Assessing the contribution of South African Insurance Firms to Systemic Risk

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Abstract

In light of the crucial contribution insurance firms make to global investment, this paper examines the extent of systemic risks facing emerging market insurance, with a particular focus on South Africa, one of the African continent's most prominent emerging economies. Contrary to past studies, the paper relies on delta conditional value at risk (ΔCoVaR) based dynamic conditional correlation (DCC)-GARCH model to this end. Moreover, the paper assesses how selected developed economies contribute to the systemic of the South African insurance industry. The results of the empirical analysis show that Santam, Sanlam, and Momentum Holdings account for the largest systemic risks. At the same time, the least contributors are Discovery and Liberty. Meanwhile, Australia and Japan appear to contribute the most to systemic risk in the South African insurance industry. Moreover, the paper finds that periods of economic turmoil significantly increased developed markets' systemic risk contributions to the South African insurance industry.

Keywords: delta conditional value at risk; dcc-gjr-garch; systemically important financial institutions.

1. Introduction.

Failures and losses of financial institutions or markets can significantly spill over financial distress to the entire global economy (Billio et al., 2012; Jonghe, 2021; Kolari et al., 2020). This is evidenced, for instance, by the 2007-2008 Global Financial Crisis (GFC), which started in 2007, primarily due to the collapse of the mortgage-backed securities market in the United States, quickly spread to the whole financial sector and the entire global economy, harming economic activities across the world (Georg, 2011). According to Weib (2014), the collapse of one of the biggest insurance company, the American International Group (AIG), not only surprised financial regulators, who assumed that systemic risk was limited to the banking sector, but also revealed that the insurance sector played a significant role in aggravating the crisis. Since then, several concerns have been raised regarding the insurance sector's contribution to systemic risk.

Studies show that the insurance sector contributes significantly to the nation’s economic growth and is viewed as a significant player in the financial sector (Mwamba and Angaman, 2021). The World Bank (2011) states that the insurance sector plays a significant role in economic and financial development by providing stability to the functioning of businesses, encouraging the goodness of savings, and generating employment for millions.

The South African insurance sector is highly concentrated and interconnected and provides a valuable environment for investigating systemic risk, as it has one of the most developed insurance sectors among emerging markets with a penetration rate of 16.99% in 2017 (Signe et al., 2020). Similarly, United Nations (2007) states that South Africa has the most developed insurance sector on the African continent and produced around $30 billion, or 79% of the Continent’s total insurance output. Considering this, the insurance sector plays a significant role in the South African financial system, including the entire economy. Thus, if one or more South African insurers or the industry fails, it may disrupt the sector and result in systemic risk.

Systemic risk has become a key concept after the GFC, and its definition is still controversial in the literature. International Monetary Fund (2009) describes systemic risk as a distressed financial sector that can harm the broader economy. They highlight institutional size and linkages between large institutions as main drivers. Likewise, Bullard et al. (2009) describe systemic risk as the collapse of an important institution that could lead to a credit crunch in the financial markets, thereby affecting the global economy. Systemic risk analysis has become crucial in the modern economy to contain the risk and plan accordingly to avoid future crises (Kolari et al., 2020).

Indeed, the aftermath of the GFC resulted in several studies that aim to develop sophisticated models to quantify systemic risk in the insurance sector. For example, Kaserer and Klein (2019) analysed insurers' contribution to systemic risk in the financial sector using credit default Swaps (CDS) implied systemic risk measure from January 2005 to December 2014. By utilising panel data of 183 significant insurers and banks, the study shows that the insurance sector contributes moderately less to overall systemic risk. Similarly, Mwamba and Angaman (2021) model systemic risk in the South African insurance sector using a Dynamic Mixture Copula Marginal Expected Shortfall (DMC-MES) model. Their results openly resist the notion that only banks are systemically risky in South Africa.

The GFC has exposed the impact of the interconnectedness of financial markets. For example, a shock in one asset class (i.e., subprime mortgages) significantly affects the instability of financial institutions and markets worldwide. This crisis has led regulators, policymakers, and academia to realise the importance of understanding systemic risk, especially in the insurance sector. However, this strand of empirical analysis still needs more study, particularly in an emerging country like South Africa, as extant studies are primarily devoted to developed economies. To that end, this study aims to empirically analyse systemic risk in the South African insurance sector, with the impetus of identifying and ranking insurers and countries that pose a systemic threat to the South African insurance sector. The paper contributes to the existing literature in several ways: First, it combines the analyses of the insurance industry's systemic risk within the domestic economy and its reaction to external systemic risk. With the latter, the paper will analyse how much cross-border systemic risk spills over from developed countries' insurance sectors to the South African insurance sector. It is worth noting that the South African regulators are yet to implement a yardstick to monitor and manage domestically important insurers. Hence, a toolkit must be implemented to ensure that insurers that pose the greatest threat to system-wide instability are designated and regulated accordingly. Secondly, the empirical analysis of systemic risk, especially the application of the delta conditional value-at-risk (ΔCoVaR) goes beyond the common methodology of Adrian and Brunnermeier's (2008) and uses a ΔCoVaR methodology based on a DCC-GJR-GARCH model.

The rest of the study is organised as follows: Section 2 presents the empirical literature review related to this study. Section 3 provides the methodology employed. Section 4 presents the results, and Section 5 concludes the study.

2. Literature Review

Literature on systemic risk in the financial sector has been broadly analysed, and the literature is clear. Since the 2007-2008 GFC, many studies with mixed views and complicated models aim to measure systemic risk in the financial sector.

For example, a pioneering study by Adrian and Brunnermeier (2008) examined systemic risk in the developed US financial market from 1986 to 2010. Here, the authors propose CoVaR, which they describe as the VaR of the entire financial sector, provided that one institution has already attained its VaR. Moreover, to measure each financial institution's contribution to systemic risk, the authors construct ΔCoVaR, which is the difference between the CoVaR conditional that a firm is under hardship and the CoVaR of the institution in its normal state. Their sample consists of time series data from 1823 financial institutions. The results show that banks contribute the most to systemic risk, particularly those with an unreasonable portion of interest-bearing deposits. Furthermore, the authors contend a powerful nexus between an institution's ΔCoVaR and VaR.

