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SYSTEMIC RISK AND REAL ECONOMIC ACTIVITY: A SOUTH AFRICAN INSURANCE STRESS INDEX OF SYSTEMIC RISK

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ABSTRACT

This study investigates the link between systemic risk in the South African insurance sector and real economic activity in South Africa. To this end, we use six systemic risk measures, the Conditional Value at Risk (CoVaR), the Marginal Conditional Value at Risk (ΔCoVaR), the Comovement and Interconnectedness of the South African insurance sector (Eigen), the Dynamic Mixture Copula Marginal Expected Shortfall (DMC-MES), the Average Conditional Volatility (Ave-vol), and the South African Volatility Index (SAVI). We first evaluate the significance of each measure by assessing its ability to forecast future economic downturns in South Africa. We find that only two systemic risk measures possess the ability to predict future economic downturns in South Africa. We then use principal component quantile regression analysis to aggregate these measures into a composite stress index of systemic risk for the South African insurance sector and assess the ability of the proposed index to predict future economic downturns in South Africa. Our results reveal that the proposed index is a good predictor of future economic downturns in South Africa. Thus, our results suggest that regulators and risk managers must develop an analysis of systemic risk in the insurance sector with particular attention to its effects on real economic activity. In addition, our index can potentially be used as an instrument to monitor and mitigate systemic risk in the insurance sector in order to ensure the stability of the financial system and the economy in South Africa.

Keywords: systemic risk, insurance sector, quantile regression, macroeconomy

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INTRODUCTION

The 2007–2009 financial crisis has revealed that the failure to provide appropriate regulatory framework of the financial system alongside extreme risk taking by some financial institutions, drove the global financial system to the edge of systemic disaster. The crisis began in the U.S. real estate sector, quickly spread to the whole financial sector through contagion with devastating effects on the global economy. According to the International Monetary Fund (IMF, 2009) systemic risk is "the risk of extensive disturbance to the delivery of financial services that is triggered by an impairment of all or parts of the financial system, which can cause severe adverse effects on economic activities."

Prior to the recent financial crisis, financial regulators were concerned with monitoring idiosyncratic risk (micro-prudential regulatory framework) but the crisis has highlighted the importance of moving from micro-prudential to macro-prudential regulatory framework. As a consequence of the crisis, policy makers and regulators such as the Dodd Frank Act, the Basel committee on Banking Supervision and Solvency II among others, have passed new regulations in the financial sector to prevent future financial crises and limit their subsequent economic impact. In addition, academics have become interested in developing tools for monitoring systemic risk. Hence, the past decade has witnessed an increase in the number of studies which develop techniques to measure systemic risk (see, for example, Adrian & Brunnermeier, 2008; Acharya et al., 2010; Brownlees & Engle, 2011; Girardi & Ergün, 2013, among others).

The role played by some insurance companies in the 2007–2009 financial crisis has raised concerned about whether the insurance sector contributes to systemic risk. Consequently, some studies have focused on the systemic risk relevance of the insurance sector. Among these studies are Acharya and Richardson (2014) who provide a ranking for 20 insurance companies in the United States by employing the Credit Default Swaps Marginal Expected Shortfall (CDS-MES). They find that Genworth Financial Inc., AMBAC Financial Group Inc, MBIA Inc, and AIG were the most systemically risky insurers, respectively, during that time. Based on their finding, they conclude that the insurance sector may contribute to systemic risk as many insurers are conducting non-traditional business activities such as CDS writing and offering financial product with non-diversifiable risk.

Bierth et al. (2015) employ ΔCoVaR, MES and SRISK as measures of systemic risk to study the exposure and contribution to systemic risk of 253 life and non-life insurers across the world. They find the interdependence between large insurers and the insurance sector to be a significant driver of the insurers' exposure to systemic risk. They also argue that the contribution of insurers to systemic risk appears to be principally driven by the insurers' leverage. Weiß and Muhlnickel (2014) examine systemic risk for 89 U.S. insurers for the period of the financial crisis using ΔCoVaR, MES, and SRISK as systemic risk measures. Their findings reveal that size is the main driver of insurers' exposure and contribution to systemic risk in the U.S., and the exposure to systemic risk additionally depends on non-traditional and non-insurance activities like CDS writing.

Nevertheless, it is important to distinguish systemic risk from the one of an 'ordinary' crisis. Eling and Pankoke (2012) explain that the difference between the two lies in the fact that an 'ordinary' crisis does not go beyond the financial system range, whereas systemic risk implies a severe impairment of financial services with an adverse effect on the rest of the economy. In this regards, some researchers have explored the link between systemic risk and real economy activities (see, for example, Hollo et al., 2012; Allen et al., 2012; Kubinschi & Barnea, 2016, among others). As mentioned in their study, Giglio et al. (2016) argue that systemic risk measures should not only be used to assess an institution's contribution or vulnerability to systemic risk but should also be demonstrably associated with real macroeconomic outcomes.

However, to the best of our knowledge, no studies have investigated the link between systemic risk in the insurance sector and macroeconomic activity. The majority of studies in this strand of the literature have focused on the whole financial sector or the banking sector. Moreover, research on the aggregation of systemic risk measures into a composite stress index and its relationship with the economy is still scarce in emerging economies like South Africa. Thus, our paper seeks to address this gap by constructing a composite stress index of systemic risk for the South African insurance sector to predict future economic downturns in South Africa.

