Modelling Systemic Risk in the South African Banking Sector Using CoVar

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ERSA working paper 709

September 2017

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September 1, 2017

Abstract

In this paper we model systemic risk by making use of the conditional quantile regression to identify the most systemically important and vulnerable banks in the South Africa (SA) banking sector. We measure the marginal contributions of each bank to systemic risk by computing the delta Conditional Value at Risk which measures the difference between system risk of individual banks when they are in a normal state and when they are in distress state. Using daily stock market closing prices of six South African banking banks from 19 June 2007 to 11 April 2016; our back tested systemic risk measures suggest that the contribution of South African banks to systemic risk tends to significantly increase during periods of financial crises. The two largest banks namely First Rand Bank and Standard Bank are found to be the highest contributors to systemic risk while the smallest bank namely African Bank is found to be the least contributor to the overall systemic risk in South African banking sector. Based on the delta Conditional Value at Risk; we show that there is a need to go beyond micro prudential regulation in order to sustain stability in the South African banking sector.

Keywords: conditional quantile, systemic risk, conditional value at risk, and banking sector

JEL: C13, C22, C58, G01, and G21

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1. Introduction

The 2007 – 2008 global financial crisis alerted the public on how interconnected financial markets are while also highlighting the fragility of the whole financial system and how a financial crisis can be damaging to the entire global economy. A crisis that had started in 2007 as a mere subprime mortgage debacle quickly spread to the whole financial sector and the entire global economy with speed, causing unimaginable damage (Allen and Carlette, 2009). From the crisis at British Bank, Northern Rock in 2007 to more than a hundred United States of America (US) lenders who filed for bankruptcy in 2008 indelibly punctuated by the fall of Lehman Brothers in September 2008. As shown by Adrian and Shin (2009); this contagious malady festered throughout the globe.

Of signal importance to the financial markets was the unexpected but overdue revelation of the septic susceptibilities to contagion engendered by the so-called synergies and other interdependencies within the banking sector not only on a domestic basis but ultimately worldwide, as financial meltdown proliferated and access to credit became constrained throughout the globe. According to Reinhart and Rogoff (2009), risk in the financial system is more than just aggregating market risk, operational risk and credit risk associated with individual firms but also includes a huge element of systemic risk. Pillar I in Basel I and II, which was the backbone of banking regulation, were mainly concerned with limiting risk of individual institutions by making sure that banks have adequate capital to cushion against unexpected losses. Thus, pre 2007-2008 crisis, financial regulation was merely concerned with limiting idiosyncratic risk hence regulators did not consider the adverse repercussions that a distressed bank could have on other banks and the broader economy.

The recent crisis has simultaneously underlined the importance of going beyond idiosyncratic risk while also detecting and managing systemic risk. The necessity of moving towards an improved regulatory framework i.e. from micro-prudential to macro-prudential; has encouraged renewed efforts in defining and measuring systemic risk among academics and regulators alike. Admittedly, the definition of systemic risk remains something of a work in progress but according to Bullard *et al* (2009), systemic risk refers to the failure of a significant individual institution that might create shortages of credit in the financial and money markets and hence impair the broader economy. The recognition that financial regulation has neglected the contributions of financial institutions to systemic risk has led to the recent rise in the number of studies which develop techniques to quantify it. One of these studies is that of Adrian and Brunnermeier (2008) who measure systemic risk in the US financial sector by developing a technique they call Conditional Value at Risk (CoVaR). They define CoVaR as the Value at Risk (VaR) of the financial system on condition that one institution is experiencing distress. By conditioning the VaR of the system on a distressed institution they are able to capture the risk spillovers from institutions to the system and also measure how much each institution contributes to systemic risk. Acharya *et al.* (2010) develop a technique called the systemic expected shortfall (SES) to measure systemic risk. Their measure looks at the firm's propensity to be undercapitalized when the whole financial sector is in its left tail. Its counterpart, the marginal expected shortfall (MES) is used to measure the contributions of financial institutions to systemic risk. Brownlees and Engle (2012) extend the MES by using a multivariate GARCH model on the assumption that the relationship between the institutions and the system changes with time. Billio *et al* (2012) apply the granger causality and principal component analysis to develop their systemic risk measure. They claim that their techniques are able to capture the interconnectedness among different financial industries namely brokers, banks and insurance firms.

Many other studies on quantifying systemic risk have been carried out in different sectors ranging from banking to sovereign debt markets. Among these studies are Girardi and Ergun (2013) who use the CoVaR method within a multivariate GARCH setting to measure systemic risk in US financial sector and find that the largest firms such as investment banks contribute the most to systemic risk. Drehmann and Tarashev (2011) use the Sharpley values to quantify the contribution of banks to systemic risk and they find that a bank's contribution largely depends on its role in the interbank market. (i.e. whether it is a net lender or a net borrower). The bulk of these studies have been undertaken in developed economies. One of the exceptions is that of Roengpitya and Rungcharonkitkal (2011) who use the CoVaR technique in Thailand's banking industry and find that the largest banks contribute the most to systemic risk.

Nevertheless, research on measuring systemic risk and its consequences on the broader economy is still scarce in developing economies. Our paper seeks to address this gap by empirically analysing systemic risk in the South African banking sector with the aim of identifying the most systemically important banks and the most vulnerable ones. The main objective of this study is to come up with rankings that express in relative terms what each bank contributes to systemic risk and which ones would pose the biggest threat to the South African banking system. This would inform regulators as to which banks to put under stricter supervision and even which to prioritise in bailing out during a financial crisis. This study focuses on 4 key areas, namely; how risky is each of the SA banks in isolation, how much does it contribute in different systemic risk scenarios, how big are the interbank linkages and also an assessment of how the results relate at different confidence levels. To this end, we apply the CoVaR technique proposed by Adrian and Brunnermeier (2008).

As in Adrian and Brunnermeier (2008) we characterise the CoVaR using quantile regression developed by Koenker and Basset (1978). Since quantile regression deals very well with the tails of a distribution, we find it to be a suitable way to estimate the CoVaR which is found on the lower quantiles of a dependent variable. In quantifying the marginal contributions of banks to systemic risk we use ΔCoVaR which is the difference between VaR of the banking system conditioned on a distressed bank and its VaR when the same bank is operating normally. We analyse systemic risk using six commercial banks namely, Barclays Africa Limited; the holding company of ABSA, First Rand Bank Limited; the holding company of First National Bank (FNB), Nedbank Limited, Capitec Bank, Standard Bank of South Africa Limited and African Bank. We cover the period June 2007 to April 2016 and our results show that the VaR of all the six banks increased considerably during the 2008 global financial crisis. We also find that African Bank is the riskiest in isolation as measured by its VaR. Our back testing results reveal that all our VaR models are accurate. During the sample period First Rand Bank was the largest contributor to systemic risk followed by Standard Bank, Barclays Africa, Nedbank, Capitec and lastly African Bank. These results indicate that the biggest banks would are systemically riskier (pose a bigger threat to the system) than the smaller banks leading us to a recognition of the too big to fail (TBTF) theory. These results clearly indicate to regulators that different banks pose different threats to the banking system and the economy at large, hence specific actions that go beyond limiting idiosyncratic risk are needed if financial stability is to be attained through macro prudential regulation. The remainder of the paper is structured as follows: Section two discusses the existing literature while section three describes the methodology. Section four and five present the results and the conclusion respectively.

