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28 March 2020

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ABSTRACT

This study conducts an empirical analysis on how the build-up of systemic risk in the financial system affects downside macroeconomic risk of the South African economy. The study outlines and apply several systemic risk measures, namely the conditional value at risk, principal component analysis, average conditional volatility and interest rate spreads. Thereafter, the study employs the quantile regression to evaluate the predictive ability of each systemic risk measures to lower quantiles of economic activity. The study reveals that each of the systemic risk measures are significant predictors of macroeconomic risk. The results of this study serve as important tools that can help South African financial regulators and policymakers to foresee and prevent systemic risk. It enables regulators to identify the build-up of systemic vulnerabilities, systemically important financial and too connected to fail institutions. These are useful in the sense that they serve as early warning signals of financial systemic risk and the consequences of such on macroeconomic outcomes.

Keywords: *systemic risk, macroeconomic risk, quantile regression, principal component analysis*

JEL Classification: G01; G21; C22; C58

1. INTRODUCTION

The 2007/8 Global Financial Crisis (GFC) and the resultant costs inflicted on economies worldwide have testified to the importance of understanding systemic risk[1] in the financial system and its potential adverse effects on the real economy. The notion of financial fragilities triggering large economic downturns which date back to the Great Depression of the 1930s (Fisher, 1933). However, recent evidence points to the bankruptcy of an investment bank in the United States, Lehman Brothers, in the autumn of 2008 that subsequently led to a systemic financial crisis. This plunged the global economy into a severe recession (Van Roye, 2014). Furthermore, a series of bailouts for troubled banks in the European Union (EU) contributed to the Eurozone Debt Crisis which led to devastating consequences on the EU economy (Kräussl, Lehnert and Stefanova, 2016).

Prior to the GFC, the established financial regulatory framework (Basel I, 1988 and Basel II, 2004) were configured on the premise that the soundness and safety of individual institutions collectively led to financial stability, as seen in microprudential policy. However, both regulators and researchers argue that by focusing on each individual institution in seclusion, systemic risk can occur unnoticed (Kahou and Lehar, 2017). During the post-crisis era there has been a renewed focus in reforming regulatory frameworks. This was a shift away from a narrow approach in regulatory policymaking to a more encompassing method with emphasis on mitigating system-wide failure and the macroeconomic costs imposed by financial instability (Borio, 2003). In light of that context, the G-20 leaders recommended in April 2009 that, *"regulatory frameworks be reinforced with a macro-prudential overlay that promotes a system-wide approach to financial regulation and oversight and mitigates the build-up of systemic risk"*. They also called for *"all financial authorities to take account of financial stability and develop effective tools to address systemic risk"*. Inspired by these calls, several empirical centred around systemic risk (see surveys by Benoit, Colliard, Hurlin and Perignon, 2017; De bandt and Hartmann, 2000 and Silva, Kimura and Sobreiro, 2017), and the modelling thereof (see studies such as Bisias, Flood, Lo, and Valavanis, 2012; and Blancher et al., 2013).

Nonetheless, despite these attempts dedicated to modelling systemic risk, several studies have extended critique of these systemic risk research. The studies argue that most of these systemic risk measures operate on a "micro-like" scale focusing exclusively on vulnerabilities in the financial system or parts thereof, with no assessment of their impact on macroeconomic activity[2]. In addressing these issues, several studies (Allen, Bali and Tang, 2012; and Giglio, Kelly and Pruitt, 2016) construct systemic risk measures and provide a macroeconomic criterion suggesting the association of the systemic risk measures to future economic downturns. Allen et al. (2012) proposes an aggregate systemic risk measure that quantifies the risk of catastrophic losses in the financial system denoted (CATFIN) and furthermore, shows that the measure can robustly forecast macroeconomic downturns for about six months. Giglio

[1] "Systemic risk generally refers to the risk of a disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences on the real economy" (IMF-BIS-FSB, 2009).

[2] See, Allen et al (2012), Benoit et al. (2013), Boucher and Maillet (2015), Giglio et al. (2016), Kleinow et al. (2017), De Nicolo and Lucchetta (2017) and Rodríguez-Moreno and Peña (2013).

et al. (2016) evaluates whether a set of proposed systemic risk measures demonstrate the ability to forecast lower quantiles of macroeconomic shocks. The analysis reveals a few measures (predominantly, volatility measures) as possessing the ability to capture macroeconomic downside tail risk. Furthermore, the analysis shows that an appropriate aggregation of the systemic risk measures encompasses the ability to robustly and significantly predict macroeconomic downside risk. Although there seems to be limited studies on systemic risk in developing countries, there are some empirical research conducted on South Africa. Bartram et al (2007) was one of the first few studies that estimated systemic risk in the international financial system and included South Africa. Two South African banks (NBS Boland Bank and Nedbank) were included in the estimation. Lopez-Espinosa et al. (2012) was also one of the first studies on systemic risk that included South Africa, but it measured the contribution of one South African bank (Standard Bank)'s contribution to systemic risk in a sample of international banks. The limitation of this study is that the focus was only on one bank. This make it difficult to draw meaning conclusions from these two studies.

There are also studies that specifically focus on South Africa. Esterhuysen, Van Vuuren and Styger (2011) utilized probabilities of default (PD) and asset return correlations to determine whether the financial crisis of 2007-2009 increased systemic risk. Foggitt, Heymans, van Vuuren and Pretorius (2017) uses the SRISK (systemic risk) index to measure the level of systemic risk in South African financial sector and then investigates which bank is the main contributor (to the systemic risk). Manguzvane and Muteba Mwamba (2017) applied the conditional value-at-risk and measured the marginal contribution of each bank to systemic risk. However, these studies did not evaluate the efficacy of the proposed measures of systemic risk as macroprudential tools. This is through the association of each systemic indicator to lower quantiles of macroeconomic activity.

The purpose of this current study is twofold. Firstly, it models the different aspects of systemic risk by constructing several measures of systemic risk for monitoring the systemic stress in the South African financial system. These measures include the conditional value-at-risk (CoVaR and ΔCoVaR), as suggested by Adrian and Brunnermeier (2016); the principal component analysis (PCA) measure of interconnectedness which was proposed by Billio, Getmansky, Lo, and Pelizzon (2012); the average conditional volatility as a measure of systemic risk for commercial banks, as proposed by Sankaran (2011); and the interest rate spread. Secondly, this current study employs the quantile approach to evaluate the efficacy of the proposed measures of systemic risk as macroprudential tools through the association of each systemic risk indicator to the lower quantiles of macroeconomic activity (that is macroeconomic risk). The current study therefore contributes to recent empirical literature on modelling systemic risk in the South African financial system. To the best of our knowledge, this is the first study to outline and apply a large set of systemic risk measures and the macroeconomic criterion to South Africa.

It is important to note that the financial sector is at the centre of the South African economy. Every citizen's life is touched by the financial sector. Through the financial sector, people are able conduct economic transactions, save and borrow in order to achieve their aspirations in the future. It enables people to insure themselves and against disaster and meet their retirement needs. The financial sector is an important enabler of economic growth, employment and development of infrastructure which are important for South Africa's sustainable development.