Adrian and Brunnermeier's (2008) study was followed by other studies examining different financial sectors and how they contribute to systemic risk. Bernal et al. (2014), for example, examine systemic risk within numerous financial sectors (i.e. insurance, banking, and other sectors) in the United States (US) and Eurozone during the 2007-2008 GFC. To correctly classify the financial sector's contribution to systemic risk, the paper supplements the ΔCoVaR method by adopting the Abadie (2002) Kolmogorov-Smirnov test, established on bootstrapping. The results show that all the financial sectors in the sample contribute significantly to systemic risk. Most importantly, they reveal that the banking sector contributes mainly to systemic risk in times of hardship in the Eurozone. At the same time, the insurance sector is found to be systemically risky in the US financial sector.

In the same vein, Drakos and Kouretas (2015) measured systemic risk in the United States (US) and United Kingdom (UK) financial sectors during the period 2000 to 2012. The authors apply traditional CoVaR and ΔCoVaR. Their results reveal that the banking sector contributes more to systemic risk in times of hardship than the insurance or other financial sectors in the US and

UK. Berdin and Sottocornola (2015) examine systemic risk in the insurance sector, banking sector, and non-financial sectors in the Eurozone. The authors use the Granger causality test, ΔCoVaR, and mean squared error (MSE), and their results show that insurers contribute significantly to systemic risk compared to bankers. In addition, Berdin and Sottocornola (2015) argue that insurers participating in non-core insurance activities tend to contribute more to systemic risk.

The early analysis of systemic risk in the insurance sector includes the study by Acharya et al. (2009). The study employs the Marginal Expected Shortfall (MES) to measure systemic risk contributions of insurance firms in the United States from 2004 to 2007. The empirical results of the study show that non-traditional insurance activities and a high degree of interconnectedness are the core drivers of insurers' systemic relevance.

Similarly, Cummins and Weiss, (2010) examine the possibility of the US insurance sector causing systemic risk events that eventually spill over to other parts of the economy. In the study, the authors identify primary factors that determine insurers' risk of being systemically risky and the contributing factors that aggravate vulnerability to systemic events. Furthermore, the authors measure systemic risk based on a comprehensive financial analysis of the insurance sector, the interconnectedness of insurers, and their role in the economy. The results show that the traditional activities of US insurers do not pose any systemic risk. However, insurers involved in non-core insurance activities are likely to be exposed to systemic risk. Most importantly, they conclude their argument by suggesting that to reduce systemic risk from non-core activities, financial regulators, supervisors, and other key players need to develop stricter mechanisms for insurers' group supervision.

Wei*b* and Muhlnickel, (2014), on the other hand, employs ΔCoVaR, MES, and SRISK to analyse systemic risk for 89 US insurers during the 2007-2008 GFC. The empirical results show that multiple insurers contributed significantly to the instability of the US financial sector during the recent GFC. The authors conclude by arguing that institutional size is the main driver of insurers' exposure and contribution to systemic risk. Chang et al., (2018) employ MES, CoVaR, and SRISK index to examine 20 Taiwan insurers' contribution and exposure to systemic risk during the period 2005 to 2015. Additionally, Chang et al., (2018) analyse the primary drivers posing as systemic risk. Their results show that non-traditional insurance activities and the interconnectedness of insurers are significant primary drivers.

One of the first studies to analyse systemic risk using GARCH models was Girardi and Ergün, (2013). Girardi and Ergün, (2013) examined systemic risk in the US financial market using extended CoVaR based on multivariate GARCH. In the study, the authors deviate from the traditional CoVaR definition suggested by Adrian and Brunnermeier, (2008) by stating that their CoVaR represents the VaR of the financial system given that single institutions are "at most" at their VaR as opposed as being strictly at VaR. This extension enables the authors to look at extreme events and to execute stress testing efficiently. The authors use data from June 2000 to February 2008, and their findings reveal that a group consisting of insurers was the smallest contributor to systemic risk. Girardi and Ergün, (2013) further contend that banks are more central to systemic risk than any other financial sector in the United States.

3. Methodology.

This section details the methodology used to construct time-varying CoVaR and ΔCoVaR which follows a four step approach. Firstly, we estimate univariate GJR GARCH models for all insurance firms and countries to measure volatility. Secondly, we estimate the VaR for all insurance firms and countries based on the univariate GJR GARCH (1,1) model in step 1. Thirdly, we estimate bivariate ARMA (1,1)-DCC-GJR-GARCH (1,1) model to estimate the joint distributions of insurance indices pairs. Lastly, we build upon the ARMA (1,1)-DCC-GJR-GARCH (1,1) estimates to calculate the CoVaR and ΔCoVaR for the SA insurance sector conditional the extreme risk (VaR) of each insurance firm or country (systemic risk contribution). Detailed steps can be seen below.

Step 1. We collect time-series data of each insurance firm or country, and the whole South African insurance sector, and estimate the univariate GJR-GARCH (1,1) model suggested by Glosten et al., (1993) to measure the volatility of the sector's returns. The presentation of the model is expressed as follows:

$$Y_t = \mu + \phi Y_{t-1} + u_t \tag{1}$$

$$\sigma_t^2 = \omega + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-1}^2 l_{t-1} + \beta \sigma_{t-1}^2 \tag{2}$$

$$I_{t-1} = \begin{cases} 1 \; if \; \epsilon_{t-1} < 0 \\ 0, \; otherwise \end{cases} \tag{3}$$

Where Y_t is the mean equation, σ_t^2 denotes the conditional forecasted variance, $a_1 \varepsilon_{t-1}^2$ is the variance that depends on previous lag error terms, I_{t-1} is the dummy variable that is activated *if the previous shock is negative ($\epsilon_{t-1} < 0$), and lastly, $a_1\varepsilon_{t-1}^2$ represents yesterday's forecasted variance.*

This model is selected mainly because of two reasons. Firstly, it can capture asymmetry in the data. Secondly, the model can capture different impacts of the positive and negative shocks on the volatility (i.e. Leverage Effect).