2. Literature Review

In this section we review some empirical literature documenting the evolution and modelling of systemic risk. While several studies have been undertaken to model systemic risk using approaches such as Conditional Value at Risk and Marginal Expected Shortfall, we are particularly interested to highlight the necessity of raising the bar from micro prudential to macro prudential regulation following the guidance of Basel III.

In a pioneering study Adrian and Brunnermeier (2008) develop a technique called Conditional Value at Risk (CoVaR) to measure systemic risk in the heavily securitised, densely interconnected and highly synergised US financial market where several banks that had to be kept afloat by the government were subsequently designated too big to fail (TBTF). They define the CoVaR as the VaR of the whole system given that one institution has already reached its VaR (in distress). They use quantile regression to model the joint dynamics of the equity returns of individual institutions and of the financial system, choosing as their independent variables including the Chicago Volatility Index (VIX), slope of the yield curve, credit spread, default spread and the equity market return. To measure the contribution of individual firms to systemic risk they make use of ΔCoVaR, which is the difference between CoVaR given that an institution is in distress and CoVaR when it is in normal state. Their findings reveal that banks, especially those with a high fraction of interest bearing deposits, have the highest contribution to systemic risk. The study also found out that there is a strong relationship between a firm's VaR and its ΔCoVaR in a time series dimension. While we calculate ΔCoVaR using the same technique, the South African commercial banks that we study are much smaller, less interlinked and relatively free from potentially toxic debt derivatives. We seek to highlight the impact of these differences.

Similarly, Bernal *et al*. (2014) use ΔCoVaR in the US and Eurozone daily stock market price data from March 2004 to March 2012, and the Kolmogorov-Simonov test in order to compare the relative contributions of the different sectors of the financial industry. Their results show that the non-insurance and non-banking sector is the highest contributor to systemic risk in the Eurozone while the insurance sector contributes the most in the US. This sensitizes us not to take any outcome for granted but to interpret results objectively as what would seem to be the forgone conclusion that banks contribute most to systemic risk in any financial system is clearly debunked.

Whereas Adrian and Brunnermeier (2008) use equities as their data to measure the systemic risk using CoVaR, other studies have used credit default swaps (CDS) or combined the two to measure systemic risk. The major difference between using CDS and equity prices is that CDS contain information on the individual and joint probabilities of default and therefore on systemic risk while on the other hand equity prices do not contain this information directly.

Among those who have used CDS are Huang *et al*. (2009) who develop a systemic risk measure called the distressed insurance price which assesses the probability of default by a financial firm within a risk neutral environment. This measure basically compares the insurance premium that a firm would pay against default during normal economic conditions to what it pays in times of market stress. Applying this strategy to 12 of the largest US financial firms they find that there is a significant increase in the insurance premium during times of financial crises with the minimum premium against financial loss increasing from around US$100 billion to US$250 billion (250%) in June 2008.

Esterhuysen, *et al* (2011) empirically examine systemic risk in the South African banking sector by applying the technique developed by Huang *et al* (2009) to determine the impact of harsh economic conditions on the insurance linked systemic risk measure. Their particular model is based on the price of insurance against default and is calculated using credit default swaps data. Using eight banks listed on the Johannesburg stock exchange, they analyse the asset returns correlations for these banks. Unavailability of credit default swaps data proved to be an insurmountable hurdle, compelling them to use physical probabilities of default as a compromise. Their findings indicate that during the 2008 global financial crisis, systemic risk in the South African banking industry increased considerably as shown by a 200 percent increase in the price of insurance against default. Comparing these results with those obtained in the US by Huang *et al*. (2009) they conclude that the crisis was less severe on the South African banking sector. While this study attracts our attention because it covers the South African banking sector like ours, it is not strictly comparable. They investigate the impact of the crisis on the whole system under comparison to the US system while we exhaust the variegated internal reciprocal impacts under stress between any given i bank, groups of banks and the entire system.

Girardi and Ergun (2013) model systematic risk in the US financial services sector using the CoVaR. Instead of using quantile regression they modify the original CoVaR by employing a multivariate GARCH model to find the VaR of the system conditional on various institutions being in distress. This modification enables them to capture the evolving relationship between the system and the individual institutions. They also deviate from the original definition by asserting that their CoVaR claiming that their CoVaR represents the VaR of the system given that individual institutions are at most at their VaR as opposed to being exactly at VaR. Their definition of CoVaR makes it possible to look at extreme events and easier to perform stress testing. Their results show that the group consisting of insurance was the least contributor to systemic risk while depository institutions contributed the most. The study was also extended to look at the relationship between firms' characteristics and their contribution to systemic risk, revealing that size, equity beta and leverage have the strongest and most significant relationship with a firm’s contribution to systemic risk. As, unlike these authors we are not using GARCH models, we have exercised our option of using a quantile regression based CoVaR and then matching their rigour by means of stress testing. We see this as a more complete approach.

A somewhat more sophisticated extension of the CoVaR approach was applied by Reberedo and Ugolini (2015) to model systemic risk within the sovereign debt market in Europe. Instead of using quantile regression or multivariate GARCH models, Reberedo and Ugolini (2015) employ the copula approach. Apart from ease of computing, they suggest that the copula approach has another advantage over the other approaches which is that it captures the tail dependence between multiple variables much better than both quantile regression and multivariate GARCH models. They use weekly data on price indices of 10year government bonds from January 2000 through October 2012. According to their findings, contribution to systemic risk was almost the same for all eight countries before the debt crisis. During the debt crisis, crisis countries like Portugal, Italy and Greece recorded increased contribution to systemic risk with non-crisis countries like Germany and France going the other way.

Acharya *et al* (2010) extend the expected shortfall to create the marginal expected shortfall (MES) so as to capture the systemic nature of risk. MES is defined by these authors as the firm's propensity to be undercapitalized when the whole financial sector is in its left tail. This means that MES of a single institution is a derivative of the whole system's Expected Shortfall with respect to the firm's market capitalization. They also claim that as a firm's leverage increases its MES will also increase. Using data on Credit Default Swaps (CDS) and equities for the period 2006-2008 they investigate systemic risk within the US financial sector. The results indicate that investment banks and AIG were the worst contributors to systemic risk, with 5 of the largest investment banks all in the ten highest contributors to systemic risk.

Brownlees and Engle (2010) extend the MES in their systemic risk analysis to account for the size and leverage of firms. They also adopt a dynamic structural approach instead of the static one, as in Acharya *et al* (2010). A multivariate GARCH model in the form of a DCC GARCH is used to develop the Systemic Risk Index (SRISK), with their results showing that this methodology provides useful rankings of systemically risky firms at various stages of the financial crisis. To illustrate the importance of their contribution to this sub-field of risk management, it may be worth noting that, a full year and a half before the Lehman bankruptcy, eight companies out of their SRISK top ten turned out to be troubled institutions. Another importance of these studies is that the MES and the SRISK can be used as an early indicator to financial stability. An ideal future in this sub-field (to which our study presumes to be a contribution), would have each study contributing its most significant attributes to some enduring and dynamic systemic risk management framework.