Despite the fact that the South African financial sector is well regulated, it is important to note that when there is a global financial crisis immense costs can be incurred. The recent global economic and financial crisis of 2007/2008 indicated that several economies incurred significant costs or losses. The financial sector of South Africa proved to be resilient during the global economic and financial crisis of 2007/2008, but the country was affected negatively. There was an indirect negative impact through job losses in the South African economy. Hence, it is important to continue regulating the financial sector properly and there should be no room for complacency. These are concerns of South African regulatory institutions who have published numerous policy papers reiterating the importance systemic risk. In the year 2011, the National Treasury published a policy paper titled "a safer financial sector to serve South Africa better". This publication was followed by a document in 2013 on "implementing a twin peaks model of financial regulation in South Africa". In 2016, SARB published a discussion paper on the new macroprudential framework for South Africa, in which it emphasised the importance of the management of systemic risk in its deliberation of macroprudential policy framework.

The results of the study indicate that the constructed measures demonstrate the ability to capture periods of extreme financial distress in the South African financial sector. In the process, we identify four largest bank in South Africa, which we call the "Big Four" banks as the systemically important financial institutions (SIFIs) and form part of the too interconnected to fail (TICTF) institutions in the banking sector, which, if unregulated, may pose grave systemic risk. It should be noted that the focus of this study is not to identify which banks are systematically important. It falls outside the scope of this study. TICTF is used in developed countries such as the USA to refer to a situation where the failure of an entity can result in systemic failure. It helps to understand which measures of resilience a country should be taking. Many advanced economies such as the USA use TICTF to decide which entity should be financially assisted. Furthermore, we show that each of the constructed systemic risk measures are significantly informative about lower tails of the distribution of South African economic activity as opposed to the median distribution of real economic activity.

The remainder of the paper is organized as follows. Section 2 provides a comprehensive literature review. Section 3 describes the methodology while section 4 presents the data and discussion of the results. Section 5 concludes the study.

2. LITERATURE REVIEW

This study reviews three strands of literature. The first strand of the literature looks at the quantitative measures of systemic risk in the financial system. Since the onset of the 2007/8 GFC, there has been a vast amount of literature focusing on the modeling of systemic risk in the financial system. Traditional measures of systemic risk such as those proposed by the IMF-BIS-FSB (2009) for size, connectedness and substitutability indicators are primarily based on balance sheets and supervisory data. However, the literature identifies certain drawbacks with the use of balance sheet-derived indicators. Rodríguez-Moreno and Peña (2013) argues that low-frequency indicators fail to inform policymakers about immediate financial distress. Huang, Zhou and Zhu (2009) finds that financial markets data is more applicable in the supervision of the financial system, rather than the infrequent publication of balance sheet information which come often with a substantial lag.

Several sophisticated stock market-derived (high frequency) systemic risk measures have been advanced in the literature. Many of these sophisticated measures have focused on measuring systemic risk on the institutional level and the contribution of individual institutions to system-wide risk, with the intention of identifying systemically relevant institutions. Adrian and Brunnermeier (2008; 2016) developed the CoVaR and ΔCoVaR as measures of systemic risk. The CoVaR measure is defined as the Value-at-Risk (VaR) of the financial system conditional on an individual financial institution being under distress. The ΔCoVaR gauges the marginal contribution of individual financial institutions to systemic risk. Both measures have proven to be advantageous in the identification and construction of rankings of systemically relevant institutions. This is demonstrated by the frequent empirical application of both systemic risk measures across research and regulatory institutions[3]. Huang et al. (2009) uses the probability of default and asset return correlations of individual financial institutions as systemic risk indicators.

Acharya et al. (2017) measures an individual financial entity's contribution to systemic risk as the systemic expected shortfall (SES). The SES measures the expected losses of an individual financial institution given that the financial system in its entirety is undercapitalized. The SES is associated with an institution's leverage and its marginal expected shortfall (MES) (i.e. its losses in the tail of the aggregate sector's loss distribution). The intended use of the SES measure is to help financial institutions recognise and embody the externalities arising from their own risk and default. Brownlees and Engle (2017) dynamically model the capital shortfall of a financial entity as a dependent factor of the firms' size, extent of leverage and its correlation as well as volatility through their systemic risk (SRISK) indices.

The second strand of the literature is on modelling interconnectedness and co-movements among financial institutions. These are other studies that focus on modelling commonality and co-movement amongst financial institutions as a source of systemic risk. Billio, Getmansky, Lo, and Pelizzon (2012), for example, model the interconnectedness of the financial system based on two econometric techniques, the Granger causality test and the PCA. The analysis focuses on four types of financial institutions. These financial institutions are hedge funds, banks, broker/dealers and insurance companies. The results revealed that the four sectors have become highly interrelated and likely increasing the level of systemic risk in the finance and insurance industries. Kritzman, Li, Page, and Rigbon (2011) developed the absorption ratio (AR), which captures the extent to which financial markets are interconnected. The idea behind the measure is that when markets are coupled, they become more susceptible to shocks. The AR proves to be coincided with many global financial crises and tracked other more complex measures of financial contagion.

Moving to less complicated yet equally relevant measures of systemic risk, we consider interest rate spreads. The TED spread which is computed as the interest rate differential between the interbank market rate and the short-term Treasury bill rates, is used amongst practitioners as a broad measure of systemic risk (IMF, 2009; Brunnermeier et al., 2009; and Rodríguez-Moreno and Peña, 2013). A widened TED spread signals liquidity pressures and

[3] Bernal et al., 2014; Castro and Ferrari, 2014; Drakos and Kouretas, 2015 and López-Espinoza et al., 2012.

uncertainty in the credit markets. According to Rodríguez-Moreno and Peña (2013), the spread is associated with systemic risk owing to its ability to indicate whether financial entities can perform their activities as suppliers of funds or are interrupted by shocks affecting liquidity, default or flight to quality.

Several empirical studies evaluated the proposed measures of systemic risk. Several studies and regulators have questioned the effectiveness and validity of the above-mentioned proposed measures of systemic risk. One cluster applies a variety of approaches to evaluate the risk metrics. Benoît et al. (2013) propose a comparison of several systemic risk measures, namely the MES, SRISK, and ΔCoVaR. The empirical analysis investigates whether the different systemic risk measures can come to the same conclusion in identifying and ranking of significant financial entities. The results reveal an inconsistency amongst the rankings of SIFIs from the different systemic risk measures. Rodríguez-Moreno and Peña (2013) compare and rank a variety of European and U.S. market-based systemic risk measures. The rankings are based on three criteria (Granger causality tests, Gonzalo and Granger metric, and correlation with an index of systemic events and policy actions). The results show that measures based on credit default swaps perform better than those based on interbank rates or stock market prices. In a later study, Kleinow et al. (2017) applies four commonly used systemic risk measures across three sectors in the financial industry, and thereafter compares the performance of each systemic risk metric. The results prove to be contradictory, with different measures indicating different levels of systemic risk across the different types of financial institutions.