To achieve our objective, we employ six systemic risk measures, the conditional value at risk (CoVaR), the marginal conditional value at risk (ΔCoVaR), the comovement and interconnectedness of the South African insurance sector (Eigen), the dynamic mixture copula marginal expected shortfall (DMC-MES), the average conditional volatility (Ave-vol), and the South African volatility index (SAVI). We first evaluate the significance of each systemic risk measure by assessing its ability to forecast future economic downturns in South Africa. We then use principal component quantile regression to aggregate these measures into a composite stress index of systemic risk and assess its ability to predict future economic downturns in South Africa. The main advantage of quantile regression analysis is that it focuses on the conditional-quantile function describing how a set of independent variables and specific quantiles of the dependent variable are related. Thus, quantile regression deals very well with the tail of a distribution, making it a suitable model to estimate the lower quantile of a dependent variable on the available set of explanatory variables.

Our focus on the South African insurance sector is not random, but rather driven by the fact that, despite being an emerging country, South Africa has an insurance sector that is well established and plays a vital role in the South African economy. The National Treasury of South Africa (2011) states that the insurance sector is an essential component of the South African financial system and economy by being the guardian of the stability of the whole financial system and an important source of capital for investment. In addition, according to the Insurance Institute of South Africa (2016), the insurance sector accounts for 23% of financial assets in South Africa in 2016 and contributed R18 billion to the country's revenue base in 2015, implying that the insurance sector is a driver of the South African economy. Thus, a failure of one or more insurance companies may disrupt the financial system, which may lead to systemic risk. Therefore, our research indicates that regulators and risk managers must develop an analysis of systemic risk in the insurance sector with particular attention to its effects on real economic activity.

Our results show that our insurance stress index of systemic risk is a significant predictor of future economic downturns in South Africa, suggesting that the proposed index can potentially be used by regulators and policy makers as a tool to monitor and mitigate systemic risk in the insurance sector to ensure the stability of the financial system and the economy in South Africa.

LITERATURE REVIEW

The literature on systemic risk has rapidly increased since the beginning of the 2007–2009 financial crisis. One strand of the literature on systemic risk assesses an institution's contribution or vulnerability to systemic risk by providing different systemic risk measures.

Billio et al. (2012) use principal component analysis and linear Granger causality test to capture the interdependence between banks, insurers, hedge funds, and brokers in the United States. The results show that all four sectors have become highly interconnected, intensifying the level of systemic risk in the finance and insurance industries.

Cummins and Weiss (2014) employ qualitative and correlation analysis to investigate systemic risk in the U.S. insurance sector. Their findings reveal that, even though traditional activities of insurers do not contribute to systemic risk, non-traditional activities of insurers (trading in derivatives, asset lending, etc.) constitute a potential source of systemic risk. Similarly, Berdin and Sottocornola (2015) apply the linear Granger causality test, ΔCoVaR, and MES to assess systemic risk in the banking sector, insurance sector, and non-financial sectors in Europe. Their results show that, although the insurance sector plays a less important role in causing systemic risk compared to the banking sector, it shows a persistent systemic relevance over time. Furthermore, Berdin and Sottocornola (2015) contend that insurance companies that engage more in non-traditional and non-insurance activities tend to pose more systemic risk.

Dungey et al. (2014) assess systemic risk in the banking sector, insurance sector, and other sectors of the U.S. economy by using the eigenvector centrality measures. They find that despite the fact that the banking sector is the most systemically risky financial sector in the U.S., the insurance sector is becoming a systemically risky sector through interdependence with the financial sector and the real economy. Similar conclusions are drawn by Denkowska and Wanat (2020), who employ a copula-DCC-GARCH model and CoVaR to analyse systemic risk in the European insurance sector between 2005–2018. They find that the European insurance sector contributes more to systemic risk during financial market distress because of the stronger interdependence between insurance companies.

Kaserer and Klein (2019) employ CDS-implied systemic risk measure to investigate how insurance companies contribute to systemic risk in the global financial system represented by 201 largest banks and insurers from 2004 to 2014. Their results show that the insurance sector contributes relatively little to the aggregate systemic risk. However, several multi-line and life insurers appear to be as systemically risky as the riskiest banks.

An alternative strand in the literature investigates the link between systemic risk and macroeconomic activity. Van Roye (2011) constructs a financial stress indicator based on principal component analysis to predict future economic activity in Germany and the Eurozone. He finds that an increase in the financial stress indicator leads to a significant dampening of GDP growth in Germany and the Eurozone. The author also finds that about 15% of the variation in real GDP growth can be accounted for variations in the proposed financial stress for Germany and about 30% in the Eurozone.

Hollo et al. (2012) construct a Composite Indicator of Systemic Stress (CISS) for the Eurozone using 15 financial, monetary, and economic indicators. Their results reveal the CISS can serve as an early warning indicator for the slowing down of economic activity in the Eurozone. Similarly, Allen et al. (2012) develop the catastrophic risk in the financial sector (CATFIN), derived from the aggregation of systemic risk measures for the U.S. banking sector. They evaluate the forecasting accuracy of the CATFIN on future economic downturns using a multivariate predictive regression model. The findings show that the CATFIN can robustly predict the downside of economic activity for about a year in advance. These results support the findings of Vermeulen et al. (2015), who develop a financial stress index for 28 OECD countries from 1980 to 2010 with the Equal Weight method using six variables from money market, capital market, banking sector, and exchange rate market. They find that their financial stress index contains relevant information on the downside of real economic activity in the 28 OECD countries.