More recently, Banulescu and Dumitrescu (2015) employ the Component Expected Shortfall (CES) to identify the systematically important financial institutions in the US. They decompose the Expected Shortfall and also take into account firm's characteristics. The study straddles the period June 2007 to June 2010, covering the global financial crisis. The result reveals that firms like AIG, Lehman Brothers and Merrill Lynch, which suffered huge losses and went into bankruptcy during the financial crisis, to have been the systemically important institutions. Their results were important, with firms they ranked highest on systemic risk being the same that posed the greatest threat to the financial system during the crisis.

3. Methodology

This section presents the methodology used in this paper. The first part of this section explains the Conditional Value at Risk (CoVaR) which we use to measure systemic risk. The second part, briefly discusses quantile regression employed to estimate our systemic risk measures: The CoVaR, and the ΔCoVaR. Thereafter, we detail the steps involved in estimating CoVaR.

3.1. *CoVaR Definition*

The CoVaR is the systemic risk measure we adopt in this study and it was developed by Adrian and Brunnermeier (2008). As in Adrian and Brunnermeier (2008) we start by defining the VaR of an institution which is the foundation for the CoVaR.

3.1.1. Value at Risk

VaR measures the maximum loss that an institution can incur during a specified period of time within a certain confidence interval. VaR is statistically the q quantile of the projected distribution of the returns (see for example in Tsay, 2010; and Muteba Mwamba, 2012). Thus VaR defined over the confidence level 1-q can be represented as follows:

$$\Pr\left(X_t^i \leq VaR_{t,q}^i\right) = q \tag{1}$$

where X_t^i are the returns of institution i and $VaR_{t,q}^i$ is the q percent VaR of institution i.

3.1.2. CoVaR

The CoVaR was developed to capture risk spillovers from one firm to another or to the whole system and is defined (Adrian and Brunnermeier, 2009) as the VaR of an institution (or the financial system) given that another institution is in distress. The conditioning event which is the other institution being in distress means that the institution is already at its VaR. In paper we contextualize the CoVaR definition to mean the VaR of the whole banking sector given that bank i is in its left tail. Similar to VaR, the CoVaR can be defined statistically over a given confidence interval as the q quantile of the predicted return's distribution of the system given that institution i is at its VaR. CoVaR can be represented as follows:

$$\Pr\left(X_t^s \leq CoVaR_{t,q}^{s|i} | X_t^i = VaR_{t,q}^i\right) = q \tag{2}$$

where X_t^s are the returns of the system and $\text{CoVaR}^{s|i}_{t,q}$ is the q percent value at risk of system when the returns of institution i are equal to its q percent VaR.

3.2. ΔCoVaR

ΔCoVaR measures the contribution of individual institutions to the risk of the entire system when the individual firm is in distress. Adrian and Brunnermeier (2008) define ΔCoVaR as the difference between CoVaR conditioned on an institution being in distress and CoVaR conditioned on an institution being in normal state. The normal state means that the returns of the institution are at the median level (q=0.5). ΔCoVaR can be represented as follows:

$$\Delta CoVaR_{\boldsymbol{t,q}}^{\boldsymbol{s|i}} = CoVaR_{\boldsymbol{t,q}}^{\boldsymbol{s|i}} - CoVaR_{\boldsymbol{t,q=0.5}}^{\boldsymbol{s|i}} \tag{3}$$

where $CoVaR_{t,q=0.5}^{s|i}$ represents the VaR of the system when bank is operating normal. The ∆CoVaR is of paramount importance since it summarizes the marginal contribution of individual institutions to systemic risk thus enabling us to rank banks in terms of their contribution to systemic risk hence pinpointing the systemically important banks.

3.3. Quantile Regression

Koenker and Basset (1978) introduced the linear quantile regression models which predict the relationship between a set of independent variables and specific quantiles of the dependent variable. The traditional ordinary least squares (OLS) technique models how on average the predictor variable influences the response variable thus does not consider the fact that the relationship between the variables might change as the dependent variable changes and also makes the assumption that the errors of the model are normally distributed. Koenker and Basset (1978) argue that if the errors of a model are not normally distributed the OLS regression will produce inefficient results. Thus they developed the quantile regression technique which does not make any assumption on the distribution of the errors to cater for that problem. This technique has also been proven to be robust to non-normal errors with Koenker and Hallock (2001) suggesting that quantile regression gives a rich characterization of data and that it provides an all-encompassing strategy for the completion of the regression techniques. Since quantile regression deals very well with the tail of a distribution it is thus a proper way to estimate the CoVaR which is found on the lower quantiles of a dependent variable. Quantile regression has been used multiply times in the field of financial economics with much of the studies using it to calculate the Value at Risk of different institutions and portfolios.

3.3.1. Computing Quantiles

Whereas in the OLS method the main aim is to minimize the sum of squared residuals, with quantile regression the idea is to minimize the sum of the absolute residuals. For example, if we were to begin with the following linear model. Given a real valued random variable Y, we can characterise it by its probability distribution

$$F(y) = P(Y = y) \tag{4}$$

where for any $0 < q < 1$ we have

$$F^{-1}(q) = inf\{x: F(y) \geq q\} \tag{5}$$

Representing the qth quantile of Y.

To solve for the q quantile, we use a simply optimization problem. We do this by first considering a loss function as follows:

$$\rho_q(y) = y(q - I(y < 0)$$

where $\rho_q(y)$ is the loss function?

To obtain the q quantile we solve for $\hat{y}$ by minimizing the expected loss. Thus we seek to minimize

$$E\rho_q(y-\hat{y}) = (q-1)\int_{-\infty}^{\hat{y}}(y-\hat{y})dF(y) + q\int_{\hat{y}}^{\infty}(y-\hat{y})dF(y) \tag{6}$$

In equation 6 we have two components, one before the plus sign and one after. The one before the plus sign represents the area where the predicted value of y is greater than the actual value and the second part represents the portion where the actual value is under predicted.

$(q-1)$ and q represent assigned weights for over prediction and under prediction respectively.

Differentiating equation (6) and setting it to zero we have

$$0 = (1-q)\int_{-\infty}^{\hat{y}} dF(y) + q\int_{\hat{y}}^{\infty} dF(y)$$

$$F(\hat{y}) = q \;\; or \;\; \hat{y} = F^{-1}(y) \tag{7}$$

Equation (7) says that $\hat{y}$ is the q quantile of the distribution of Y. “Since F is monotone any element of $\{y: F(\hat{y}) = q\}$ minimises the expected loss” (Koenker,2005).

3.4. CoVaR Estimation Procedure

The following details the procedure involved in estimating the CoVaR and ΔCoVaR.