Step 2. Based on the parameter estimates fitted in GJR-GARCH models, in step 2 we estimate time-varying VaR of all insurance returns. The formula can be represented as follows:

$$VaR_{q,t}^{i} = \Phi^{-1}(q)\sigma_t^i \tag{4}$$

Where Φ^{-1} denotes the distribution of data, q is the confidence interval, and σ_t^i is the standard deviation of insurance firm or sector i.

Step 3. In step 3, we continue and estimate a bivariate GJR-GARCH model based on Engle's (2002) DCC specification. This will help us capture the dynamic time-varying conditional correlation between the SA insurance sector and each insurance firm and country.

The speculation of the DCC model assumes that 1×K vector of assets returns r_t are conditional normally distributed with zero mean and conditional covariance matrix M_t.This can be expressed as follows:

$$Z_t|\Gamma_{t-1} \sim N(0, D_t R_r D_t) \tag{5}$$

Where Z_t represents the residual error term, Γ_{t-1} represents the information set at time t-1, and $D_t R_r D_t$ denotes the conditional covariance matrix which can be expressed as follows:

$$M_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}} \tag{6}$$

In equation (6) the diagonal matrix D_t represents the time varying standard deviation matrix and can also be expressed as follows:

$$D_t = diag\left[\sqrt{s_{1,t}}, \sqrt{s_{2,t.}}\ \right] \tag{7}$$

Where $s_{i,t}$ represents the conditional covariance σ_t^2 which can be obtained from GJR-GARCH in equation (2).

R_t in equation (6) represents the conditional correlation coefficient matrix of the standardised returns $\tau_t = D_t^{-1} r_t$ and can be expressed as follows:

$$R_t = \begin{bmatrix} 1 & q_{12,t} \\ q_{21,t} & 1 \end{bmatrix} \tag{8}$$

The 2×2 matrix R_t can also be decomposed as follows:

$$R_t = Q_t^{-1/2} Q_t Q_t^{-1/2} \tag{9}$$

Where $Q_t = (q_{ij,t})$ is a positive definite matrix and denotes the time-varying conditional covariance matrix of standardised returns, $Q_t^{-1/2}$ can be expressed as follows:

$$Q_t^{-1/2} = \begin{bmatrix} 1/\sqrt{q_{11,t}} & 0 \\ 0 & 1/\sqrt{q_{22,t}} \end{bmatrix} \tag{10}$$

Therefore, the Dynamic Conditional Correlation DCC (1,1) model can be expressed as follows.

$$Q_t = \mathrm{a} + \mathrm{a}\tau_{t-1}\tau'_{t-1} + \boldsymbol{\beta} Q_{t-1} \tag{11}$$

Where $\mathrm{a} = (1 - \mathrm{a} - \boldsymbol{\beta})\overline{\boldsymbol{Q}}$; and $\overline{\boldsymbol{Q}} = \boldsymbol{E}(\tau_t \tau'_t)$ represents the unconditional variance matrix; and it meets when $a + \boldsymbol{\beta} < \mathbf{1}$

Furthermore, we can obtain the dynamic conditional correlation coefficient as follows:

$$\rho_{12t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \tag{12}$$

Step 4. In the last step we proceed and obtain $CoVaR_{t,\beta}^{z|i}$ under the assumption of skewed student t innovation. Following Ben Amor et al., (2019) the formula can be represented as follows:

$$CoVaR_{t,\beta}^{z|i} = \Phi^{-1}(\beta)\sigma_t^z \sqrt{1 - \rho_{zi,t}^2} + \Phi^{-1}(\beta)\rho_{zi,t}\sigma_t^z \tag{13}$$

Given that, $VaR_{\beta,t}^z = \Phi^{-1}(\beta)\sigma_t^z$, equation 22 can be rewritten as:

$$CoVaR_{t,\beta}^{z|i} = VaR_{\beta,t}^z \sqrt{1 - \rho_{zi,t}^2} + VaR_{\beta,t}^z \rho_{zi,t} \tag{14}$$

Where $\mathrm{VaR}_{\beta,t}^{z}$ is the VaR of the SA insurance sector and $\rho_{zi,t}$ is the correlation coefficient between SA insurance returns and insurance firms.

We use ΔCoVaR to evaluate specific firm or country systemic risk contribution to the whole SA insurance. This measure can be calculated as follows:

$$\Delta\mathrm{CoVaR}_{t}^{z/i,\beta} = CoVaR_{t}^{z/i\beta,} - CoVaR_{t}^{z/b^{i},\beta} \tag{15}$$

Given that $\Phi^{-1}(0.5) = 0$ we deduce $\Delta CoVaR$ at each time as follows.

$$\Delta CoVaR_{t,\beta}^{z|i} = \Phi^{-1}(\beta)\rho_{zi,t}\sigma_{t}^{z} \tag{16}$$

Which can also be rewritten as:

$$\Delta CoVaR_{t,\beta}^{z|i} = VaR_{\beta,t}^{z}\rho_{zi,t} \tag{17}$$

Where $\Delta\mathrm{CoVaR}_{t,\beta}^{z|i}$ represents the contribution of each insurer or country, $\mathrm{VaR}_{\beta,t}^{z}$ is the VaR of the SA insurance sector and $\rho_{zi,t}$ is the correlation coefficient between SA insurance returns and insurance firms.

This model is selected because, unlike copulas and wavelet models, it is computationally easy to estimate and provides dynamic correlation and asymmetric volatility, which is found efficient in identifying possible systemic risks (see, Zhou et al., 2021).