The third strand of the literature focuses on the interaction of systemic risk and the macro-economy. Allen et al. (2012) thus devised a measure of aggregate financial systemic risk based on historical stock returns of U.S. financial institutions (CATFIN). The study then applied a multivariate predictive regression to assess the predictive ability of CATFIN on future macroeconomic activity. In similar research, Neumann (2014) constructs an aggregate financial sector tail risk measure derived from option prices of financial sector firms in the US. The study further employs a predictive regression to investigate the measure's ability to predict future real economic activity. Both studies make use of a range of indicators that represent real economic activity in the US economy and evaluate the robustness of their models. Both studies find that their respective measures of systemic risk demonstrate the ability to significantly forecast economic activity for several periods in both an in- and out-sampling setting.

Boucher and Maillet (2015), and Giglio et al. (2016) embark on similar research, with both studies applying and examining a large set of proposed measures of systemic risk on the ability to predict low quantiles of the distribution of macroeconomic indicators. Both studies employ the QR approach. However, these two studies differ in terms of the focus of the downside risk of macroeconomic variables. Giglio et al. (2016) focus on the 20th percentile, whilst Boucher and Maillet (2015) considers the fifth percentile as representative of severe crises. Giglio et al. (2016) finds that only a few measures (mainly financial sector volatility measures) possess the ability to capture macroeconomic downside tail risk. Furthermore, the study shows that an appropriate aggregation of the systemic risk measures encompasses the ability to robustly and significantly predict macroeconomic risk. Whilst Boucher and Maillet (2015) finds that financial stress indicators, especially the default spread contain significant information on the downside of the distribution of real economic activity.

Regarding the South African literature, a limited number of studies has been published with regards to the phenomenon of systemic risk in the country's financial system. Each of the existing studies focus on a particular facet of systemic risk in the South African banking industry. Esterhuysen et al. (2011) tailors a technique developed by Huang et al. (2009) to determine the impact of strained economic conditions on systemic risk in the South African banking sector. Their results show that the GFC increased systemic risk in South Africa, but to a lesser extent than other large international banks and economies. Manguzvane and Mwamba (2017; 2019) applies the CoVaR and ΔCoVaR proposed by Adrian and Brunnermeier (2008) to identify and rank systemically important banks in the South African banking industry. Over the sample period 2007 to 2016 they find that FirstRand Limited was the largest contributor to systemic risk followed by Standard Bank, ABSA, Nedbank, Capitec Bank and lastly African Bank. The results suggest that systemic risk is largely associated with the size of the financial institutions. Foggitt et al. (2017) applies the SRISK to quantify the capital shortfall of South African banking entities during extreme distress in the entire financial sector. Interestingly, the study identifies the smallest bank in the sample as the largest contributor to systemic risk during tranquility. However, during periods of financial turmoil, the contributions of other larger banks increased.

A review of the above empirical studies in both developed and developing (in particular, South Africa) countries lead to a conclusion that systemic risk is a complex and multifaceted phenomenon which cannot be captured or represented by using a single measure. Thus, this study models and evaluates a range of systemic risk measures to assist regulators in monitoring vulnerabilities in the financial system and deciphering whether the vulnerabilities arising from the financial sector poses significant risk to the macroeconomic activity. Such an approach will provide regulators with enough time to implement policy responses to neutralize the impact of vulnerabilities and address these vulnerabilities.

3. METHODOLOGY

3.1 Quantile Regression

This study employs the quantile regression (QR) approach developed by Koenker and Bassett (1978) to investigate how distress in the financial system may influence macroeconomic risk. Macroeconomic risk can be measured by estimating the value-at-risk (VaR), which is the worst potential outcome at a given probability. The QR approach allows for directly modelling the quantile of interest for VaR estimation. Macroeconomic risk relates to the τ^{th} quantile of the economic activity distribution (see Figure 1).

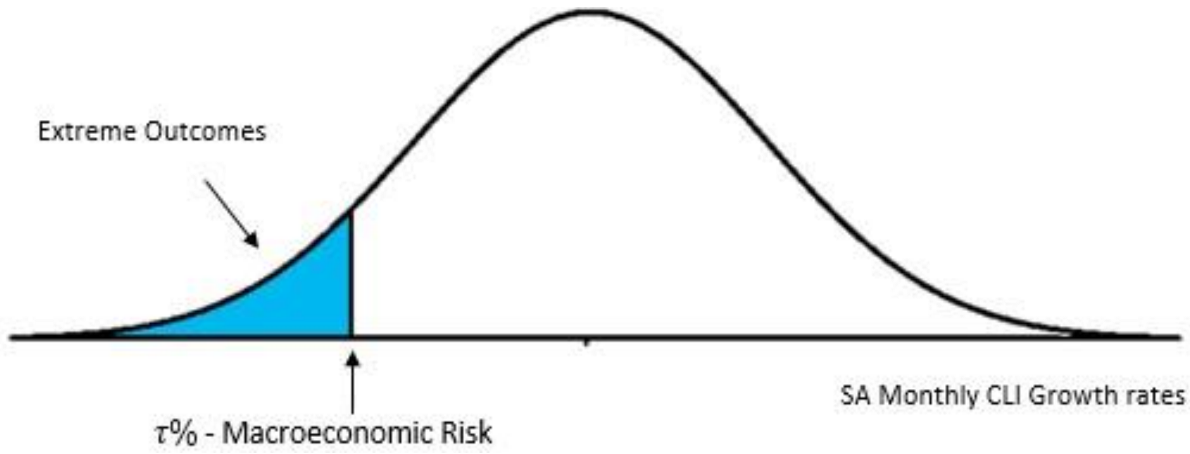


Figure 1: Macroeconomic risk

The QR can calculate macroeconomic risk through its ability to model the conditional quantile of South African economic activity distribution G_t on available information Z (i.e. systemic risk measures).

This linear conditional quantile function is

$$G_t = Z_t\beta' + \varepsilon_t \qquad (1)$$

where ε_t are iid mean zero random variables with quantile function $Q_\varepsilon(\tau)$ and Z_t are k-by-1 vector of regressors, including an intercept term and lagged residuals. Then, conditional on the regressor Z_t, the τ^{th} quantile of G is a linear function of Z_t

$$Q_{G_t}(\tau|Z_t) = Z_t\beta' + Q_\varepsilon(\tau) = \beta(\tau)'Z_t \qquad (2)$$

where $\beta(\tau)' = (\beta_1 + Q_\varepsilon(\tau), \beta_2, \ldots \beta_k$. The τ^{th} conditional quantile of G can be estimated by

$$\hat{Q}_{G_t}(\tau|Z_t) = Z_t'\hat{\beta}(\tau) \qquad (3)$$

where

$$\hat{\beta}(\tau) = \arg\min_{\beta\in R^k} [\textstyle\sum_{t\in\{t:G_t\geq Z_t\beta\}} \tau|g_t - z_t'\beta| + \sum_{t\in\{t:G_t<Z_t\beta\}}(1-\tau)|g_t - z_t'\beta| \qquad (4)$$

is called the regression quantiles. Let $\rho_\tau(\varepsilon) = \varepsilon(\tau - I(\varepsilon < 0))$, then

$$\hat{\beta}(\tau) = arg\min_{\beta\in R^k} \textstyle\sum_{i=1}^{n} \rho_\tau(g_t - z_t'\beta) \qquad (5)$$

The QR function is used to measure the effect of individual systemic risk measures on South African economic activity, both in the lower tails and median of outcome distribution. In order to serve the purpose of this paper, we will typically be focused on the extreme lower quantiles of the QR function $\tau = 0.05$.