Step 1

We begin by a running a q percent quantile regression with the returns of the banks as the dependent variable and a set of state variables that capture the time variation in moments of asset returns as independent variables. The regression model is specified as follows:

$$X_t^i = \alpha_q^i + \beta_q^i N_t + \varepsilon_t^i \tag{8}$$

where X_t^i represents the returns of bank i and N_t represents a vector of state variables such as equity market return, market volatility and the yield spread and ε_t^i is the error term with mean zero and variance equal to 1. Where the value of q is not stipulated it should be taken to represent a lower quantile for example 1 percent.

Step 2

Having estimated the parameters α_q^i and β_q^i in step one, this step we obtain the time varying VaR for all the six banks by generating the predicted values from the quantile regression in step one.

$$VaR_{t,q}^i = \widehat{\alpha_q^i} + \widehat{\beta_q^i} N_t \tag{9}$$

where $VaR_{t,q}^i$ is the q percent value at risk of bank i and $\widehat{\alpha_q^i}$ and $\widehat{\beta_q^i}$ are estimated from equation (8). The results we obtain in this step don’t just give us one number but a daily VaR series.[1]

Step 3

Next we run a quantile regression model that is similar to that in step one but here the returns of the whole banking sector (banking system) are the dependent variable. The same state

[1] q represents a lower quantile for example 1 percent unless stated otherwise

variable used in step one are also used here but we also add the returns of the individual banks to the list of independent variables. The regression model will be as follows:

$$X_t^s = \alpha_{0,q}^s + \alpha_{1.q}^s X_t^i + \beta_q^s N_t + \varepsilon_t^s \tag{10}$$

where $X_{t,}^i$ represents the returns of the individual banks.

Step 4

In this step we compute the CoVaR for the system by generating the predicted values from the estimation in step 3. The parameters $\widehat{\alpha_{0,q}^s}$, $\alpha_{1,q}^s$ and $\widehat{\beta_q^s}N_t$ are obtained from running the regression in step 3.

$$VaR_{t,q}^{s|i} = \widehat{\alpha_{0,q}^s} + \widehat{\alpha_{1,q}^s} X_{t,}^i + \widehat{\beta_q^s} N_t \tag{11}$$

where $VaR_{t,q}^{s|i}$ is the q percent value at risk of the system conditioned on the returns of the bank i. But we are interested in the Value at Risk of the system conditioned on bank i being in distress (i.e. bank i being at its VaR). Thus by replacing the returns of bank i in equation 11 by its VaR ($X_{t,}^i = VaR_{t,q}^i$) we get the CoVaR.

$$CoVaR_{t,q}^{s|i=distress} = \widehat{\alpha_{0,q}^s} + \widehat{\alpha_{1,q}^s} VaR_{t,q}^i + \widehat{\beta_q^s} N_t \tag{12}$$

where $CoVaR_{t,q}^{s|i=distress}$ is the VaR of the system when institution i is in distress

Step 5

We obtain the marginal contributions of individual banks to systemic risk by calculating ΔCoVaR. This is done by subtracting the CoVaR conditioned on an institution being in normal state from CoVaR conditioned on an institution being in distress (calculated in equation (12)). Basically CoVaR is the VaR of the system and can be calculate under different conditions. In the previous step we calculated CoVaR on condition of distress. CoVaR can also be calculated on condition that an institution in a normal state. But in both cases CoVaR is calculated at the same quantile, meaning that what only changes are the quantile of the conditioning event (i.e. we change from q percent VaR to 50 percent VaR) not the estimated parameters.

$$CoVaR_{t,q}^{s|i=normal\ state} = \widehat{\alpha_{0,q}^s} + \widehat{\alpha_{1,q}^s} VaR_{t,q=0.50}^i + \widehat{\beta_q^s} N_t \tag{13}$$

where $CoVaR_{t,q}^{s|i=normal\ state}$ is the VaR of the system given that institution i is operating normally and $VaR_{t,q=0.5}^i$ is the 50 percent VaR of institution i and is used to represent an institution that is in operating normal

$$\Delta CoVaR_{t,q}^{s|i} = CoVaR_{t,q}^{s|i=distress} - CoVaR_{t,q}^{s|i=normal\ state}$$

$$\Delta CoVaR_{t,q}^{s|i} = (\widehat{\alpha_{0,q}^s} + \widehat{\alpha_{1,q}^s} VaR_{t,q}^i + \widehat{\beta_q^s} N_t) - (\widehat{\alpha_{0,q}^s} + \widehat{\alpha_{1,q}^s} VaR_{t,q=0.50}^i + \widehat{\beta_{q=}^s} N_t)$$

$$\Delta CoVaR_{t,q}^{s|i} = \widehat{\alpha_{1,q}^s} VaR_{t,q}^i - \widehat{\alpha_{1,q}^s} VaR_{t,q=0.5}^i$$

$$\Delta CoVaR_{t,q}^{s|i} = \widehat{\alpha_{1,q}^{s}}(VaR_{t,q}^{i} - VaR_{t,q=0.5}^{i}) \tag{14}$$

where $\Delta CoVaR_{t,q}^{s|i}$ (henceforth referred to as ΔCoVaR) is the marginal contribution of institution i to systemic risk.

The results we obtain from step 5 give us a time varying ΔCoVaR. This means that the result we obtain in step five is not just a constant number but reveal to us the different daily marginal contributions of institution i to systemic risk.

3.5. Back Testing

The CoVaR measure is based on the VaR of different institutions. Thus to make sure that our CoVaR is accurate we have to back test the VaR for all the banks before using it to calculate the CoVaR. The Basel Committee on Banking Supervision (BCBS) (2010) defines the back test as a statistical procedure that validates a model by comparing actual outcomes to forecasted outcomes. Jorion (2007) suggests that a VaR model is useful only if it can accurately predict the future. There are several techniques used to back test VaR models with the most prominent being the unconditional coverage test of Kupiec (1995) and the independence test of Christoffersen (1998). The unconditional test investigates whether the number of exceptions in the VaR model are in line with the confidence interval which the VaR is defined over. An exception is defined as a case where the actual loss exceeds the estimated VaR. A very good VaR model would have the expected number of exceptions equal the actual exceptions according to the Kupiec test. In the independence test Christoffersen (1998) does not only focus on the number of exceptions but also examines the dispersion of the exceptions. A VaR model with clustered exceptions will be inaccurate because it will fail to take into account correlations and volatility in the market. In this paper we employ both the Kupiec and Independence tests.

3.6. Stress Testing

Dominguez and Alfonso (2004) argue that stress testing helps identify the vulnerabilities of institutions in times of crises by developing hypothetical crisis scenarios. Stress testing is a technique used to identify potential losses that can occur as a result of adverse movements in the market. Dowd (1998) classifies stress testing techniques into 3 different categories which are historical scenarios of crisis, hypothetical events and stylized scenarios. Historical scenarios replicate crises and disasters that took place in the past for example the Asian Crisis of 1997 and the global financial crisis of 2008. The stylized scenarios which we will use in this study deals with simulating adverse movements in market variables such as exchange rates and interest rate. In applying the stylized scenarios approach to stress test our VaR models we will follow suggestions made by the Derivatives Policy Group (1995). To stress test its VaR model an institution should change the stock index by plus or minus 10 percent, change the volatility by plus or minus 20 percent, and change the parallel yield curve by plus or minus 1 percent and also change the currency by plus or minus 6 percent (Derivatives Policy Group, 1995).