4. Empirical Analysis

4.1 Data.

This paper uses data from five South African insurance firms collected from INET BFA Database. Due to data availability, our sample spans from 5 January 2006 to 3 February 2022. This sample period covers a wide range of events and unexpected changes in global dynamics, such as the 2008 GFC and the Covid-19 crisis. Data on country insurance indices is obtained from Thomson Reuters Database and covers the same sample period. Due to data availability, four developed countries were selected: the USA, Germany, Japan, and Australia. As a proxy for the whole South African insurance sector, we use the JSE Non-Life and Life insurance indices. Therefore, after obtaining all the relevant data, the formula $r_i = 100 * \ln({}^{p_t}/_{p_{t-1}})$ is used to compute daily compound returns.

Table 1: Descriptive statistics

	Discovery	*Sanlam*	*Santam*	*Momentum*	*Liberty*	
Panel A: Descriptive Statistics of Insurance return.						
Mean	-0.0481	-0.0356	-0.0306	-0.10109	-0.00517	
Standard De	1.91751	1.92681	1.73157	1.83990	1.95381	
Kurtosis	8.48211	4.37218	10.0830	4.10688	23.7989	
Skewness	0,43419	0,40112	0,42226	0,19030	0.33472	
Minimum	-16.398	-11.872	-11.8061	-12.198	-22.4343	
Maximum	16.3663	15.3899	20.97205	11.3944	28.0733	
Jarque-B Test	12204*	3316*	17187*	2854.5*	95170*	
Serial Corr	26.228*	59.495*	50.369*	43.286*	30.936*	
	USA	Germany	Japan	Australia	Non-Life	Life-Ins
Panel B: Country Indices						
Mean	-0.0288	-0.03328	0.00158	-0.00326	-0.0371	-0.0222
Standard De	1.39872	1.88832	2.04371	1.70762	1.65777	1.65808
Kurtosis	14.947	13.7974	4.76486	7.700563	4.15235	5.28012
Skewness	0.46820	-0.18709	0.07199	-0.58777	-0.1606	0.38412
Minimum	15.5651	-20.456	-1.1877	-15.3824	-11.557	-9.6864
Maximum	12.0424	18.3717	1.46881	12.6856	10.522	12.7141
Jarque-B Test	38288*	32521*	3880.7*	10360*	2924*	799*
Serial Corr	158.78*	34.207*	34.799*	91.688*	56.579*	17.017*

Note(s): *** reflects coefficients that are statistically significant at 10%, ** reflects coefficients that are significant at 5%, * reflects coefficients that are significant at 1%.

The results shown in Table 1 (Panel A) reveal that Momentum has the highest average returns, while Liberty happens to have the lowest returns. Liberty is also observed to be the most volatile insurer. Looking at the skewness values, one can observe that the return series is non-zero, showing that the distribution of all returns exhibits fat tail distribution with the mean around zero. Furthermore, in all the cases, the null hypothesis of normality is rejected at 1% confidence level, implying that the financial time series is not normally distributed. For this reason, this study chooses skewed student t distribution to describe price returns patterns, which is compatible with the characteristics of the data itself. The results in Table 1 (Panel B) reveal that, on average, Germany's insurance sector has the highest returns, whereas Japan happens to have the lowest returns. One can see that Japan is the most volatile country. On the other hand, the USA is found to be the least volatile country. Observing the skewness values, one can see that the return series is non-zero.

4.2. Results of Univariate ARMA (1,1) GJR-GARCH Model.

After conducting all the necessary tests on the data collected, we considered several GARCH models as candidates. We found that ARMA (1,1) GJR-GARCH (1,1) is the best model for marginal returns distribution. Table 5 below shows the results of the model.

Table 2: Univariate ARMA (1,1)-GJR-Garch-GARCH model results

	Discovery	*Sanlam*	*Santam*	*Momentum*	*Liberty*
a	-0.04951**	-0.0411**	-0.03414	-0.032924	-0.032721
AR(1)	-0.93119*	0.76987*	0.20389	0.48603***	0.62280*
MA(1)	0.936614*	-0.83349*	-0.2999***	-0.54315**	-0.67407*
ω	0.039815*	0.068542*	0.771795*	0.086039*	0.03245*
Alpha	0.104674*	0.110555*	0.256835*	0.094923*	0.05283*
Beta	0.911010*	0.903621*	0.552239*	0.897463*	0.966480*
Gamma	-0.04966*	-0.06609*	-0.00622*	-0.03098**	-0.0586*
LLC	-7685.827	-7863.058	-7432.08	-7746.03	-7617.118
AIC	3.8093	3.8971	3.6837	3.8391	3.7753
BIC	3.8234	3.9111	3.6977	3.8532	3.7893

*Note(s): *** reflects coefficients that are statistically significant at 10%, ** reflects coefficients that are significant at 5%, * reflects coefficients that are significant at 1%.*

The results in Table 2 above reveal that the parameters of Autoregressive (AR) and Moving Average (MA) models are significant at 1%, 5%, and 10% for most insurance companies. This justifies their inclusion in the overall model. In terms of ARCH and GARCH parameters, the results show that alpha and beta are significant in all the models at 1%, 5%, and 10% confidence levels. This implies that the current volatility of the return series is simply impacted by the information in the previous period. Moreover, the sum of both parameters is close to 1% for all companies, suggesting high persistent volatilities. Looking at Gamma (leverage effect parameters) for all insurance companies, one may observe that the parameters are statistically significant at 1% level except for Santam. Interestingly, Gamma is negative for all the companies. This suggests that insurers' positive shocks increase volatility more than negative shocks. Furthermore, we conduct the Ljung-Box test and ARCH LM tests to assess whether the model is adequate. The results are shown in Table 3. The results show evidence that the ARMA (1,1) GJR-GARCH (1,1) model under skewed student t distribution can secure the residuals at a conventional level.