Giglio et al. (2016) apply several systemic risk measures to predict the downside macroeconomic activity in the U.S., the U.K. and the European Union countries. They employ principal component quantile regression analysis and partial quantile regression to aggregate the systemic measures into a composite stress index. Their main finding reveals that the proposed index can significantly predict macroeconomic downturns in the U.S., the U.K. and European Union countries. Similarly, Chen and Zhou (2016) construct systemic risk measures at the macro and micro levels (CATFIN, DCI, MES, SES, CES, SRISK, CoVaR, and Tail Risk) to monitor systemic risk in the Chinese financial sector and identify the systemically important financial institutions (SIFIs) in China. Their results show that, on the macro level, both CATFIN (tail risk measure) and DCI (Comovement index) have strong predictive power for future economic downturns in China. In this study, we investigate the link between systemic risk in the South African insurance sector and the macroeconomy activity in South Africa as the insurance sector in South Africa plays an essential role in the South African financial system and economy.

In addition, as in Giglio et al. (2016), we employ principal component quantile regression analysis to aggregate the systemic risk measures used in our study into a composite stress index of systemic risk for the South African insurance sector and assess its ability to predict future economy downturns in South Africa.

METHODOLOGY

This section presents an overview of the methodology employed to investigate the relationship between systemic risk in the South African insurance sector and real economic activity.

Quantile Regression

Quantile regression, developed by Koenker and Bassett (1978), is a linear model that studies the relationship between a set of independent variables and specific quantiles of the dependent variable. While the least-square regression focuses on modeling the conditional mean, the quantile regression model is concerned with estimating the conditional quantile of the dependent variable. The key advantage of the quantile regression model is that it does not require any assumption on the distribution of the errors, making it a flexible and convenient model to utilise. Consequently, quantile regression has been widely used in many disciplines such as Biostatistics, Physics, Finance and Economics, etc.

Let us indicate the target variable as y_t. The τ^{th} quantile of y_t is its inverse probability distribution function, denoted

$$Q_\tau (y_t) = inf\{y{:}P(y_t < y) \geq \tau\} \tag{1}$$

The quantile function is also given by solving the optimisation problem below.

$$\underbrace{\min}_{\alpha_\tau \in R} \sum\nolimits_{t=1}^{n} \rho_\tau (y_t - X_{t-1}\alpha_\tau) \tag{2}$$

where $\rho_\tau(x) = x(\tau - I_{x<0})$ denotes the quantile loss function, $0 < \tau < 1$, X_{t-1} represents a set of lagged independent variables, and $I(.)$ denotes the indicator function which can be viewed as a natural extension of ordinary least square.

The conditional quantiles of y_t are linear functions of observables X_{t-1} and it is written as

$$Q_\tau(y_t | X_{t-1}) = \alpha_{\tau,0} + \alpha'_{\tau,x} X_{t-1} \tag{3}$$

A benefit of quantile regression is that the coefficients $\alpha_{\tau,0}$ and $\alpha'_{\tau,x}$ can vary across quantiles, making it a flexible model to apply (Giglio et al., 2016). Thus, in our analysis, we used quantile regression (at $\tau = 0.05$) to assess the impact of each lagged systemic risk measure on the South African GDP growth.

Systemic Risk Measures

In this section, we present how we construct the six systemic risk measures used in our analysis. We summarised the systemic risk measures into three categories as in (Giglio et al., 2016).

Institutional-specific risk

Institution-specific measures assess a specific financial institution's contribution to systemic risk. In our analysis, we apply the conditional value at risk (CoVaR) and the marginal conditional value at risk (ΔCoVaR) developed by Adrian and Brunnermeier (2016). We also use a dynamic-mixture-copula marginal expected shortfall (DMC-MES), a version of the marginal expected shortfall proposed by Eckernkemper (2018).

CoVaR and ΔCoVaR

The CoVaR determines the value at risk (VaR) of the financial system as a whole, given that a specific financial institution is under financial stress. The VaR of a particular financial institution is given as

$$Pr(X^i \leq VaR_q^i) = q\% \tag{4}$$

where X^i represents the (return) loss of institution i for which the value at risk (VaR_q^i) is defined and $q\%$ is the quantile of the conditional probability distribution.

The CoVaR of the financial system given that a specific financial institution i is at its VaR_q^i is expressed as:

$$Pr(X^{sys} \leq CoVaR_q^{sys|i} \mid X^i = VaR_q^i) = q\% \tag{5}$$

where X^{sys} denotes the return loss of the financial system, and $CoVaR_q^{sys|i}$ is the value at risk of the financial system subject to some event of institution i. We use quantile regression to estimate the above equation, with $q = 0.05$.