3.2. Pseudo R (Goodness of Fit)

According to Koenker and Machado (1999), R^1 is used as a measure of goodness of fit at the particular (τ) quantile. Let

$$V(\tau) = arg \min_{\beta \in R^P} \sum_{i=1}^{n} \rho_\tau (g_i - z_t^{'} \beta_\tau) \quad (6)$$

where G_t is the monthly time series of economic activity and z_t' is a vector of systemic risk proxies. Let $\hat{\beta}(\tau)$ and $\tilde{\beta}(\tau)$ be the coefficient estimates for the unrestricted and restricted model respectively and let $\hat{V}$ and $\tilde{V}$ be the corresponding V terms.

They define the goodness of fit criterion $R^1(\tau) = 1 - \frac{\hat{V}}{\tilde{V}}$.

3.3 Institutional-specific Risk: Conditional Value-at-Risk, $CoVaR_t$ and Delta CoVaR, $DCoVaR_t$

Well-recognized measure of systemic risk proposed by Adrian and Brunnermeier (2009) the CoVaR. The value-at-risk of the financial system as a whole given that an individual financial institution is under distress. The value-at-risk of an individual financial institution captures the distressed state of a particular institution:

$$Pr\left(X \leq {VaR_q}^i\right) = q \quad (7)$$

The CoVaR of the financial system given that a particular financial institution (i) is at its VaR is defined as:

$$Pr\left(X^{sys} < {CoVaR_q}^{sys|i} \middle| X^i = {VaR^i}_q\right) = q \quad (8)$$

The above equation is estimated with a conditional quantile regression whereby $q = 0.05$.

ΔCoVaR measures the contribution to systemic risk given that an institution moves from a "normal" state to "stressed" state.

$$\Delta CoVaR^{sys|i} = {CoVaR_{0.05}}^{sys|i} - CoVaR_{0.5}^{sys|i} \quad (9)$$

3.4 Co-Movement and Interconnectedness: Principal Component Analysis of bank returns, eigenvalue returns

Recent studies on systemic risk have made use of the principal component analysis to measure the co-movement, cross-correlation and contagion amongst securities or financial sectors

(Zheng et al, 2012; Kritzman et al, 2011; Billio et al, 2012). The following measure is used to measure the interrelation and concentration of the South African financial system.

In measuring the commonality in the South African banking sector as an indication of systemic risk, this study uses a principal component analysis (PCA) to decompose the covariance matrix of the six banks as in Billio et al (2012). The covariance matrix of the returns of the six banks is estimated as:

$$\hat{\Sigma} \equiv \frac{1}{T-6}\sum_{t=1}^{T}(R_t - \bar{R})(R_t - \bar{R})' \tag{10}$$

Where T represents the number of observations in the sample period and $\bar{R}$ represents the vector of average returns. Through the covariance matrix, six eigenvalues and six eigenvectors estimated. In this analysis, we apply a 24-month rolling window principal component analysis to track the time variation in the magnitude of the eigenvalue of the returns. This allows us to detect increasing correlation, connections and integration amongst the banks, which can contribute to systemic risk. Billio et al (2012) states that the reasoning behind the use of the PCA is that systemic risk is more apparent when the largest eigenvalue explains most of the variation of the data. Thus, a sharp rise in PCA may serve as an indication of systemic risk Zheng et al (2012).

According to Billio et al (2012), the "commonality" between the six institutions is expressed by the loadings of each respective bank corresponding to the largest eigenvalues. More specifically, if the institutions eigenvector corresponding to the largest eigenvalue has similar entries, then all six institutions have similar exposure to this principal component. This is an indication of systemic risk through contagion.

3.5 Volatility

High levels of volatility in the financial market has been associated with financial crises. High levels volatility is largely seen as an indication of uncertainty and undermining the stability of the financial system. Moreover, according to Danielsson et al (2016) "forward-looking economic agents" can see high volatility as a signal of the increased risk of adverse future outcomes and a pending crisis. We consider two measures of volatility as an indication of systemic risk. These are average conditional volatility and exchange rate volatility.

Average Conditional Volatility

We model the average conditional volatility of the six South African banks using GARCH models, as a measure of systemic risk in the South African banking industry as suggested by Sankaran (2011). Due to the inherent leverage effects and fat tail distributions[4] in equity prices we employ one of the asymmetric GARCH models and assume the errors follow a Student's *t-distribution.* The mean equation is specified as follows:

$$\Delta \ln(r_t) = \beta_0 + \beta_1 \Delta \ln(r_{t-1}) + \epsilon_t \tag{11}$$

The variance equation is specified by EGARCH (1, 1) model:

$$\log(\sigma_t^2) = \omega + \alpha \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta\, log(\sigma_{t-1}^2) \tag{12}$$

We use weekly data to calculate the conditional volatility of an individual bank and thereafter aggregate the series of volatility by averaging the conditional volatility amongst the six banks.

Exchange rate Volatility

With the South African economy extensively involved in world trade, the exchange rate and the volatility thereof are a pivotal component that influences economic activity in South Africa. To model the uncertainty of the Rand relative to the US Dollar, this paper applies one of the variations of the volatility model introduced by Engle (1982) the Generalized autoregressive conditional heteroscedasticity GARCH (1, 1) with a skewed student *t-distribution*.

The general framework of the GARCH (p, q) is expressed as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{13}$$

Derived from the above equation the GARCH (1, 1) is expressed by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_0 + \beta_j \sigma_{t-1}^2 \tag{14}$$

The study used daily exchange rate data to construct the exchange rate volatility and thereafter averaged it over monthly intervals.

[4] Explain leverage effects and fat tail distribution of equity prices

3.6 Interest rate spreads

This study estimate or consider two measures of interest rate spreads. These are long term spreads ($\mathrm{LTS_t}$) and short term spread ($\mathrm{TED_t}$). The long term spread ($\mathrm{LTS_t}$) is the difference in the yields of a ten-year government bond and the three-month Treasury bill.

$$LTS_n = i_{10yr} - i_{3M\,TB} \tag{15}$$

The short term spread (TED_t) is constructed by subtracting the South African three-month T-bill rate from the 3-month Johannesburg Interbank Average Rate (JIBAR).

$$TED = i_{JIBAR} - i_{3M\,TB} \tag{16}$$

3.6. Construction and evaluation of the Systemic Risk Index

Systemic risk is complex in nature needing different measures to capture the different aspects of systemic risk. Following the intuition of Gigilo et al. (2016), supposing that all systemic risk measures are imperfectly measured versions of an unobservable systemic risk factor this essay intends to capture the different aspect of systemic risk by aggregating the different measures into a single measure of systemic risk called the "*Systemic Stress Index of South Africa*". Therefore, we use data reduction techniques in modelling covariability of the data in terms of a few number of unobserved latent factors on the conditional quantile of GDP growth. Once more, we follow the intuition of Giglio et al (2016) by conducting a two-stage procedure known as the principal component quantile regression (PCQR). Firstly, a principal component analysis is conducted to aggregate the large set of predictors into a small number of predictors. Secondly, the output of the PCA is used as regressors in the estimation of extremal downside quantile of GDP growth i.e. macroeconomic risk.