Table 3: Diagnostics Test results

	Discovery	Sanlam	Santam	Momentum	Liberty
Q(5)	2.3523	1.60344	2.609	3.8915	1.4921
	(0.8501)	(0.995)	(0.7175)	(0.0871)	(0.9981)
$Q^2(5)$	2.610	2.91743	1.5029	4.545	0.02524
	(0.4828)	(0.4223)	(0.7392)	(0.1934)	0.9999
ARCH(5)	0.25296	1.5851	0.8398	1.6530	0.03803
	0.9525	(0.5702)	(0.7810)	(0.5530)	(0.9967)

Note(s): *** reflects coefficients that are statistically significant at 10%, ** reflects coefficients that are significant at 5%, * reflects coefficients that are significant at 1%. The number in brackets represent the probability value of the coefficients.

4.3. Value at Risk Results

After obtaining the univariate GJR-GARCH estimates in the previous step, the next step is to estimate time-varying VaR for all insurance companies. The results are shown below.

Table 4: Descriptive statistics for 1% VaR.

	Discovery	*Sanlam*	*Santam*	*Momentum*	*Liberty*
Mean	-9.535	-9.248	-9.162	-9.086	-9.501
Standard De	0.014343	9.63046	9.43343	6.89023	8.87224
Minimum	-240.992	-158.43	-338.54	-96.378	-121.936
Maximum	-1.769	2.196	-4.664	-3.018	-1.633

Table 4 above presents the descriptive statistics results of time-varying VaR for the entire sample period. The results show that on average, Discovery is the riskiest insurer in isolation with -9.535 VaR followed by Liberty and Sanlam with VaR's of -9.501 and -9.248, respectively. On the other hand, Momentum, on average, is the least risky insurer, with a VaR of -9.086. Santam is found to be the second least risky insurer with a -9.248 VaR. To better understand the implications of these results, we take Discovery and Liberty as examples and state that there is a 99% probability that Discovery and Liberty will lose more than 9.53% and 9.501%, respectively, on average, on a given day. Observing the standard deviation results in Table 4, the third riskiest insurer, Sanlam, is found to have the most volatile VaR, followed by Santam and Liberty, with standard deviations of 9.433 and 8.872, respectively. Discovery and Momentum are the least volatile insurers in South Africa, with standard deviations of 0.01434 and 6.89023. Figure 3 below illustrates the dynamics of time-varying VaR at 1% for all insurers.

Figure 3: Provides daily VaR time-series plots for all Companies at q = 1%.

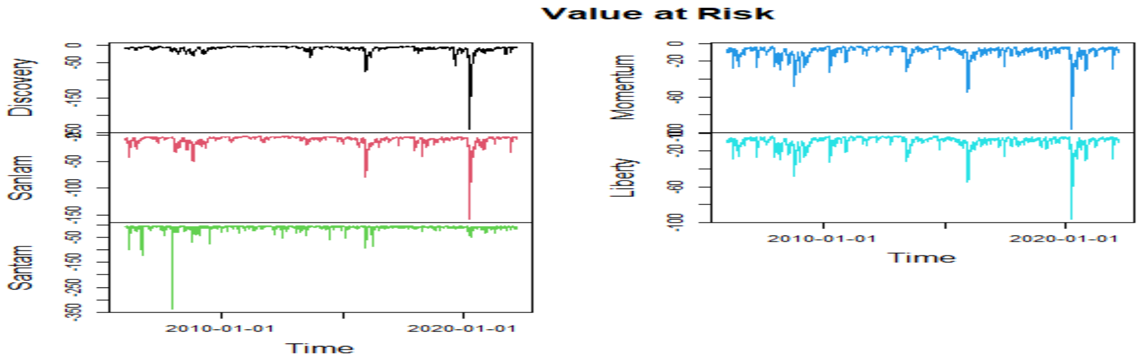


Figure 3 above illustrates the dynamics of time-varying VaR at 1% for all insurance firms. The graphical evidence shows that insurers' VaR values followed similar time-varying patterns but with different magnitudes during the 2008 GFC and the ongoing Covid-19 crisis. However, as we have emphasised, these unconditional VaR alone are inadequate in analysing systemic risk, thus the need for CoVaR.

4.4. DCC-GJR-GARCH Results

In this step, we estimate the DCC-GJR-GARCH model; the results are reported in Table 5 below.

Table 5: DCC-GARCH parameters

	Discovery-Insurance Sector	*Sanlam-Insurance Sector*	*Santam-Insurance Sector*	*Momentum-Insurance Sector*	*Liberty-Insurance sector*
a	0.028718**	0.022095	0.079934**	0.033193*	0.049967*
	(0.0434)	(0.2487)	(0.0134)	(0.0060)	(0.0000)
b	0.965448*	0.974005*	0.869291*	0.951831*	0.922914*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
(a+b)	0.994166	0.9961	0.949225	0.985024	0.972881

*Note(s): *** reflects coefficients that are statistically significant at 10%, ** reflects coefficients that are significant at 5%, * reflects coefficients that are significant at 1%. The number in brackets represent the probability value of the coefficients.*

Table 5 reports the DCC-GARCH model results for all insurance companies. The short-run dynamic volatility impact (a) for insurers is statistically significant at 5% level except for Sanlam. This suggests the presence of short-run dynamic volatility impact. To clearly understand this, we take Discovery as an example and state that there is short-run dynamic volatility of 0.028 from Discovery to the South African Insurance sector. Meanwhile, looking at long-run dynamic volatility (b), the results show that all the parameters are significant at 1%

and close to 1%, implying a long-run volatility spill-over. Again, taking Discovery as an example, we observe a long–run dynamic volatility of 0.965 from Discovery to the insurance sector. In addition, we can state that the DCC-GARCH model is accurate as (a+b) is less than 1, and we can conclude that the volatility of recent markets has essential influences on the dynamic nexus between insurers and the insurance sector. Having obtained these parameters, we proceed and estimate CoVaR and ΔCoVaR.