The ΔCoVaR evaluates the contribution to systemic risk given that a financial firm shifts from a "normal" state to a "stressed" state:

$$\Delta CoVaR^{sys|i} = CoVaR_{0.05}^{sys|i} - CoVaR_{0.5}^{sys|i} \tag{6}$$

DMC-MES

The marginal expected shortfall measures a financial institution's expected equity loss when the market falls below a certain threshold over a given period. The key advantage of the DMC-MES is that it can capture dynamic, symmetric, and asymmetric dependence together in one framework. It is expressed as follows:

$$\begin{aligned} DMC\text{-}MES_{i,t} = \widetilde{w}\ \frac{\sigma_{i,t}}{\alpha} \int_0^1 G_i^{-1}(v_i)\ .\ \frac{\partial C_{1,t}(v_i, \alpha; \theta_{1,t})}{\partial v_i}\ dv_i \\ + (1 - \widetilde{w})\ \frac{\sigma_{i,t}}{\alpha} \int_0^1 G_i^{-1}(v_i)\ .\ \frac{\partial C_{2,t}(v_i, \alpha; \theta_{2,t})}{\partial v_i}\ dv_i \end{aligned} \tag{7}$$

where $\widetilde{w}$ is the copula weight, $\sigma_{m,t}$, $\sigma_{i,t}$ represent the volatility of the market and an institution i, $\alpha = G_m(\kappa)$, with $\kappa = \dfrac{C_t}{\sigma_{m,t}}$, $C_t = 0.05$, G_m is the marginal distribution of the market. G_i^{-1} is the quantile function, C_t represents the copula of the market and institution innovation and θ_t is the dynamic copula parameter, $v_i = G_i(\varepsilon_i)$ with G_i is the marginal distribution of institution i, and is institution i innovation.

Comovement and interconnectedness

Comovement and interconnectedness among the asset returns of the five insurers can be found by using principal components analysis (PCA), a dimensionality reduction technique that is often used to reduce the number of variables of a dataset while preserving as much information as possible. We compute the five insurers covariance matrix as follows:

Let us assume that the first K principal components, the P_{jt}, j = 1 to 5, explain most of the variability in returns, the model is:

$$R_{it} = \alpha_i + \beta_1 P_{1t} + \ldots + \beta_5 P_{5t} + \varepsilon_{it} \tag{8}$$

where $E[\varepsilon_{it}\varepsilon_{i't}] = 0$ for any $i \neq i'$. Using matrices, the covariance matrix Σ of the vector of returns is:

$$Var[R_t] \equiv \Sigma = G\Theta G', \Theta = \begin{bmatrix} \Theta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Theta_5 \end{bmatrix} \tag{9}$$

where the diagonal elements of Θ, Θ_1 to Θ_5, are the eigenvalues, and G is the matrix of eigenvectors.

Volatility

Volatility is commonly described as a sign of uncertainty, posing a threat to the stability of the financial system. Hence, in this section, we consider two volatility measures as an indication of systemic risk.

1. *South African Volatility Index (SAVI)*: Introduced by the Johannesburg Stock Exchange in 2007, the SAVI provides information on distress in the South African financial sector and market sentiment.
2. *Average Conditional Volatility:* We used the GJR-GARCH model developed by Glosten et al. (1993) to estimate the average conditional volatility of the five South African insurers used in this study.

The mean equation is given as

$$r_t = \mu + \varepsilon_t \tag{10}$$

where μ is the expected return and ε_t is a zero-mean white noise.

The variance equation is expressed as

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{11}$$

where $I_{t-1} = 0$ if $\gamma_{t-1} \geq \mu$ or $I_{t-1} = 1$ if $\gamma_{t-1} < \mu$.

However, due to data availability, especially in terms of time series length, we did not include in our study measures like exchange rate volatility, the TED spread, or the long-term spread (LTS), etc.

The South African Insurance Stress Index of systemic risk

This section presents how we construct the South African Insurance Stress Index of systemic risk. We apply principal component quantile regression to aggregate the six systemic risk measures into a composite stress index of systemic risk for the South African insurance sector. We then use the proposed index as a regressor to estimate the lower quantile ($\tau = 0.05$) of the South African GDP growth. Let us assume that the τ^{th} quantile of H_t conditional on available information L_{t-1} is a function of unobservable latent factors f_{t-1}:

$$Q_\tau(H_t|L_{t-1}) = \gamma f_{t-1} \tag{12}$$

The group of candidate predictors (systemic risk measures) is summarised as an N-dimensional vector s_t, where:

$$s_t = \Lambda F_t + \varepsilon_t \tag{13}$$

where F_t is an r-dimensional vector of latent factors and ε_t denotes the idiosyncratic measurement errors.

The principal components quantile regression predictor of:

$$Q_\tau(H_t|L_{t-1}) = \gamma' F_t = \gamma f_{t-1} \tag{14}$$

is given by $\hat{\gamma}' \hat{F}_t$, where $\hat{F}$ denotes the first P principal components, and $\hat{\gamma}$ is the quantile regression coefficient on those components.

Granger-causality Test

We investigate the directionality of the relationship between the Insurance Stress Index and the South African GDP growth by employing the Granger-causality test, a statistical notion of causality based on the relative predictive power of two variables. Let us denote the series of the South African GDP growth and the Insurance Stress Index by Y and X, respectively. The linear inter-relationship is given as

$$Y_t = \sum\nolimits_{i=1}^{m} a_i X_{t-i} + \sum\nolimits_{i=1}^{n} b_i Y_{t-i} + \epsilon_t \tag{15}$$

$$X_t = \sum_{i=1}^{m} c_i X_{t-i} + \sum_{i=1}^{n} d_i Y_{t-i} + \mu_t \tag{16}$$

where ϵ_t and μ_t are uncorrelated white noise processes, a_i, b_i, c_i and d_i are coefficients in the model, and m and n are the numbers of lags.