In doing so, we put forth the assumption that the τ^{th} quantile of G_t, conditional on available information $\mathcal{F}_{t-1}$ is a function of unobservable latent factors:

$$Q_\tau(G_t|\mathcal{F}_{t-1}) = \delta f_t \tag{17}$$

The large set of predictors are defined as vector z_t where:

$$z_t = \Lambda F_t + \varepsilon_t \tag{18}$$

Where ε_t is a vector of idiosyncratic disturbances.

$$G_{\tau|t} = \beta_F' F_t + \varepsilon_t \quad (19)$$

Estimate $\hat{F}_t$ by $(\Lambda'\Lambda)^{-1}\Lambda' x_t$ for Λ the K eigenvectors associated with the K largest eigenvalues of $\sum_{t=1}^{T} x_t x_t'$. $\hat{F}_t \equiv (\hat{F}_1, \ldots, \hat{F}_T)$ is a matrix of K eigenvectors associated with the K largest eigenvalues.

Time series quantile regression

$$Q_\tau(G_t|\mathcal{F}_{t-1}) = \delta' F_t = \delta f_t \quad (20)$$

$$(\widehat{\delta_0}\hat{\delta}) = arg \min_{\delta 0, \delta} \frac{1}{T} \sum_{i=1}^{n} \rho_\tau (g_t - \delta' F_t) \quad (21)$$

Where $\hat{\delta}$ is the quantile regression coefficient on the components.

4. DATA AND ESTIMATION RESULTS

4.1 Data and descriptive statistics

Following an extensive review of the empirical literature on modelling systemic risk, this study uses weekly equity prices of the six largest banks in South Africa (ABSA, “bga”; Capitec Bank, “cpi”; FirstRand Limited, “fsr”; Nedbank, “ned”; Standard Bank, “sbk” and Investec, “inl”). According to Jackson and Perraudin (2002), the banking sector is generally perceived to pose threats to the financial system, given its important functions therein. Moreover, Tarashev, Borio, and Tsatsaronis (2010) consider banks’ relative size as a driver of systemic importance. Furthermore, we use the USD/ZAR exchange rate and a combination of long- and short-term interest rates namely the 3-month Treasury bill (3M T-bill), Johannesburg interbank average rate (JIBAR) and the 10 year bond rates. These data is easily accessible on I-net BFA [5]and DataStream[6].

The composite leading indicator (CLI) for South Africa, as sourced from the South African Reserve Bank is used in this analysis to represent real economic activity. The South African CLI is calculated using SA GDP growth rates as the reference series. It is intended to provide early signals of turning points in business cycles. This view is supported by the South African Reserve Bank. The data is available on the South African Reserve Bank database. This study uses a sample period of nine years spanning from 31/03/2007 – 31/03/2016. That means the study conducting an analysis using 109 monthly observations. However, the sample period used includes significant downturns such as the one that occurred in 2008.

[5] I-Net BFA are providers of economic and financial market data.
[6] Thomson Reuters DataStream.

Table 1: Descriptive statistics of weekly log returns of the six banks (31/03/2007 - 31/03/2016)

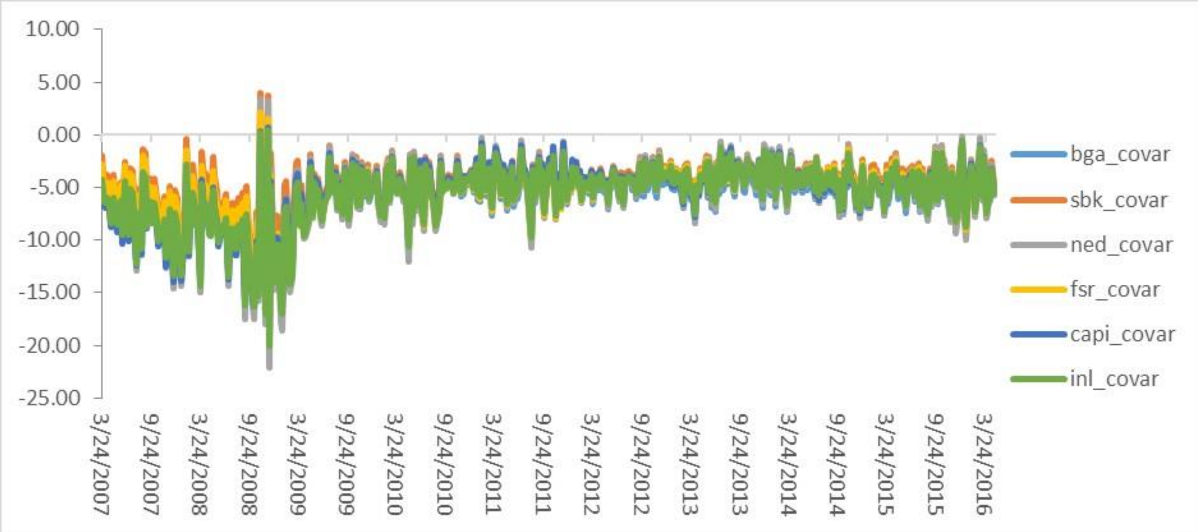
	ABSA	Standard Bank	Nedbank	FirstRand Limited	Capitec Bank	Investec
Mean	0.0078	0.0412	0.0568	0.1383	0.5891	0.0339
Std. Dev.	3.7105	3.7541	3.6621	4.1541	4.1002	4.4505
Maximum	16.0773	21.9157	14.1618	18.5964	13.8500	19.0320
Minimum	-16.3847	-17.2675	-15.8317	-24.1804	-16.6751	-18.6650
Skewness	-0.1668	0.2424	-0.2288	-0.4449	-0.2850	-0.3253
Kurtosis	5.6215	7.5354	4.9694	7.9396	4.3087	5.7796
Jarque-Bera	138.2211	411.7658	80.91502	498.6014	40.33057	161.305

Table 1 presents the descriptive statistics of the weekly equity return series of all banks included in the study. Table 1 shows that the average weekly equity returns series of all the banks are positive, with Capitec Bank and ABSA recording the highest and lowest average weekly returns respectively. The return series of all the banks is extremely volatile as shown by the standard deviation. Standard Bank profited the most during the upswing. It recorded the largest maximum value. Whilst First Rand recorded the largest loss during the downswing with the largest minimum value. The return series of all the banks are characterized by extreme negative values as exhibited by the negative skewness, with the exception of Standard Bank. Furthermore, all the returns series exhibit excess kurtosis suggesting that the returns are not normally distributed. This is further confirmed by the Jarque-Bera test which reject the normality of the distributions for all the returns.