4. Empirical Analysis

4.1. Data

In this paper we investigate systemic risk for 6 commercial banks, being the 5 largest South African banks listed on the Johannesburg Stock Exchange (JSE) and the formerly listed African Bank, which is undergoing rehabilitation after having collapsed under bad loans. We cover the period 19 June 2007 to 11 April 2016 using daily stock market prices for the six banks where applicable. The 5 listed banks are Barclays Africa Limited, the holding company of ABSA, First Rand Bank Limited, the holding company to FNB, Nedbank Limited, Capitec Bank and Standard Bank of South Africa Limited. African Bank went bankrupt and last traded on the JSE on 10 August 2014. Consequently, its data runs until the 7th of August 2014. As a proxy for the whole banking industry we used the JSE banks index. To calculate the returns for the individual banks and the banking system we used the following formula:

$$X_t = \left[\ln\left(\frac{P_t}{P_{t-1}}\right)\right] * 100 \tag{15}$$

Where X_t is the return and P_t and P_{t-1} are the current and the previous stock prices respectively.

We use state variables to estimate the returns of the banks using quantile regression. The variables are chosen on the basis that they capture the time variation in the asset returns' conditional moments. These variables are presented as state variables because they change the assets prices' conditional moments and are sufficient for use in predicting the future path of the asset prices. We utilize such an optimal number of state variables as to keep the model parsimonious. In choosing the state variables we follow the example of Adrian and Brunnermeier (2009) resulting in the following state variables being used as risk factors:

Equity Market Return: As a proxy for the equity market return we use the JSE All Share Index (ALSI). The ALSI is calculated as a weighted index and comprises of 164 companies which make up for almost the entire market capitalization of the companies listed on the JSE. It is the most widely used measure for the average performance of the equities in South Africa.

Market Volatility: To measure the volatility of the market we use the JSE South African Volatility Index (SAVI). The SAVI is South Africa's equivalent of US's Chicago Board of Options Exchange Volatility Index (CBOE VIX) and is intended to capture the risk within the equity market. It measures the volatility of the looking three months forward.

Yield Spread: The yield spread is used to proxy the business cycle and is measured by taking difference between the yield of a 10-year South African Government bond and a 3-month Treasury bill (T-bill). This variable is considered to be able to predict future economic performance hence it has been labelled as a leading indicator.

4.2. VaR Results

Table 1 below reports the 1% quantile regression results for the six banks' returns. These estimations are used to obtain the VaR for the banks understudy. We run our quantile regressions, using equation 8 in the methodology with the three state variables we have chosen namely equity market return, market volatility and yield spread being our independent variables while the banks' returns are the dependent variable.

Table 1: Quantile Regression @ 1% results for individual banks

	Barclays	Standard Bank	African Bank	First Rand	Nedbank	Capitec
Intercept	-4.127*	-3.149*	-8.208*	-2.586**	-3.498	-7.380*
	(1.394)	(0.707)	(1.794)	(1.013)	(1.231)	(1.058)
Equity Return	0.799*	1.087*	0.266*	1.027*	0.991*	0.672*
	(0.227)	(0.121)	(0.396)	(0.208)	(0.250)	(0.190)
Volatility Index	-0.019**	-0.043***	0.064**	-0.081**	-0.039*	0.023*
	(0.057)	(0.027)	(0.054)	(0.037)	(0.041)	(0.042)
Yield Spread	0.510*	0.454*	-0.129	0.514*	0.471***	1.139*
	(0.184)	(0.135)	(0.369)	(0.184)	(0.267)	(0.162)

**means the coefficient is significant at 1 % **means a coefficient is significant at 5 %, the number in brackets represent standard errors*

The results show that the equity market return coefficient is significant and positively affects the returns of all banks. The volatility index is also significant but the impact varies with the banks. The coefficient of the volatility index is negative for the four largest banks in our sample namely Standard bank, Barclays Africa, Nedbank and First Rand Bank. For Capitec and African bank the coefficient of the volatility index is positive. The difference in market volatility effects can be attributed to different ways in which banks rely on non-traditional sources of funds, the different levels of non-performing loans and the proportion of loans in their assets. This implies that under circumstances of high market volatility only African bank and Capitec bank would be attractive investments. The yield spread was found to be significant at 10 percent level of significance for Nedbank while being significant at 1 percent for all other banks. The results indicate that the yield spread does not influence the returns of African Bank at the one percent quantile since the variable was found to be insignificant but at the same time negatively affecting the returns of all the other banks. While we expect returns to fall as the yield spread increases, African Bank appears to be insulated from that reality by its own peculiar situation during our sample period. As the yield spread is used a proxy for the business cycle a higher yield spread indicates future sluggish growth and higher inflation hence with the higher expected inflation stock prices tend to be negatively affected due to higher interest rates.

Having gotten the regression results the next step is to calculate 1 percent VaR for all the banks using equation (9). Table 2 below presents the summary statistics daily 1 % VaR.