Vector Autoregressive Model

The Vector autoregressive (VAR) model is an econometric model representing the correlations among a set of variables, often used to analyse certain aspects of the relationships between the variables of interest. It is a multi-equation system where all the variables are treated as endogenous (dependent). We perform the VAR model through the impulse response function to determine the effect of the Insurance Stress Index on the South African GDP growth.

The VAR(p) model is given by:

$$Y_t = a + A_1 Y_{t-2} + \mathrm{A}_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{17}$$

Where:
$Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$: an $(n \times 1)$ vector of time series variables;
a : an $(n \times 1)$ vector of intercepts;
A_i $(i = 1, 2, \ldots, p)$: an $(n \times n)$ coefficient matrices;
ε_t : an $(n \times 1)$ vector of unobservable *i.i.d* zero mean error term.

The Impulse Response Function enables us to know the response of one variable to an impulse in another variable in a system that involves many variables.

EMPIRICAL ANALYSIS

Data

This paper uses equity prices data for five South African insurance companies and the South African volatility index to construct the systemic risk measures. Data were obtained from the I-net BFA expert-Iress Database spanning the period from November 2007 to June 2020 in order to consider the 2007–2009 financial crisis in our analysis. For the macroeconomic data, as indicated by the OECD (2012), it is possible to use GDP growth as the reference for business cycle fluctuations. Thus, we use the South African GDP growth to represent the business cycle fluctuations in South Africa. The data is available monthly on the OECD database. Due to data availability, we used a sample period spanning from 2008M10–2020M04. Table 1 below provides the list of the South African insurance companies used in our analysis.

Table 1
List of the five South African insurance companies

Company	Symbol	Sector
Discovery Limited	DSY	Life Insurance
Liberty Holdings Limited	LBH	Life Insurance
Momentum Metropolitan Holdings	MTM	Life Insurance
Sanlam Limited	SLM	Life Insurance
Santam Limited	SNT	Nonlife Insurance

Table 2 shows the descriptive statistics for our sample. We observe that Discovery and Sanlam have the highest average daily returns (4.1% and 3%, respectively) while Liberty has the lowest average daily returns (−0.5%) over the sample period. On the other hand, we notice that Sanlam and Discovery exhibit a higher risk, measured by the standard deviation than other insurers with an average standard deviation of 1.959 and 1.957, respectively. In addition, it can be seen from the table that the skewness of the insurers' returns is nonzero while the kurtosis results of the insurers' returns are all above 3, implying that the empirical distributions of the returns exhibit fat tail distribution with means around zero. Hence, our series presents the properties of financial time series. Lastly, when performing the Jarque-Bera test for normality at 5% confidence level, the results show that the null hypothesis of normal distribution is rejected for all series at 5% confidence level, indicating that the series is not normally distributed.

Table 2
Descriptive statistics

	Discovery	Liberty	Momentum	Sanlam	Santam
Mean	0.041	−0.005	0.005	0.03	0.026
S. D.	1.957	1.892	1.868	1.959	1.712
Skewness	−0.527	0.129	−0132	−0.429	−0.474
Kurtosis	12.695	17.853	7.183	7.703	14.13
JB test *p*-value	0.001	0.001	0.001	0.001	0.001

Note: Descriptive statistics of the five insurers' stock returns. JB test, the *p*-value is the probability that the returns are normally distributed, according to Jarque–Bera normality test. The sample period is from 13 November 2007 to 15 June 2020.

Estimation Results

Institutional-specific risk

Table 3 reports the results of the average CoVaR, ΔCoVaR, and DMC-MES for each insurer understudy. We can see that the average CoVaR given that Santam is in distress is the highest while Sanlam has the lowest average CoVaR. Our result would seem to support the inference that on average, the 5% VaR of the insurance sector tends to be highest when Santam is in distress compared to when any other insurer is in distress. However, this is not sufficient to justify the conclusion that Santam contributes the most to systemic risk in the insurance sector as CoVaR alone cannot assert that information. Hence, we would need ΔCoVaR for this purpose. When we look at ΔCoVaR in Table 3, we can observe that Sanlam is, on average the most systemically important insurer in South Africa with an average ΔCoVaR of −0.91. This implies that 0.91 basis point is being added to the VaR of the insurance sector when Sanlam moves from a normal state into a distress state. Since Sanlam is one of the biggest insurers in South Africa, our result is in line with the too big to fail (TBTF) assumption suggesting that financial institutions tend to be systemically important as they are large. The second systemically important insurer, Discovery, has a ΔCoVaR of −0.78, followed by Momentum with ΔCoVaR −0.72, Liberty with ΔCoVaR −0.63, and Santam with ΔCoVaR –0.55.

As far as the DMC-MES measure is concerned, Table 3 tells us that Sanlam is the largest contributor to systemic risk with an average DMC-MES of 1.942, followed by Discovery, Momentum, Liberty, and Santam with an average DMC-MES of 0.983, 0.805, 0.583, and −0.007, respectively. This result supports the previous results obtained in the ΔCoVaR measure.

To sum up, Sanlam and Discovery are the largest contributors to systemic risk, and Santam is the lowest contributor to systemic risk in South Africa based on ΔCoVaR and DMC-MES systemic risk measures.