4.2 Empirical Results

4.2.1 Results for CoVaR and ΔCoVaR

The results of the CoVaR and *Δ*CoVaR are presented in Figure 2. Figure 2 depicts the time series of the 5% VaR of the South African banking sector when each of the six banks are in distress (i.e. returns are at the 5% VaR level).



Notes: bga_covar, CoVaR granted Barclays Africa at VaR; sbk_covar, CoVaR granted Standard Bank at VaR; ned_covar, CoVaR granted Nedbank at VaR; fsr_covar, CoVaR granted FirstRand at VaR; capi_covar, CoVaR granted Capitec Bank at VaR; inl_covar, CoVaR granted Investec Ltd at VaR.

Figure 2: Weekly 5% CoVaR by each bank (31/03/2007 - 31/03/2016)

Essentially, Figure 2 shows the spill-over effects of systemic risk when each of the banks are deemed to be in distress over the sample period. Across the timeline, the entire time series move in tandem, indicating that the spill-over effect of each of the South African banks to the system is on average evenly balanced. More importantly, the results prove to be consistent even during periods of crises, with no bank possessing excessive spill-overs to the entire system. Such results may also be an indication of high interconnectedness in the South African banking system. These results compares favourably with previous studies on South Africa, such as Manguzvane and Mwamba (2017). This is despite the fact that Manguzvane and Mwamba (2017) identified FirstRand Limited as the leading contributor to systemic risk. This is compared to this current study that identified ABSA as the largest contributor to systemic risk as presented in Figure 2.

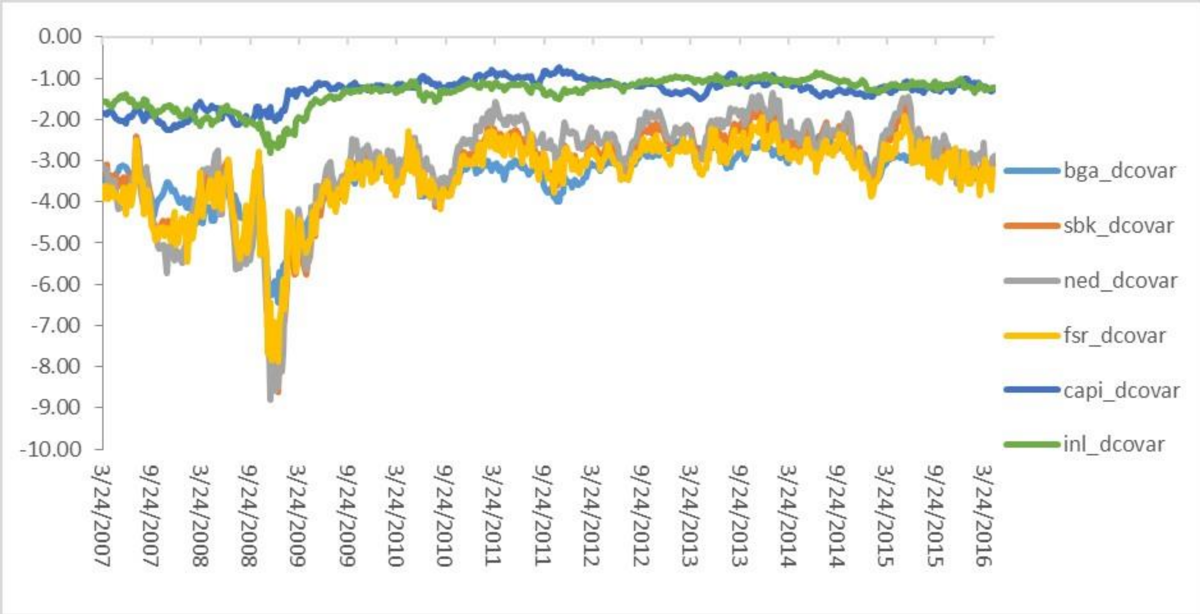


Figure 3: Weekly ΔCoVaR by each bank (31/03/2007 - 31/03/2016)

Figure 3 depicts the time series of the marginal systemic risk contribution of each bank measured by taking the difference between the distress-state (5%) CoVaR of an institution and the benchmark-state (50%) CoVaR of that institution. This gives a clear understanding of the dynamics of the banks' contributions to systemic risk over time. Two distinct patterns amongst the sample of banks across the timeline can be seen. Capitec Bank and Investec had the smallest effect on the system over the entire sample period. These two banks were the smallest contributors to systemic risk as they are consistently above those of the other banks. Figure 3 reveals that the other four banks (ABSA, Standard Bank, Nedbank and FirstRand Limited), are always moving together and seem to follow a common trend. Figure 3 also shows that during the 2008 global financial crisis, the ΔCoVaRs of these banks increased dramatically. This implies that during the crisis, the banks' contribution to systemic risk increased. These results are contrary to previous studies conducted in South Africa (such as Foggit et al, 2017). Foggit et al (2017) concluded that the smallest banks (Capitec Bank and Investec) were the largest contributor to systemic risk.

Table 2: Average weekly ΔCoVaR by bank (31/03/2007 – 31/03/2016)

ABSA	Standard Bank	Nedbank	FirstRand Limited	Capitec Bank	Investec
-3.37727	-3.1945	-3.03915	-3.36813	-1.32179	-1.35438

Table 2 presents the cross-section average marginal contribution of systemic risk by each bank. Table 2 indicates that on average ABSA adds 3.377 percentage points to the VaR of the banking system when it moves from operating normally to a state of distress. The number is also the largest of the average ΔCoVaRs. This means that over the sample period, ABSA was the largest contributor to systemic risk in the South African banking system. FirstRand

Limited (which contributed 3.368 percent) and Standard Bank (which contributed 3.19 percent) were on average the second and third largest contributors respectively. Nedbank contributed 3.039 percent to the systemic risk in the banking sector. The two smallest banks, Capitec Bank and Investec were the smallest contributors to systemic risk. In line with the too big to fail theory, we can thus classify the "Big Four" banks (ABSA, Standard Bank, FirstRand Limited and Nedbank) as the SIFIs in the South African banking sector. These results are not consistent with those of Foggit et al (2017).

4.2.2 Results of Rolling PCA

Figure 4 displays the dynamics of the six principal components (PCs) of the monthly return series of South African banks during the period 2006 to 2016 over a 12-month rolling window. This approach allows us to detect the degree of commonality and concentration amongst the banks, which can contribute to systemic risk.