4.5. CoVaR and ΔCoVaR results.

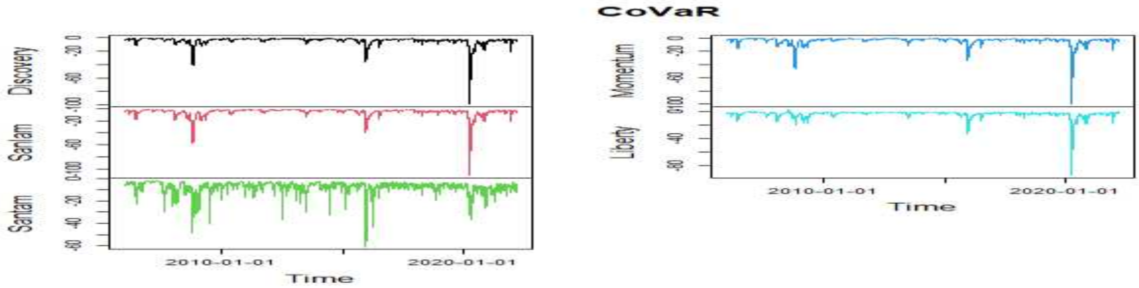
Having obtained unconditional VaR models and dynamic time-varying conditional correlation between insurers and the insurance sector, in the last step, we use the results of the previous steps to estimate CoVaR and ΔCoVaR.

Table 6: Descriptive statistics for 1% CoVaR

	Discovery	*Sanlam*	*Santam*	*Momentum*	*Liberty*
Mean	-9.175	-9.163	-9.981	-9.369	-9.028
Standard De	0.018430	0.01145	6.64715	0.01202	0.01160
Minimum	-163.309	-151.021	-68.490	-162.81	-165.292
Maximum	-2.114	-2.252	-3.481	-2.147	-2.124

CoVaR gives us the expected maximum loss the financial system suffers when individual insurers are at their VaR. Therefore, high/low negative values of CoVaR reveal high/low spillover effects on the financial system. The descriptive Statistics of 1% CoVaRs are shown in Table 6. The results reveal that, on average, the largest spillover effect on the insurance sector seems to arise from Santam. This indicates that if the return losses of Santam are at most at 1% VaR, the insurance sector's estimated 1% VaR value would be 9.981%. Momentum is found to have the second highest CoVaR of -9.369. On the other hand, on average, the VaR of the insurance sector, given that Liberty is at most at its VaR, is found to be the least. This can be seen from -9.028 CoVaR. Comparing these results with VaR results, one may observe that insurers with the lowest VaRs are not necessarily insurers with the lowest CoVaR values, and the converse is also true. Figure 4 below illustrates the dynamics of time-varying CoVaR at 1% for all insurers.

Figure 4: Provides daily CoVaR time-series plots for all Companies at q = 1%.



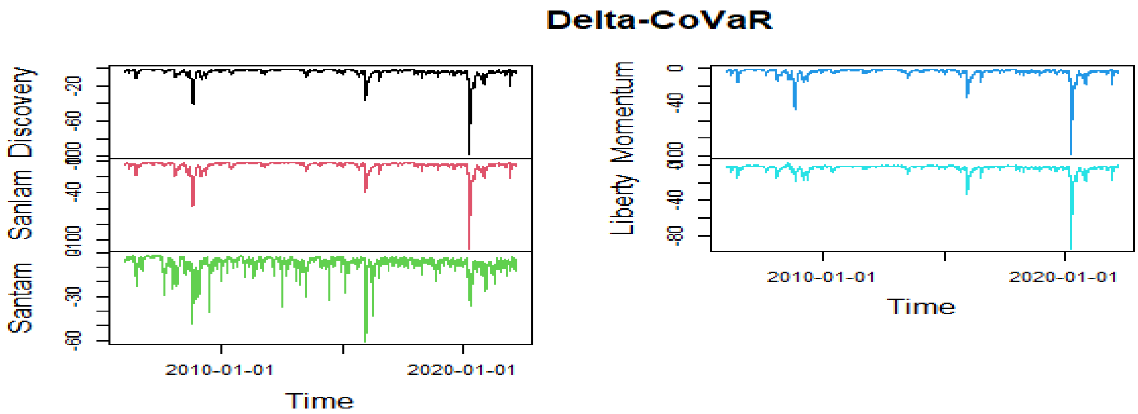
From the results in Figure 4, it is evident that the CoVaR measure can accurately pick up the tail risk. Figure 4 also reveals that time-varying CoVaR captures the effect of the 2008 GFC and ongoing Covid-19 crisis, with a huge surge in the CoVaR for all the insurance companies during these periods. As such, we can infer that the systemic risk of most insurers increased sharply in 2008 and 2020.

Table 7: Descriptive statistics for 1% ΔCoVaR

	Discovery	*Sanlam*	*Santam*	*Momentum*	*Liberty*
Mean	-4.0994	-5.519	-7.798	-4.1659	-3.474
Standard De	6.436046	7.60029	5.36209	6.48598	5.67416
Minimum	-98.9452	-111.071	-60.808	-99.8212	-94.311
Maximum	-0.2689	-1.105	-2.061	-0.2271	3.348
Ranking	**4**	**2**	**1**	**3**	**5**