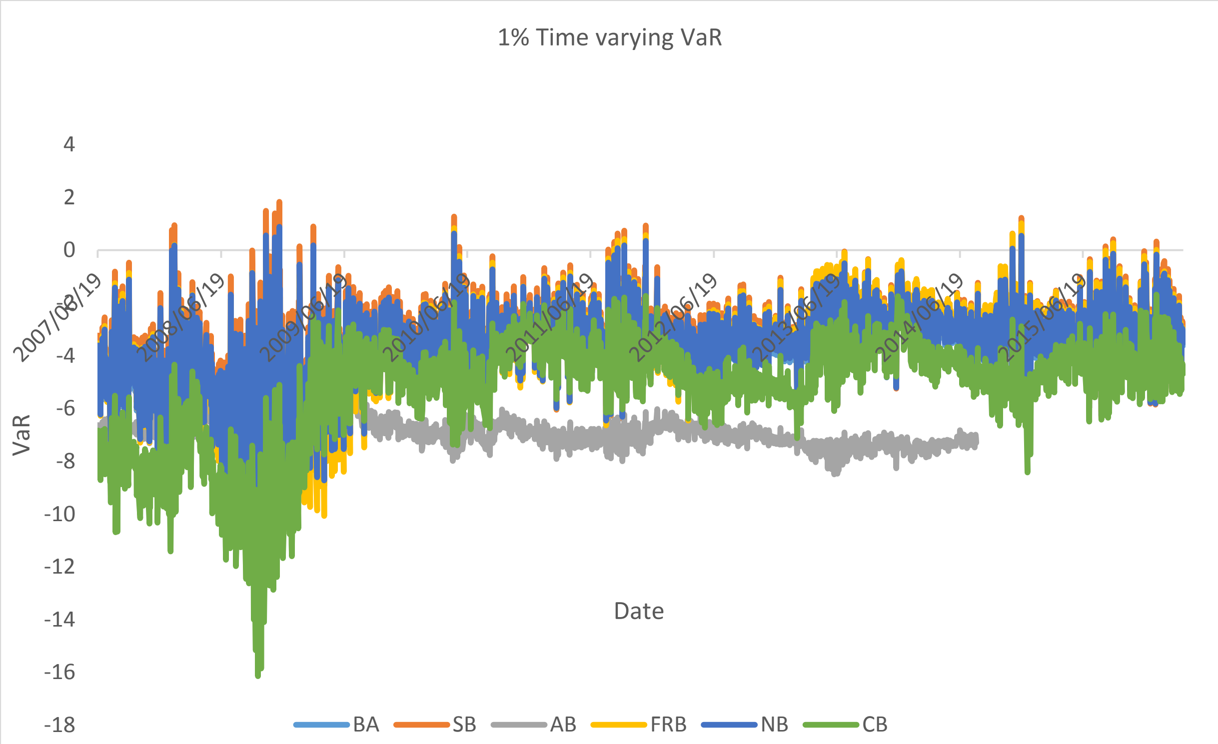
Table 2: Summary statistics for 1% VaR

	mean	st.d	min	max
Barclays Africa	-3.867	1.387	-12.510	-0.283
Standard Bank	-3.498	1.685	-14.010	1.830
African Bank	-6.803	0.659	-8.492	-3.696
First Rand Bank	-3.734	1.776	-14.060	1.016
Nedbank	-3.745	1.588	-13.620	-0.885
Capitec Bank	-5.254	2.040	-16.140	-1.677

Table 2 shows that over our sample period Standard bank was on average the least risky bank with an average VaR of -3.498 while at -6.803 (on average) African Bank seems to be the riskiest bank in isolation. Capitec is found to be the second most risky bank (-5.254) and has the most volatile VaR as measured by the standard deviation, while also interestingly having the highest VaR recorded over the sample period. We can sum up table six by stating that there is 99% probability that African bank, Nedbank, First Rand and Standard Bank will on average lose more than 6.8%, 3.7%,3.7% and 3.5% respectively. To have a clear understanding of the dynamics of the VaR over time we plot the 1% VaR for all the six banks. From Figure 1 below we notice that all the bank's VaR follow a similar pattern to the corresponding returns with VaR increasing abruptly for all banks during the 2008 global financial crisis. This is in line with what we expect since stock prices tend to drop during crises hence leading to an increase in risk. Overall, we observe that the VaR for Capitec and African bank seem to be always higher than that of all the other banks suggesting that at the 99% confidence level they are the riskiest banks in isolation. Before 2010 market stability prevailed with all banks alternating randomly in having the highest VaR. However, as from mid-2010 African bank's deteriorating

Figure 1: 1% VaR

market position can be deduced from its having the consistently highest VaR until its bankruptcy in 2014.



Before proceeding to estimate the CoVaR we implement the Kupiec Test and the Independence test to back test the VaR for all banks. The results are presented in Table 3 and Table 4 below.

Table 3: Unconditional coverage test results

	Actual exceed	expected.exceed	critical.v	LRstat
Barclays Africa	19	22	6,634	0.444
Standard Bank	20	22	6,634	0.196
African Bank	17	17	6,634	0.04
First Rand Bank	20	22	6,634	0.196
Nedbank	21	22	6,634	0.05
Capitec Bank	20	22	6,634	0.196

The LR statistic is less than the LR critical for all the banks leading us to conclude that we fail to reject the Null hypothesis of correct exceedances. The results indicate that all the VaR models are good.

Table 4: Joint test results

	Critical value	LRstat
Barclays Africa	9.210	2.465
Standard Bank	9.210	2.041
African Bank	9.210	7.075
First Rand Bank	9.210	6.502
Nedbank	9.210	1.730
Capitec Bank	9.210	

The joint test whose results are the in Table 8 show that our VaR models are accurate as we couldn't reject the null hypothesis of correct and independent exceedances. Thus we can conclude that our VaR models have both correct and independent exceptions, hence we can proceed to use them in calculating the CoVaR.

4.3. CoVaR

After successfully back testing our VaR models and proving that the models are credible we thereafter estimate the returns of the banking system using quantile regression at 1 percentile. To this end we ran the quantile regression of the banking system's returns six times since we have six different banks. Equity market return, market volatility, yield spread and individual bank returns are our independent variables, with the banking system returns now becoming our dependent variable. The estimation results are presented in Table 5.

Table 5: Quantile Regression for system on individual banks

	SystemBA	SystemSB	SystemAB	SystemFR	SystemNED	SystemCAP
Intercept	-1.927*	-1.324*	-2.773*	-1.220*	-1.622*	-2.745*
	(0,511)	(0,319)	(0,526)	(0,334)	(0,602)	(0,493)
Equity Return	0.356**	0.292*	0.922*	0.223*	0.477*	0.941*
	(0,146)	(0,08)	(0,129)	(0,042)	(0,155)	(0,095)
Volatility Index	-0.026***	-0,016	-0,024	-0.034**	-0.047**	-0,03
	(0,016)	(0,015)	(0,016)	(0,015)	(0,021)	(0,021)
Yield Spread	0.255**	0.176*	0.431*	0.181*	0.344*	0.463*
	(0,11)	(0,029)	(0,111)	(0,04)	(0,113)	(0,071)
Barclays Africa	0.668*	-	-	-	-	-
	(0,101)					
Standard	-	0.740*	-	-	-	-
		(0,049)				
African Bank	-	-	0,034	-	-	-
			(0,059)			
First Rand	-	-	-	0.730*	-	-
				(0,036)		
Nedbank	-	-	-	-	0.585*	-
					(0,099)	
Capitec	-	-	-	-	-	0.227*
						(0,049)

*Xi denotes the returns of bank i *means the coefficient is significant at 1 % **means a coefficient is significant at 5 %, the number in brackets represent standard errors*

Table 5 shows that the equity market return and yield spread are both significant and positively affect the returns of the banking system. The volatility index is significant and negatively affect the returns of the banking sector as expected except when we run the model involving Capitec and African bank where the variable was found to be insignificant. The returns of all the banks were found to be significantly influencing the returns of the banking sector except for African Bank. The results also indicate that market equity return positively influences the banking sector's returns. Having ran a quantile regression of the returns of the banking sector, we calculated the CoVaR which was obtained from the predicted values of the regression results with the 1 percent VaR of the banks now replacing the returns of the banks (see equation (12)). We replace the banks' returns because the CoVaR is the VaR of the banking system given that the individual banks are in distress (i.e. at their VaR). Table 6 reports the descriptive statistics of the VaR of the banking system given that the different banks are in distress (i.e. CoVaR). The average CoVaR given that Barclays Africa is in distress is shown to be the highest whilst that of African bank is observed to be the lowest. Our table would seem to support the inference that on average the 1 percent VaR of the banking system tends to be highest when Barclays Africa is in distress compared to when any other bank is in distress. However, this is not sufficient to justify the conclusion that Barclays Africa contributes most to systemic risk as CoVaR alone cannot convey that information and we would need ΔCoVaR for the purpose. The CoVaR reaches its highest value when Capitec bank is in distress with the banking sector having a 99 percent probability of losing more than 15.9 percent on a given day.