Table 3
Average weekly CoVaR, ΔCoVaR, and DMC-MES for each insurer (07/1/2008 – 08/6/2020)

	Discovery	Liberty	Momentum	Sanlam	Santam
CoVaR	−1.35	−1.29	−1.36	−1.24	−1.39
ΔCoVaR	−0.78	−0.63	−0.72	−0.91	−0.55
DMC-MES	0.983	0.583	0.805	1.942	−0.007

Figure 1 plots the weekly 5% ΔCoVaR for the five insurers. The graph shows that the five insurers have ΔCoVaRs that move together and are very volatile, with the highest contribution from the insurers coming in the middle of the global financial crisis in 2008 and at the beginning of the Coronavirus pandemic that hits the world in 2020. This is illustrated in Figure 1 by the massive drop in the five plots representing the five insurers. Figure 1 also indicates that Sanlam and Discovery are the two largest contributors to systemic risk, with their plots alternating as most lowly placed for the entire period under consideration.

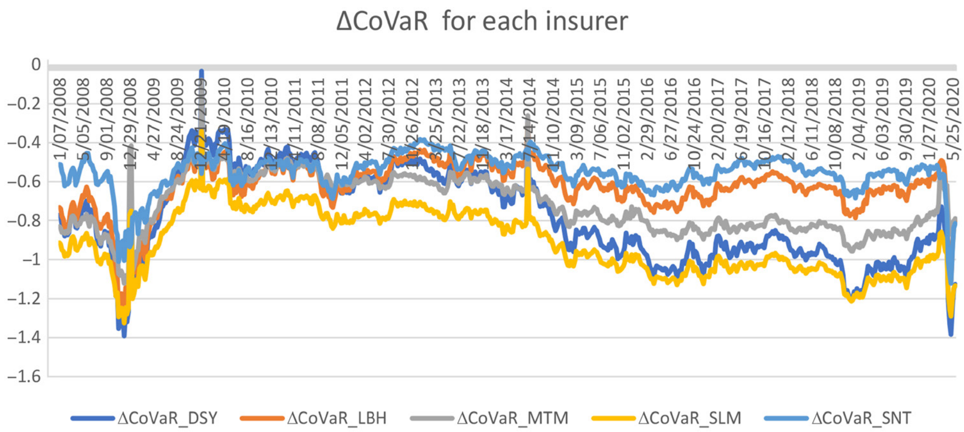

Figure 1. ΔCoVaR of the five insurers (07/1/2008–08/6/2020)

Comovement and interconnectedness

Table 4 presents the different loadings of each insurer on the first component. Based on their results, Zheng et al. (2012) argue that Principal Component Analysis with short-time windows can serve as a measure for systemic risk. Hence, we use a 12-month rolling window in our analysis and find that the first principal component (PC1) has the highest eigenvalue with most of the return variation (70.96%) over the sample period and may serve as an indicator of systemic risk. Our results are in line with Zheng et al. (2012) where they argue that systemic risk is higher when the largest eigenvalue explains most of the variation of the data. In addition, our results show that all insurers have significant loadings on the first component, implying that there is a sign of a high degree of interconnectedness and similar exposure of the insurers (Billio et al., 2012). The results also indicate that the five insurers form part of what is known as the Too Interconnected to Fail (TICTF) institutions, suggesting that South Africa's financial system would be more exposed to systemic risk if one of the insurers is in financial distress.

Table 4
Eigenvectors loadings of PC1

Variables	Discovery	Liberty	Momentum	Sanlam	Santam
PC1	0.44	0.45	0.42	0.5	0.42

Average conditional volatility

Figure 2 exhibits the weekly average conditional volatility of the five insurers using the GJR-GARCH (1, 1) volatility model from 2007 to 2020. From the plot, we identify three periods of instability in the South African insurance sector, which indicates an increase in systemic risk. The first period of instability represents the 2007–2009 financial crisis, implying that the South African insurance sector is exposed to external financial shocks. The second period of volatility begins in late 2015, the indicator rapidly shoots up, indicating a significant increase in systemic risk in the South African insurance sector. Finally, the indicator leads to a significant rise and peak at the beginning of 2020, showing a considerable rise in systemic risk in the South African insurance sector, probably due to the COVID-19 pandemic.

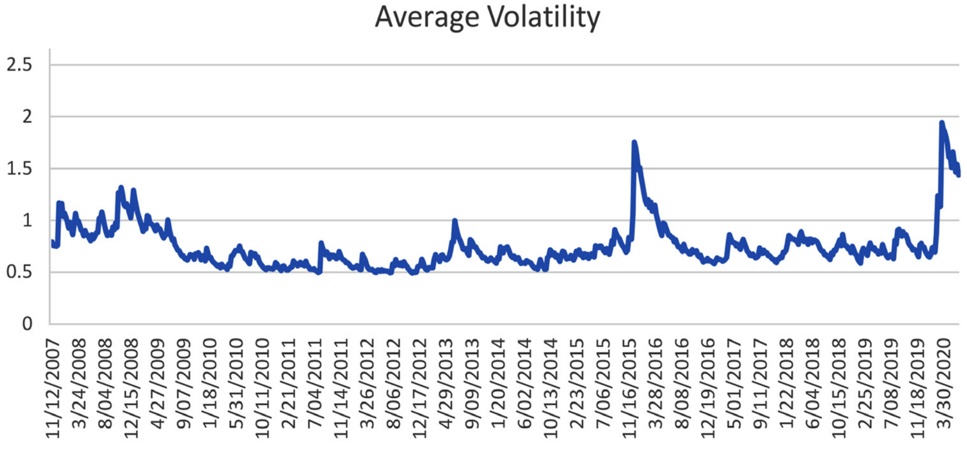

Figure 2. Average conditional volatility of the five insurers (11/12/2007–27/4/2020)

Estimation of Systemic Risk Measures

To assess the forecasting ability of the systemic risk measures, we perform a bivariate quantile estimation of each lagged systemic risk measure on the central tendency (τ = 0.5) and lower quantiles (τ = 0.05) of the South African GDP growth. The results of the estimation are reported in Table 5. It can be observed from the table that, individually, only two systemic risk measures (SAVI and

Eigen) can significantly predict the lower quantile ($\tau = 0.05$) of GDP growth in South Africa.

