation should be implemented.

5. Conclusion and recommendations

The 2008 global financial crisis not only negatively affected the US economy but also resulted in risk spillover to the global market. Its far-reaching impact sparked the need to better understand systemic risk with regards to which firms' contribute the most to systemic risk as well as how are shocks transmitted within the financial system. There is limited research regarding systemic risk in developing regions and inadequate studies in South Africa that assess banks, insurance firms, and financial services firms, as predominantly only the banking sector has been explored. Understanding systemic risk in the financial market is important in preventing risk spillover to other institutes, sectors and the real economy. This study applies two systemic risk measures, CoVaR and Granger-causality tests, to 22 financial institutions for the sample period March 2005 - December 2017, in order to evaluate systemic risk ahead of the financial crisis and post the financial crisis. The empirical analysis that is carried out presents the main contributors to systemic risk and the significant interactions within the financial system. This is to aid policymakers in better understanding the nature of the South African financial system so that financial stability can be upheld.

The widely used CoVaR methodology by Adrian and Brunnermeier (2011) which analyses accounting data, established that banks and insurance firms are the biggest contributors to systemic risk within the SA financial system. This is consistent with the findings of Billio *et al*. (2012) who report that banks and insurance firms are systemically important. The "big four" retail banks which dominate the banking sector in terms of assets held also dominate in terms of CoVaR ranking. This is in line with the view of Walters *et al*. (2018), that a collapse of the banking system will impose negative externalities on the economy due to banks being the centre of the financial system. The largest bank in terms of total assets, although being a significant contributor to systemic risk is not the largest contributor, affirming Vauhkonen's (2008) testimony that systemic importance is not only represented by size.

The interconnectedness of the financial system and the direction of causality was explored by applying Granger-causality tests proposed by Billio *et al*. (2012) to daily stock return data. This demonstrated that the degree of interconnectedness in the system is dynamic and tends to intensify during times of distress. Financial services had the highest number of significant causal relationships across all periods while banks tend to instigate more spillover effects during a crisis period than they cause during normal conditions. Acharya and Richardson (2014) and Bernal *et al.* (2014) both share the view that insurance firms are more connected with the financial system. As our results confirm, the insurance sector is interconnected with other insurance firms, banks, and financial services firms and is the second highest contributor to spillovers during pre and post the financial crisis. The dynamic causality index is estimated from daily return data using a 12-month rolling window sample on a quarterly basis to measure the level of interconnectedness in the system. The DCI also demonstrates the dynamic nature of the financial system. The emergence of peaks is witnessed during distressed market conditions, illustrating how losses spread during stressed periods (Drakos & Koureta, 2014).

The modern financial system is a complex network and therefore policy should consider the financial system as a whole rather than consider a firm's idiosyncratic risk in isolation. Firms themselves do not consider the risk they pose to the stability of the financial system as their risk management efforts relate to managing their own risk. A systemic perspective is thus necessary for preventing systemic events. The first step in effective policy implementation is identifying the vulnerable role players in the system who should be closely monitored and examining the interconnectedness that exists. This study can, therefore, aid policymakers and regulators as it has shown how the financial system is connected along with which are the systemically important financial firms.

Bank capital requirements have been an important component of policy regulation since the implementation of the Basel I accord in 1988, with the changes to Basel II and Basel III altering how capital requirements are determined. For financial institutions to be able to internalise the negative externalities that they can impose on the financial system capital buffers are crucial in this regard, to prevent financial crises as well as to minimise the need for government bailouts. However, these capital requirements should not be determined on bank size alone but should be a factor of a firms systemic risk contribution. This research has shown that banks are not the only systemically important financial institutions within the financial system, as insurance and financial services firms are also contributors to systemic risk. Those firms identified should be closely monitored, and capital requirements should therefore apply. The differences in capital structures of the various institutes should also be considered when applying capital requirements as banks being deposit-taking institutes have a highly leveraged capital structure as opposed to insurance firms and financial services institutes. The financial system is highly dynamic as a firm's systemic risk contributions are time-varying and the interconnections within the financial system change during normal and distressed periods. This is important for policy implementation, as policies need to be regularly reviewed and updated.

Further research investigating insurance and financial services firms in South Africa would be valuable in better understanding of how these sectors can influence financial stability. Later research could also focus on other identified systemically important institutes like hedge funds and real estate investments. Application of other systemic risk measures could be applied to enable a comparison of findings, along with applying copulas rather than quantile regression could result in improved CoVaR estimates. This study investigates the linear causal relationships, however non-linear Granger causality measures by Billio *et al.* (2012) can also be employed in future research to measure the volatility-based interconnectedness within the financial system.

Biographical notes

Chanelle Leukes holds a BSc in Chemical Engineering from the University of Cape Town and a Masters of Management in Finance and Investments from Wits Business School, with a specialisation in capital markets and financial engineering. She has 7 years' experience in the petrochemical industry working as a process engineer and business analyst.

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