Table 6: Summary statistics for 1% CoVaR (bank i in distress)

	CoVaR-BA	*CoVaR-SB*	*CoVaR-FRB*	*CoVaR-NB*	*CoVaR-CB*	*CoVaR-AB*
Mean	-4,773	-4,051	-4,487	-4,417	-3,988	-3,036
Median	-4,469	-3,761	-4,133	-4,066	-3,628	-2,781
Standard Dev	1,612	1,759	1,807	1,879	1,92	1,516
Kurtosis	3,284	3,383	2,629	3,042	3,559	3,286
Skewness	-1,362	-1,230	-1,246	-1,295	-1,374	-1,21
Range	13,75	16,018	14,727	15,87	16,861	13,722
Minimum	-14,515	-14,935	-14,604	-15,516	-15,936	-12,163
Maximum	-0,766	1,083	0,123	0,354	0,925	1,559

CoVaR-BA stands for CoVaR given Barclays Africa, CoVaR-SB stands for CoVaR given Standard Bank, CoVaR-AB stands for CoVaR given African Bank, CoVaR-NB stands for CoVaR given Nedbank, CoVaR-CB stands for CoVaR given Capitec, CoVaR-FRB stands for CoVaR given First Rand,

4.4. ΔCoVaR Results: Contribution of banks to systemic risk

Having estimated CoVaR we can now deduce the marginal contributions of each bank to the banking sector's systemic risk by calculating ΔCoVaR. We use equation (14) to obtain ΔCoVaR which reports the increase in the VaR of the banking sector when bank i is in distress (i.e. at its VAR). ΔCoVaR is the difference between the VaR of the system when a bank is operating normally and its VaR the bank is in distress (at its 1% VaR). ΔCoVaRs are negative but the interpretation is based on absolute values as we are only interested in the additional

VaR imposed to the banking system by bank i when it moves from normality to distress. Thus the bank with the largest absolute ΔCoVaR contributes most to systemic risk.

To rank the banks in terms of their contribution to systemic risk of the banking sector we take a look at the summary statistics for ΔCoVaR in Table 7.

Table 7: Summary Statistics for 1% ΔCoVaRs for all banks

	mean	st.d	min	max	Ranking
Barclays Africa	-2,586	0,606	-4,65	-1,542	2
Standard Bank	-2,587	0,669	-5,172	-1,443	2
African Bank	-0,232	0,018	-0,262	-0,159	6
First Rand Bank	-2,780	0,829	-5,253	-1,539	1
Nedbank	-2,177	0,514	-4,148	-1,303	4
Capitec Bank	-1,214	0,42	-3,157	-0,525	5

Table 7 reveals that First Rand is on average the most systemically important bank in South Africa with an average ΔCoVaR of -2.78. In practical terms, 2.78 basis points is being added to the VaR of the banking system when First Rand Bank moves from a normal state into distress. This result is in keeping with the too big to fail (TBTF) thinking which holds that banks tend to be as systemically important as they are large. The second largest bank, Standard bank has the second highest contribution to systemic risk with a ΔCoVaR of -2.587. Following according to size are Barclays Africa at ΔCoVaR -2.586, Nedbank at ΔCoVaR – 2.177, Capitec at ΔCoVaR -1.214 and African Bank at ΔCoVaR -0.232.

Figure 2 below plots daily 1% ΔCoVaR for the six banks. The graph shows that African Bank's ΔCoVaR is always close to zero and its plot is always above those of the other banks. This means that African bank is the least contributor to systemic risk of the banking sector over the sample period even though it is the riskiest in isolation as measured by its VaR. A closer look at the graph shows that African bank's contribution to systemic risk did not change much between 2007 and 2014. Capitec Bank is the 2nd least contributor to systemic risk but its contribution, unlike that of African Bank, changes over time with a significant increase coming during the 2008 global financial crisis.

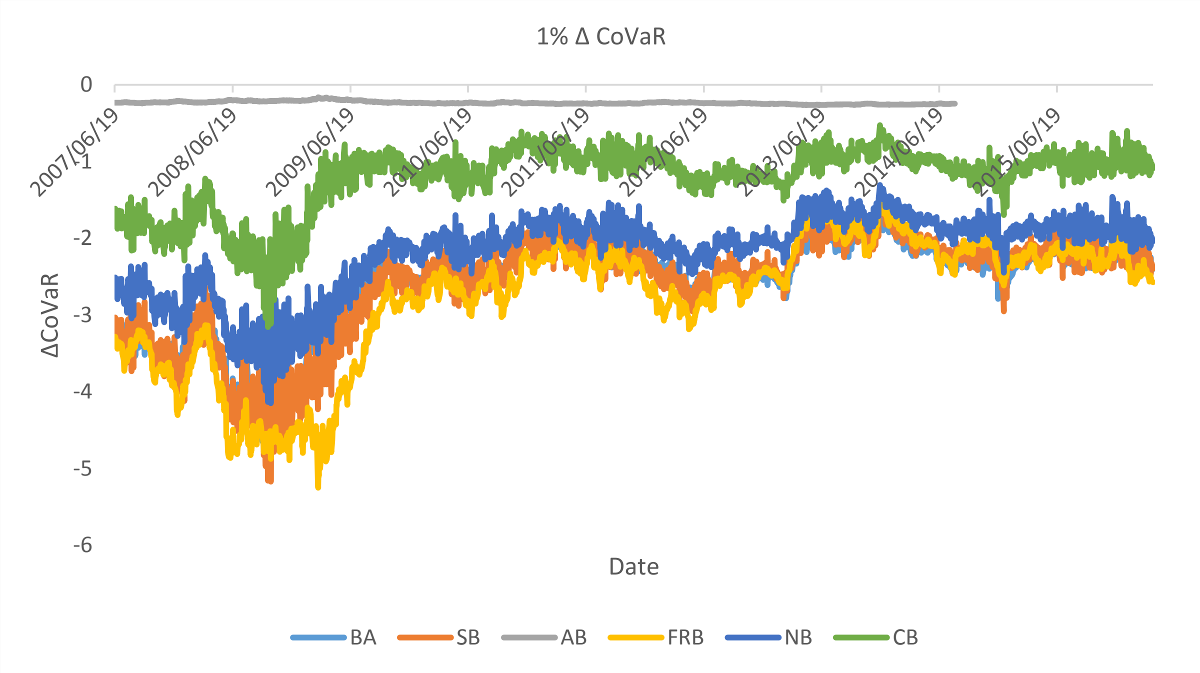


Figure 2: Δ CoVaR

The other four banks have ΔCoVaRs that move together and are very volatile with the highest contribution from these banks coming in the middle of the global financial crisis in 2008. This is illustrated in Figure 2 by the huge drop in the four plots representing the four largest banks. Figure 2 also shows that Standard and First Rand Bank are the two biggest contributors to systemic risk with their plots alternating as most lowly placed for the entire period under consideration.