As far as the central tendency of macroeconomic shocks is concerned, Table 5 indicates that the ΔCoVaR and the SAVI possess predictive ability for the median shock of South African GDP growth.

In summary, our findings indicate that few systemic risk measures are able to significantly predict the lower tail of GDP growth in South Africa. In addition, we find that majority of systemic risk measures are not associated with median shock of the South African GDP growth. Therefore, our results suggest that systemic risk measures capture different facets of macroeconomic shocks as they could be subject to substantial noise.

Table 5
Bivariate quantile regression

Predictors	τ(0.05)	τ(0.5)
CoVaR_{t-1}	−0.45 (−0.52)	−0.07 (−1.45)
ΔCoVaR_{t-1}	−0.62 (−0.73)	−0.15*** (−2.86)
Eigen_{t-1}	−0.42*** (−2.27)	0.07 (1.44)
SAVI_{t-1}	−1.25*** (−7.88)	−0.24*** (−4.52)
$\text{Ave} - \text{vol}_{t-1}$	0.22 (0.97)	−0.02 (−0.24)
$\text{DMC} - \text{MES}_{t-1}$	0.29 (0.67)	0.08 (1.54)

Note: Table reports bivariate quantile forecast regression at τ (5%). Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Only the coefficient and *t*-stat () of the systemic risk measure are reported. Sample is 2008M10 – 2020M02. All dependent and independent variables are normalised before estimation.

The South African Insurance Stress Index of Systemic Risk and the Macroeconomy

Based on our previous findings, we decided to aggregate the systemic risk measures into a more informative composite stress index. Thus, this section presents the step-by-step procedure to get a composite stress index of systemic risk for the South African insurance sector, which we call the Insurance Stress Index. We first use principal component analysis to aggregate the systemic risk measures into a composite stress index. Second, we assess the forecasting ability of the proposed index on future economic downturns in South Africa using quantile regression analysis. Lastly, we perform a robustness test by employing a Vector Autoregression (VAR) model through an impulse response function to determine the response of GDP growth following a shock of the proposed index.

Evaluation of the Insurance Stress Index of systemic risk

As mentioned above, we use principal component analysis to obtain our Insurance Stress Index of systemic risk. Principal component analysis is a technique that helps to produce a smaller number of linear combinations on variables so that the reduced variables account for and explain most of the variance in the correlation matrix pattern.

Table 6 presents the contribution of each systemic risk measure to the first component (PC1). It can be seen from the table that PC1 is responsible for the majority of the variation in the dataset (57.58%). Moreover, the loadings reveal that most of the systemic risk measures are well represented in the common factor, with DMC-MES having the lowest contribution of 18.8% and CoVaR having the highest contribution of 50.9%. Thus, our results reveal that PC1 is indeed the composite stress index for the South African insurance sector.

Table 6
Factor loadings of PC 1

Variables	PC1
SAVI	–0.279
CoVaR	0.509
ΔCoVar	0.473
Eigen	0.445
Ave_Vol	–0.452
DMC_MES	–0.188
PC1	57.58%

Insurance Stress Index and the South African GDP growth

In this section, we employ a bivariate quantile regression of the lagged Insurance Stress Index on the lower tail ($\tau = 0.05$), central tendency ($\tau = 0.5$), and the upper tail ($\tau = 0.8$) of the South African GDP growth.

Table 7 shows the results of the quantile forecast. We can notice that the Insurance Stress Index is significantly related to the lower tail of the South African GDP growth but not to the central tendency and the upper tail of the South African GDP growth. Our findings imply that an increase in the insurance stress index will lead to a decrease in economic output in South Africa. Thus, our proposed index is a significant predictor of future economic downturns in

South Africa. Our results corroborate the claim that systemic risk measures are more informative about the lower tail of macroeconomic shocks than about their central tendency or upper tail.

Table 7
GDP growth shock quantile forecasts: Insurance index

	τ(0.05)	τ(0.5)	τ(0.8)
Insurance Stress Index	−0.295*** (−5.75)	−0.027 (−1.17)	−0.069 (−1.60)
Observations	137		

Note: Table reports quantile forecast regression at τ (5%), τ (50%), and τ (80%). Statistical significance at 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Only the coefficient and t-stat () of the insurance index are reported. Sample is 2008M10 – 2020M02**.**

Robustness test

We compute a VAR model to test both causality and the impulse response function between the Insurance Stress Index and the South African GDP growth. We first check for stationarity of the variables by employing the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test developed by Kwiatkowski et al. (1992) together with the Phillips-Perron (PP) unit root test introduced by Phillips and Perron (1988). We then perform the Granger-Causality test to investigate the possibility of a lead-lag relationship between the Insurance Stress Index and GDP growth.