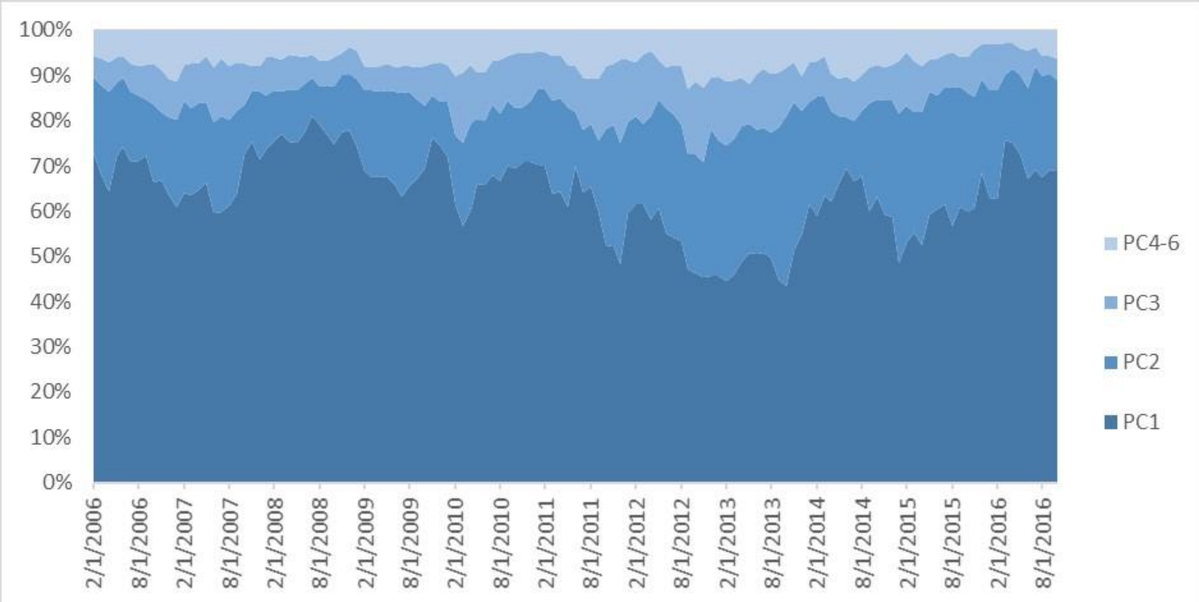


Figure 4: Dynamic Principal component analysis of monthly return of six banks

The results show that first principal component (PC1) has the highest eigenvalue, capturing most of the return variation (64%) over the sample period. The first eigenvalue of returns approximately captures the variation ranging from approximately 43% to 81%. We observe that the proportion of the variance explained by PC1 increases from June 2007 and reaches its peak in July 2008, indicating a highly interrelated financial system during times of crisis. This is indicative of herding behaviour, which amplifies the effects of an initial shock to the system and increases systemic risk within the entire system. Upon further investigation of the results, we identify the "Big Four" banks (ABSA, Standard Bank, FirstRand Limited and Nedbank) as having larger loadings on PC1 than Capitec Bank and Investec. This further suggests that the "Big Four" banks form part of what is known as the too interconnected to fail (TICTF) institutions. This concentration of the banking sector may present an upside. However, it too poses a grave downside should a negative event take place, leaving South Africa more susceptible to systemic risk.

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4.2.3 *Results of volatility measures*

Figure 5 plots the (weekly) average conditional volatility of six banks using the EGARCH (1, 1) volatility model from 2007 to 2016. The South African banking industry is characterised by two periods of volatility clustering, which represent an increase in systemic risk.

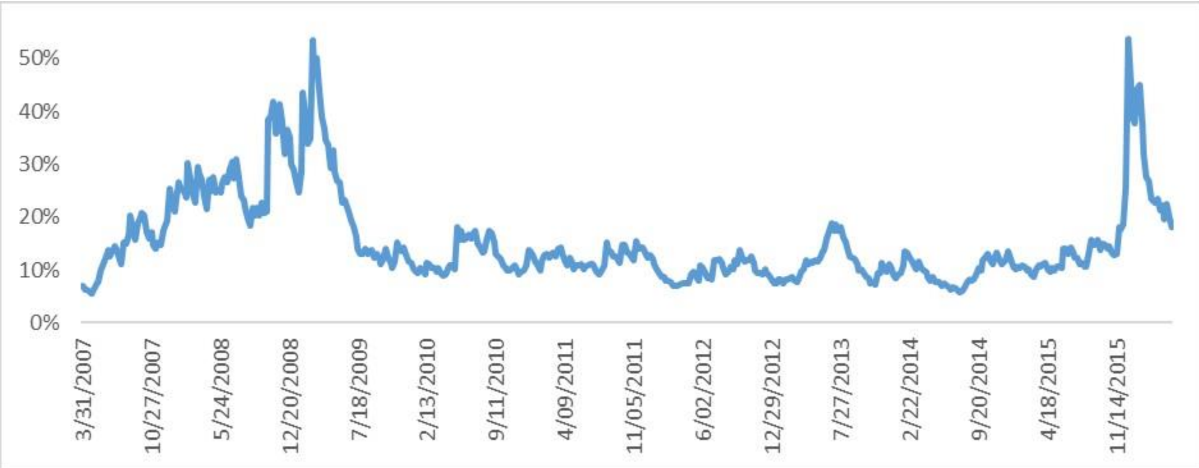

Figure 5: Average weekly conditional volatility of the six banks (31/03/2007 - 31/03/2016)

The indicator demonstrates the ability to detect the 2008 global financial crisis and, in addition, it is useful as it identifies the development of vulnerabilities in the banking industry. This can be seen in the average volatility and volatility clustering of 2007 which led to a significant rise and peak in late 2008. In late 2015, the indicator rapidly shoots up, indicating a significant increase in systemic risk in the South African banking industry which was partly attributed to political uncertainty during that period. This was met with a negative reaction from the financial sector (thus owing to domestic factors). The second incident may possibly be attribute to the fact that the Chinese stock market was in turbulence (thus owing to international factors).

4.2.4 Results of interest rate spread

Figure 6 depicts the progression of both the LTS and TED spreads over the sample period. According to theory, a positive TED spread and negative LTS spread (i.e. inverted bond yield curve) signal financial and economic turmoil.

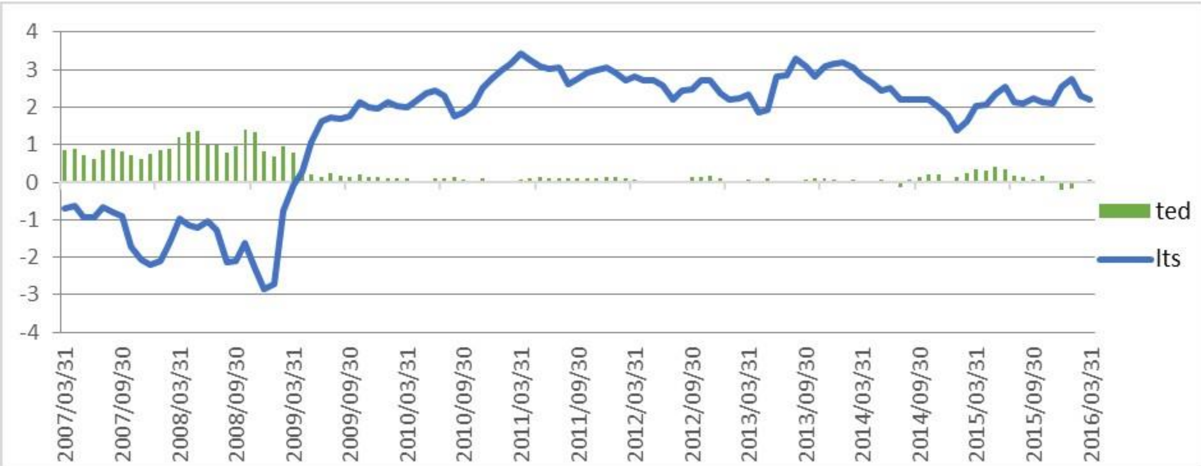

Figure 6: Term and Ted spread (31/03/2007 - 31/03/2016)

Figure 6 shows that during the pre-crisis period, both positive TED and negative TERM spread are visible, signalling the commencement of the subprime crisis. Furthermore, in the last quarter of 2008, a further widening of the interest rate differentials can be observed respectively. This provided signals for the extreme financial and economic stress. In the subsequent period, the TED spread contracts and the LTS spread reverts to positive values. This is an indication of the end to uncertainty and turmoil. The results are consistent with those of the empirical literature conducted in other emerging economies.