Table 7 shows the descriptive statistics results of daily ΔCoVaR. Recall that these particular values are essential to the study because they give us the marginal contribution of each insurance firm to overall systemic risk of the insurance sector. The results in Table 7 show that Santam the third largest insurance company in our sample, on average, contributes the most to systemic risk (i.e., the one with the most negative ΔCoVaR). For example, this insurer added 7.798 basis points to the 1% VaR of the insurance system during the sample period. On the other hand, Sanlam the biggest insurer in South Africa is found to be the second largest contributor to systemic risk, followed by Momentum with ΔCoVaR of -5.519 and -4.1659, respectively. These two companies contributed 5.519 and 4.1659 basis points, respectively, to the 1% VaR of the insurance sector. Based on the literature, it can be inferred that Santam, Sanlam, and Momentum are involved in non-conventional insurance activities such as Securities Lending, and Credit Default Swaps (to mention a few). Liberty is the smallest contributor to systemic risk in the insurance sector with ΔCoVaR of -3.474, followed by Discovery with -4.0989. In practical terms, these companies contributed 3.474 and 4.0989 basis points to 1% VaR of the insurance sector. These results contradict the Too Big to Fail (TBTF) theory, which asserts that the greater the size of a financial institution, the more it contributes to systemic risk. Our results show that the contribution of insurers to systemic risk is not necessarily attributed to the size of the insurer. These results are backed by Labonte (2014) who states that in certain circumstances, the TBTF theory may not always hold, as some larger financial institutions could be more resilient to failure due to greater diversification or better risk management. Given these findings, we can conclude that Santam, Sanlam, and Momentum are systemically important financial institutions in the South African insurance sector. In addition, to get a clear picture of companies' contributions to systemic risk, Figure 5 below illustrates the time-varying dynamics of insurers' contributions to systemic risk.

Figure 5: Provides daily ΔCoVaR time series plots for all Companies at q = 1%



The graphical evidence in Figure 5 shows that insurers' contribution to systemic risk followed similar time-varying patterns but with different magnitudes during the 2008 GFC and the ongoing Covid-19 crisis. The evidence depicted in the plots also reveals that insurers contributed more to systemic risk during these two crises. Besides these two crises, one may also observe a considerable surge in systemic risk contribution in 2016 for all insurance firms. This surge depicts the effects of the 2016 Chinese stock market turbulence. Among the five insurers, Santam clearly stands out: its ΔCoVaR rose sharply during this period, implying that Santam contributed the most to systemic risk during the 2016 Chinese stock market crisis. This is because of its connectedness with the Chinese financial market. Overall, the results show that notable externalities may exist; thus, regulators should pay due attention to systemic risk.

Following similar steps as insurance companies in the previous section, this section presents the VaR, CoVaR, and ΔCoVaR results of countries included in our sample.

Table 8: Descriptive statistics for 1% VaR

	USA	Germany	Japan	Australia
Mean	-4.3073	-8.931	-10.638	-6.82693
Standard De	0.010302	1.49841	1.3593	7.98841
Minimum	-194.760	-157.911	-173.06	-97.7777
Maximum	-0.6104	-1.322	-2.277	-1.53161

Table 8 above illustrates the descriptive statistics for 1% VaR averages of all the chosen countries throughout the sample period. The results reveal that on average, Japan has the riskiest insurance sector in isolation in our sample, with 10.638 VaR (in absolute terms). Germany has the second riskiest insurance sector in isolation with 8.931 VaR, followed by Australia with 6.82693 VaR. The USA is found to be the least risky insurance sector in isolation, with a VaR of 4.3073. To simplify the results, we can state that there is a 99% probability that Japan, Germany, Australia, and the USA will lose more than 10.638%, 8.931%, 6.82693%, and 4.3073%, on average, on a given day. In addition, Australia is found to have the most volatile insurance sector. This is shown by the standard deviation of 7.98841, followed by Germany and Japan. On the other side, the USA is found to have the least volatile insurance sector. This is evident from the 0.010302 standard deviation.

Figure 6: Provides daily VaR time-series plots for all Countries at q = 1%

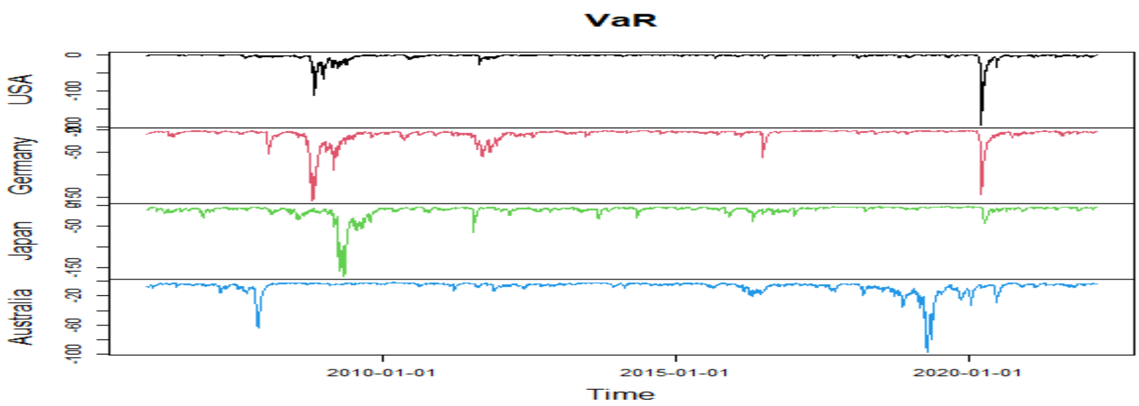


Figure 6 above illustrates the dynamics of time-varying VaR at 1% for all countries. Based on the graphics above, it can be seen that countries VaR values followed similar time-varying patterns but with different magnitudes during the 2008 GFC and the current Covid-19 crisis. One may also observe that a persistent spike appears in 2011 in most countries; this shows the effects of the 2011 European debt crisis. These results also reveal that countries facing low (high) market volatility tend to have a smaller (greater) risk of distress during the 2008 GFC and Covid-19 crisis.