Table 8 reports the results for the stationarity tests. We can observe that the Insurance Stress Index and the South African GDP growth are stationary as we failed to reject the null hypothesis of stationary for the KPSS test, while we reject the null hypothesis of a unit root for the PP test.

Table 8
KPSS and PP unit root test

	Deterministic specification	KPSS	PP
South African GDP	Intercept	0.12***	−3.72***
	Trend and intercept	0.11***	−3.56**
Insurance Stress Index	Intercept	0.45*	−3.11**
	Trend and intercept	0.19**	−4.16***

Note: Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Only the coefficients of the South African GDP growth and the systemic risk measure are reported. Sample is 2008M10 – 2020M02.

Table 9 presents the results of the Granger-causality test using four lags. Based on the outcomes, we reject the null hypothesis of no causality from the Insurance Stress Index to the South African GDP growth at 10% significance level. On the other hand, we cannot reject the null hypothesis of causality from the South African GDP growth to the Insurance Stress Index at 10% significance level. Therefore, we can conclude that the Insurance Stress Index Granger causes the South African GDP growth reinforcing the ability of the Insurance Stress Index to predict future economic downturns in South Africa.

Table 9
Granger-causality test

Dependent variable	Excluded	Chi^2	Prob.
GDP	Insurance Stress Index	8.69	0.0693*
GDP	All	8.69	0.0693*
Insurance Stress Index	GDP	1.68	0.7949
Insurance Stress Index	All	1.68	0.7949

Note: Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. Only the coefficients of the South African GDP growth and the systemic risk measure are reported. Sample is 2008M10 – 2020M02.

Finally, we use a Cholesky decomposition to identify how structural shocks of the Insurance Stress Index impact the South African GDP growth. Figure 3 displays the impulse response of the South African GDP growth to the proposed index. We can observe a decline of the South African GDP growth to the negative region from periods 1 to 6 to a one standard deviation shock to the Insurance Stress Index. Afterward, it reaches a steady-state from periods 6 and 7 and starts increasing from period 8 until the positive region. Therefore, this finding indicates that the Insurance Stress Index can be used as an early warning indicator in predicting future macroeconomic downturns in South Africa. Thus, our index can potentially be employed as an instrument to monitor and mitigate systemic risk in the insurance sector to ensure the stability of the financial system and the economy in South Africa.

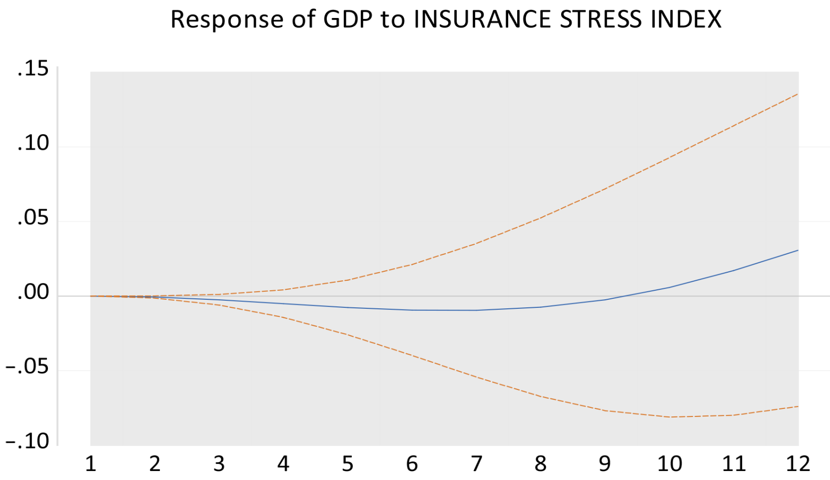

Figure 3. Impulse response function: Response of GDP growth to Insurance Stress Index shock

CONCLUSION

This paper investigates the link between systemic risk in the South African insurance sector and real economic activity in South Africa. In doing so, we use six systemic risk measures and evaluate the significance of each of them by assessing their ability to predict future economic downturns in South Africa. We find that only two systemic risk measures can significantly predict future economic downturns in South Africa. We then aggregate the six systemic risk measures into a composite stress index of systemic risk (Insurance Stress Index) using principal component quantile regression analysis and assess the Insurance Stress Index's ability to predict future economic downturns in South Africa. Our results show that the Insurance Stress Index possesses the ability to significantly predict future macroeconomic shocks in South Africa as opposed to the central tendency and upper quantile of South Africa GDP growth. Thus, the Insurance Stress Index appears to be a reliable means in monitoring the dynamics of systemic risk in the South African insurance sector. Therefore, our findings could be useful for South African regulators and managers of insurance companies at two levels. First, our results indicate that regulators and risk managers must develop an analysis of systemic risk in the insurance sector with particular attention to its effects on real economic activity. Secondly, our results suggest that the proposed index can potentially be used as an instrument to monitor and mitigate systemic risk in the insurance sector in order to ensure financial stability in South Africa.

Due to data availability, we could not include in our study all of the insurance companies listed in the Johannesburg Stock Exchange. This study could be extended by including more systemic risk measures and other financial institutions such as the banking sector, real estate sector, and investment companies in order to have a broader picture of how systemic risk in the financial sector may impact real economic activity in South Africa. In addition, a possible extension of the study would be to consider the partial quantile Regression (PQR), an adaptation of the partial least square, combine with out-sample forecasting criterion in order to understand better the complex dynamics between systemic risk and real economic activity.

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