4.2.5 Evaluation of systemic risk measures

This sub-section presents the results of the QR approach for evaluating systemic risk measures based on its ability to forecast macroeconomic risk. In doing so, we conduct a series of univariate quantile estimation of each lagged systemic risk measure on the downside extremal quantiles (5%) of CLI growth.[7] The results are presented in Table 3.

[7] We also estimate the median regression (50%) of CLI growth

Table 3: Predictive quantile regression (macro. risk)

Covariates	τ (0.05)	Pseudo R (%)
$\mathbf{CoVaR_{t-1}}$	0.7323***	44.2292
	(3.6798)	
$\mathbf{DCoVaR_{t-1}}$	2.0866***	48.4327
	(5.8806)	
$\mathbf{PC1_{t-1}}$	-15.4947***	37.6218
	(-11.4721)	
$\mathbf{Ave\_cond\_volatility_{t-1}}$	-0.18298***	51.7607
	(-4.8648)	
$\mathbf{Ted\ Spread\ _{t-1}}$	-4.1391***	42.9112
	(-6.6781)	
$\mathbf{Term\ Spread_{t-1}}$	0.9833***	57.0804
	(11.4367)	
Observations	**109**	

Notes: Table reports univariate quantile regression at τ (5%). Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and *** respectively. Only the coefficient, t-stat () and Pseudo R-squared of the systemic risk measure are reported. Boot strapped standard errors with 1000 replications. Sample is 2007M03 – 2016M03.

Table 3 presents a series of univariate QR estimation of each lagged systemic risk measure on the fifth percentile of SA CLI growth from 03/2007 (heron referred to as 2007M3) to 03/2016 (2016M3). The table presents the estimated coefficients along with the significance and goodness of fit statistics computed using bootstrapped standard errors. We find that each and every single systemic risk measure exhibit significant predictive and explanatory power on the downside tail of macroeconomic risk. According to the results, high levels of commonality within the banking industry demonstrates the largest impact on the lower quantile of real activity. This is followed by the widening in the TED spread, which falls in line with economic theory. Regarding explanatory power, interest spreads contain the most information on downside macroeconomic risk followed by the volatility, institutional-specific risk and commonality metrics.

Table 4: Predictive quantile regression (median)

Covariates	τ (0.50)	Pseudo R (%)
$\mathbf{CoVaR_{t-1}}$	0.5225***	18.7781
	(4.5428)	
$\mathbf{DCoVaR_{t-1}}$	1.4046***	19.6309
	(5.8848)	
$\mathbf{PC1_{t-1}}$	-4.4477***	7.6186
	(-2.9979)	
$\mathbf{ave\_cond\_volatility_{t-1}}$	-0.1490***	26.8983
	(-8.0857)	
$\mathbf{Ted\ Spread\ _{t-1}}$	-2.6794***	17.8561
	(-5.7637)	
$\mathbf{Term\ Spread_{t-1}}$	0.6019***	15.8704
	(2.9885)	
Observations	**109**	

Notes: Table reports univariate quantile regression at τ (5%). Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and *** respectively. Only the coefficient, t-stat () and Pseudo R-squared of the systemic risk measure are reported. Boot strapped standard errors with 1000 replications. Sample is 2007M03 – 2016M03.

In comparison to the central tendency, Table 4 presents the results of the predictive QR on the median of South African CLI growth. Regarding the significance of the systemic risk measures, the results prove to be consistent with that of the lower quantiles. Furthermore, the measures of systemic risk exhibit weaker predictive and explanatory power in the median quantile than those of the lower quantiles. The results provide evidence that the constructed systemic risk measures are indeed not only associated with real economic activity, but are significant predictors of downside macroeconomic risk.

5. CONCLUSION

This study conducted an empirical analysis on systemic and macroeconomic risk in the South African economy. We modelled the different aspects of systemic risk by constructing several measures of systemic risk. These are CoVaR, ΔCoVaR, principal component analysis (PCA), average conditional volatility and interest rate spreads to monitor the systemic stress in the South African financial system. Thereafter, we evaluated the importance of each candidate measure by testing its ability to predict lower quantiles of economic activity (macroeconomic risk).

The results revealed that individually, the constructed measures demonstrate the ability to capture periods of extreme financial disturbance in the South African financial sector. In the process, we could identify the largest banks in South Africa and call them "Big Four" as the SIFIs and forming part of the TICTF institutions in the banking sector. If these are not properly regulated (or weak regulation) may pose grave systemic risk. Furthermore, we provided evidence that the constructed systemic risk measures are significantly informative about future economic downswings in the South African economy as opposed to the median distribution of real economic activity.

This study goes beyond other empirical studies in both developed and developing countries and specifically South Africa. The results of this study reveals that systemic risk is a complex and multifaceted phenomenon. Systemic risk cannot be represented by means of using a single measure. This study was therefore able to model and evaluates a range of systemic risk measures to assist regulators in monitoring vulnerabilities in the financial system and untangling whether the vulnerabilities arising from the financial sector poses significant risk to the macroeconomic activity. The results of this study are expected to provide regulators with enough time to implement policy responses that can neutralize and lessen the impact of systemic risk on South Africa's macroeconomic activities. Although the results compares favourably with previous studies in South Africa, it is in some cases contrary to one previous study conducted (in South Africa). This is not unexpected because the current study used different methodologies compared to previous research.

The main implication of this study lies in its provision of tools to assist South African regulators with the surveillance of the South African financial system by identifying build-ups of systemic vulnerabilities, SIFIs and TICTF institutions. Moreover, the tools provided by this study are useful in the early warning analysis of financial systemic risk and the consequences of systemic risk on macroeconomic outcomes. Such an approach will provide regulators with enough time to implement policy responses to neutralize the impact of vulnerabilities and address these vulnerabilities.

Suggestions for future research would be to include other financial institutions in the dataset such as insurance and investment companies to have a broader understanding of systemic stress in the South African financial system. Moreover, we suggest an application of the regime-switching model to better understand the complex dynamics between systemic risk and macroeconomic outcomes. Lastly, we recommend the application of alternative significance criterion such as out-sample forecasting or back testing to evaluate effectiveness of the tools as indicators of systemic risk and assist in the identification of appropriate measures of systemic risk suitable for South African regulators.

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