What would have happened if one of the larger banks had collapsed instead? Would the banking system have survived? The relatively larger ΔCoVaR of all the other banks would seem to suggest that a crisis would have ensued in the banking sector. As the top four banks are heavily interconnected through interbank clearing and are all consider TBTF it is very likely that there would have been a domino effect of negative contagion. This validates our results as in line with those of Banulescu and Dumitrescu (2015) who find that the largest financial institutions pose the biggest threat to the system when they are in distress. In isolation, smaller banks like Capitec seem to be as risky as the larger banks as measured by the 1% VaR. In the current micro prudential regulatory environment smaller banks like African Bank and Capitec are subjected to the same level of oversight and heightened capital requirements as the larger banks even if they are not too big to fail. But if we are to look at the impact of these banks on the whole system we realize that this kind of regulation isn't enough because of systemic risk. The answer would seem to be macro prudential regulation as suggested in Basel III and to which this study is intended as contribution.

4.5. Network ΔCoVaR: The linkages in the banking sector

The previous section focused on examining the impact of a stressed bank on the entire banking sector. In order to show the linkages that exist in our banking sector we employ the concept of Network CoVaR which investigates the impact of an individual distressed bank on another bank not on the system. Network CoVaR also allows us to investigate the direct reciprocities between two banks in terms ΔCoVaR and to rank all the banks according to how they are affected by an individual distressed bank. To develop the network CoVaR we modify the definition of the CoVaR. Instead of measuring the VaR of the banking system when bank i is in distress, now we calculate the VaR of bank j given that bank i is in distress. This can be represented as follows

$$\Pr\left(X_t^j \leq CoVaR_{t,q}^{j|i} | X_t^i = VaR_{t,q}^i\right) = q \tag{16}$$

Where X_t^j are the returns of bank j and X_t^i are the returns of bank i.

$$\Delta CoVaR_{t,q}^{j|i} = CoVaR_{t,q}^{j|i} - CoVaR_{t,q=0.5}^{j|i} \tag{17}$$

The estimation steps are similar to those used in finding the ΔCoVaR in the previous section. Table 8 presents the average ΔCoVaR for bank j given bank i. The columns represent banks that are in distress while the rows represent banks that are being affected by the distress of bank i. This ΔCoVaR is what bank i adds to the VaR of bank j when it's in distress.

Table 8: 1% Network ΔCoVaR

BANK j/BANK i	Barclays Africa	Standard	African Bank	First Rand	Nedbank	Capitec
Barclays Africa		-2,575	-1,12	-2,962	-2,491	-1,636
Standard Bank	-2,380		-0,328	-2,231	-1,975	-1,177
African Bank	-2,380	-0,413		-0,714	-0,033	-1,184
First Rand Bank	-2,948	-2,848	-0,409		-0,481	-1,303
Nedbank	-2,366	-2,423	-0,033	-2,241		-1,584
Capitec Bank	-1,843	-0,8594	-0,954	-1,617	-1,643	

For example, in row one column two we have -2.575 meaning that when Standard bank moves from being in a normal state to being in distress (1 percent VaR), Barclays Africa's VaR increases by 2.575 basis points. However, looking at row two column one we can see that Barclays by being in distress they increase the VaR of Standard bank by 2.380 basis points. These results show that Barclays has a larger impact on Standard bank than Standard has on it. We also observe that Capitec bank is the bank that suffers the least while First Rand suffers the most if Barclays Africa were to go into distress meaning that Capitec is the most vulnerable to Barclays Africa. If Standard bank were to get into financial trouble the VaR of First Rand will increase by 2.848 basis points making it the biggest loser. On the other hand, if First Rand were to go into crisis Standard bank will not be the biggest loser, that position will be taken by Barclays Africa. A distressed African Bank seems to have the smallest impact on other banks as was borne out by the facts in 2014 when the bank was placed into curatorship by the South African Reserve Bank. A move from its median state to a state of distress by Capitec also poses little threat to other banks but Barclays seems to be the most linked bank to Capitec with the highest ΔCoVaR. The results further reinforce the need to especially regulate the too big to fail banks as it is clear that impact of distressed larger banks on the others much bigger compared to that of the smaller banks. The too big to fail banks appear to have a case of interlinkages and interconnectedness as revealed by reciprocal network ΔCoVaR.

5. Conclusion

The recent global financial crisis highlighted, to regulators and academics alike, the importance of understanding the causes and effects of systemic risk, particularly in the financial and capital markets but also in the broader economy. Our study's objective was to empirically investigate systemic risk within the South African banking sector using the most current analytical and modelling tools available, with the aim of identifying the most systemically important banks over the relevant period. We make use of Adrian and Brunnermeier's (2008) CoVaR technique which is defined as the VaR of the whole banking sector given that one of the banks is in distress. Quantile regression is employed to estimate the daily VaR and then CoVaR. In both these processes we use equity market return, market volatility and yield spread as independent variables in the quantile regression.

All our VaR models are validated by employing back testing procedures by Kupiec (1995) and Christoffersen (1998). To measure the marginal contributions of each bank to systemic risk, we then calculate ΔCoVaR which is the difference between CoVaR when individual banks are in a normal state and CoVaR when they are in distress.

Using data collected for the period 19 June 2007 to 11 April 2016, our results indicate that First Rand Bank is the largest contributor to the banking sector's systemic risk. Our findings also indicate that the contribution of banks to systemic risk is linked to the size of the banks, with the larger banks contributing more than the smaller ones. Thus African bank was found to have the smallest impact on the system hence in the event, African Bank became insolvent during the course of 2014 and the relative efficiency with which the resulting threat of contagion was managed would appear to support our results.

Overall the results show that the named 4 larger banks contribute more to systemic risk than the 2 smaller banks. This would imply that greater market instability is to be expected when any number of the larger banks are in distress than when the smaller banks suffer the same fate. The results we found are in line with those of Roengpitya and Rungcharonkitkal (2010) who concluded that in the Thai banking sector the bigger banks pose the largest threat to the banking system and support the now widely held opinion that no financial institution should be too big to fail (TBTF).

Another interesting observation from our 1% ΔCoVaR we made is that the contribution of banks to systemic risk tends to increase during times of financial crises with African bank being an interesting exception probably because its ΔCoVaR is much lower. After applying the network ΔCoVaR we found that there are very strong linkages within the South African banking sector, implying that if one bank were to go into a crisis the other banks would be disproportionately negatively affected. However, African bank is seen to have very little impact on other banks when it is in distress. Seen from an operational vantage, this could be because African Bank enjoys little presence as a clearing institution but is a significant personal lending business. Therefore, its propensity to spread negative contagion is curtailed in proportion with its interbank activity.

While we have elected to use quantile regression to estimate CoVaR, other methods like Copulas and Multivariate GARCH models which are equally usable and somewhat more extensible in that they can explain the tail dependence between the returns of the banks and those of the system can be used. There is great scope for further research. A direction that may be useful to follow would bel to substitute the returns of the banks with relevant data from their financial statements thereby utilising a class of data that is more closely related to the supply of credit in the economy.

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