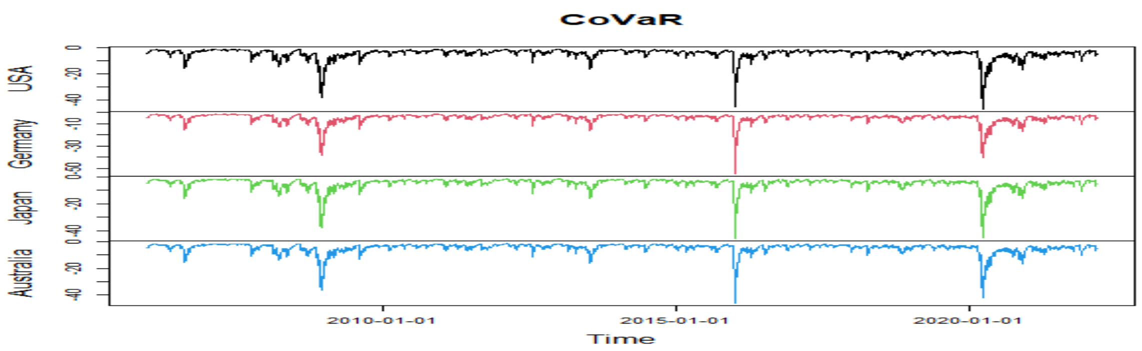
Using the DCC-GJR-GARCH parameters the next step is to calculate systemic risk measures.

Table 9: Descriptive statistics for 1% CoVaR

	USA	*Germany*	*Japan*	*Australia*
Mean	-4.656	-4.691	-4.698	-4.54004
Standard De	3.86714	3.924625	3.8207	3.701550
Minimum	-47.217	-55.189	-46.034	-46.567
Maximum	-1.418	-1.407	-1.436	-1.379

The results in Table 9 show that the Japanese insurance markets had the highest mean CoVaR value among the four countries. The country received, on average, -4.698 CoVaR. On the other hand, Germany has the second highest CoVaR followed by the USA. These countries received, on average, -4.691 and -4.656 CoVaR respectively. The VaR of the SA insurance sector, given that Australia is at most at its VaR, is found to be the least. This can be seen from -4.54004 CoVaR. The CoVaR comes to its maximum value when Germany is in hardship, with the insurance sector having a 99% chance of losing more than 55% on a given day. Figure 7 below graphically illustrates time-varying daily CoVaR for all countries in our sample.

Figure 7: Provides daily CoVaR time-series plots for all countries at q = 1%



The estimated CoVaR in Figure 7 shows that during the GFC and Covid-19 crises, the risk measure explodes, implying an increase in systemic risk during these periods. Furthermore, comparing Figure 7 with Figure 6 (time-varying VaR), one may observe that both CoVaR and VaR stabilise with a few non-persistent spikes.

Table 10: Descriptive statistics for 1% ΔCoVaR

	USA	*Germany*	*Japan*	*Australia*
Mean	-0.03066	-0.06830	-0.07332	0.08568
Standard De	0.213095	0.31791	0.15513	0.06985
Minimum	-4.29164	-8.50335	-2.39019	0.02602
Maximum	1.839766	2.41092	1.60440	0.87881
Ranking	**4**	**3**	**2**	**1**

Table 10 above present the descriptive statistics for daily ΔCoVaR values of individual countries during the entire sample period. The sample results reveal that Australia had the highest mean ΔCoVaR value among the four countries. The country contributed, on average, 0.08568% points to the VaR of the insurance system when it moved from operating normally to a state of hardship. This means that the Australian insurance sector was the largest contributor to systemic risk over our sample period. On the other hand, one sees that Japan is the second largest contributor to systemic risk, with an average ΔCoVaR of -0.07332, followed by Germany. These countries contribute, on average, 0.07332% and 0.06830% points to the VaR of the insurance system when they move from operating normally to a state of hardship. Furthermore, the USA is found to be the smallest systemic risk contributor with -0.03066 ΔCoVaR. With these results, we can conclude that Australia and Japan have the most systemically important insurance sectors in our entire sample. One may also observe that countries with the highest VaR do not necessarily contribute the most to systemic risk in the South African insurance sector.

5. Conclusion

The GFC has exposed the negative side of the interconnectedness of financial markets. A shock in one asset class can significantly affect the stability of financial institutions and markets worldwide. To that end, the objective of this study was to empirically analyse systemic risk in the South African insurance sector, with the impetus of identifying and ranking insurers and countries that pose a systemic threat to the South African financial sector. The contribution of the paper was twofold; first, it combines the analyses of the insurance industry's systemic risk within the domestic economy and its reaction to external systemic risk. Secondly, the empirical analysis of systemic risk, especially the application of the delta conditional value-at-risk (ΔCoVaR) went beyond the common methodology of Adrian and Brunnermeier's (2008) and uses a ΔCoVaR methodology based on a DCC-GJR-GARCH model. The results of the empirical analysis show that Santam, on average, is the most systemically important insurer in

South Africa. For example, Santam added 7.798 basis points to the 1% VaR of the insurance system during the sample period. At the same time, Sanlam the biggest insurer in South Africa is found to be the second most systemically important insurer, followed by Momentum. Liberty, the smallest insurer in our sample, is found to be the smallest contributor to systemic risk, followed by Discovery. These findings suggest that the contribution of insurance companies to systemic risk is not determined by their size, but rather by their risk management practices. Moreover, the results show that four developed countries in our sample contribute significantly to systemic risk in South Africa. For example, Australia, which has one of the most developed insurance sectors in the world, is found to be the largest contributor to systemic risk in South Africa, followed by Japan and Germany, respectively. These three countries contributed, on average, 0.08568%, 0.07332%, and 0.0683% points to the VaR of the South African insurance system when they move from operating normally to a state of hardship. Interestingly, our results found that the United States insurance sector is our sample's smallest contributor to systemic risk. The results of this study have important policy implications, for instance: The study recommends that financial regulators, policymakers, and others alike should impose stricter financial regulation tools on systemically important insurers and countries to enhance the flexibility of risk supervision. Financial regulators in South Africa should implement policies that minimise or reduce the ripple effects of insurers' failure or country-level events. The study suggests that in addition to current regulations such as the twin peaks model and King codes regulation, insurers should make sure that they have sufficient capital reserves to mitigate the effects of external shocks

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