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Shadow banking and systemic risk in South Africa: does size matter?

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Abstract

Purpose – The relationship between the size of financial institutions and systemic risk remains a subject of interest among regulators, and research on this subject has focused mostly on banks, while overlooking the shadow banking sector. This paper examines the relationship between the size of shadow banking and systemic risk in South Africa.

Design/methodology/approach – The study employed the conditional value-at-risk (CoVaR), using the returns of fixed-income funds, funds-of-funds, money market funds and multi-asset funds from January 2015 to December 2021, to measure systemic risk. Ordinary Least Squares and quantile regressions were used to estimate the models.

Findings – The results reveal a positive relationship between the size of shadow banking and systemic risk, and the relationship is stronger for retail multi-asset funds sponsored by asset managers. However, we did not find any relationship between the size of fixed-income funds, funds-of-funds and money market funds and systemic risk.

Practical implications – The regulator should monitor the rapid growth of multi-asset funds and the concomitant systemic risk implications, and fund managers should shift their attention from idiosyncratic risk to the prevention and management of systemic risk.

Originality/value – To the best of the author's knowledge, this is the first study to examine the relationship between the size of shadow banking and systemic risk with a focus on sponsor and investor types.

Keywords CoVaR, Size, Shadow banking, Systemic risk

Paper type Research article

1. Introduction

The tight regulation of banks, technological progress and financial innovation after the global financial crisis spurred the growth of shadow banking (Plantin, 2015; Ordoñez, 2018), leading to the establishment of large and complex shadow banking entities. Large financial institutions pose a risk to the financial system due to the financial assets they mobilise, the extent of diversification and their provision of irreplaceable financial services (Zhou, 2010; Laeven *et al*., 2014; Banwo *et al*., 2019). According to systemic risk literature that focuses mostly on banks, the general conclusion is that larger banks contribute more to systemic risk (Mensah and Premaratne, 2017; Varotto and Zhao, 2018; Leukes and Mensah, 2019; Manguzvane and Mwamba, 2019; Borri and Giorgio, 2022). However, some studies report that size alone is not the predictor of systemic risk, as both small and large banks contribute to systemic risk (Lehar, 2005; Zhou, 2010; Gauthier *et al*., 2012; Barth and Schnabel, 2013; Weiß *et al*., 2014). Therefore, whether there is a link between the size of a financial institution and systemic risk remains a relevant academic inquiry. This study, therefore, examines the relationship between the size of shadow banking and systemic risk.

Examining the linkages between the size of shadow banking and systemic risk is important for several reasons. Firstly, shadow banking is growing at a rapid rate in emerging economies and is becoming significant in size and scope, with a potential implication for systemic risk (Financial Stability Board, 2020). Secondly, shadow banking entities perform the core functions of traditional banks, including credit intermediation involving maturity and liquidity

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transformation, without or with limited supervision and backstop support from the central bank (Pozsar *et al.*, 2012). The lack of access to explicit central bank liquidity or public sector credit guarantees makes shadow banking susceptible to runs (Shleifer and Vishny, 2011). Lastly, shadow banking is connected to the rest of the financial system, particularly banks, through investments, counterparty contracts and securitisation (Abad *et al.*, 2022; Bakk-Simon *et al.*, 2012; Gennaioli *et al.*, 2013; Kemp, 2017; Pozsar *et al.*, 2012) and these linkages create a channel for shocks spilling over to the rest of the financial sector.

This paper contributes to academic literature by providing empirical evidence on systemic risk posed by large shadow banks in the South African context. South Africa provides an interesting case study as the country recorded a rapid growth of shadow banking (FSB, 2020) among emerging economies, evidenced by growth in the sector by 62% from R1.6 trillion in 2015 to more than 2.6 trillion in 2021 (Figure 1). Prior studies on the relationship between the size of shadow banking and systemic risk in China and Europe focused on money market funds and financial services only (Pellegrini *et al.*, 2022a, b; Delawar and Sagi, 2024), owing to the differences in structure and composition of shadow banking between the regions (FSB, 2020). For example, shadow banking in China is dominated by trust companies and broker-dealers sponsored by state-owned banks (Allen and Gu, 2021). In Europe, money market funds, repo markets, securitisation and hedge funds are dominant entities (Allen and Gu, 2021), while the South African shadow banking is dominated by multi-asset funds, followed by fixed-income funds, funds-of-funds and money market funds (Figure 1).

To the best of the authors' knowledge, this is the first study to explore the relationship between the size of shadow banking and systemic risk at disaggregated levels, introducing the type of sponsor and shadow banking classification in the analysis. The sponsors are banks, insurers and asset managers and the shadow banking entities are classified as institutional or retail. The disaggregation is motivated by the fact that banks, insurers and asset managers hold assets of retail and institutional investors and participate in shadow banking through off-balance sheet activities and counterparty contracts, and leading to a perception that shadow banking entities will be bailed out by their sponsors in the event of failure (Bengtsson, 2016; Huang, 2018; Foley-Fisher *et al.*, 2020). Implicit guarantees create an enforcement problem

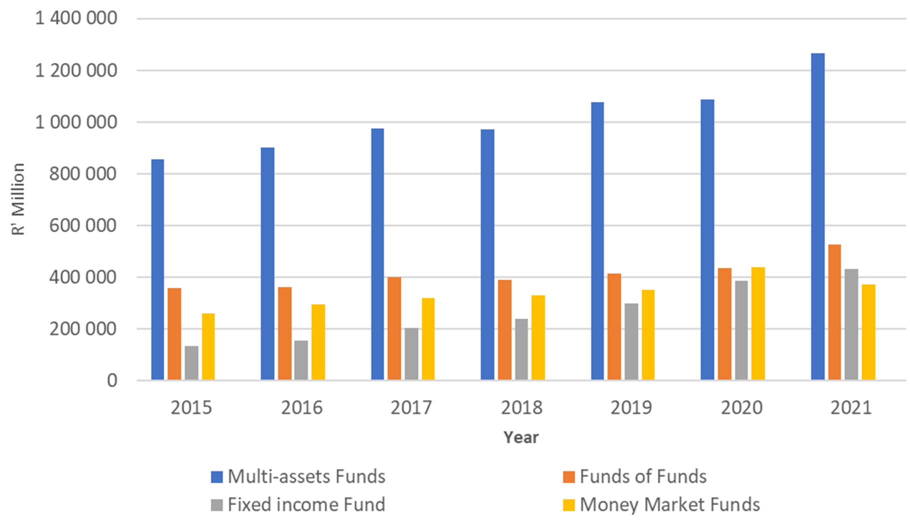


Figure 1. Shadow banking assets in South Africa. The figures show the assets of fixed-income funds, funds-of-funds, money market funds, and multi-asset funds. Multi-asset funds are the largest, and their assets are more than double those of all other funds. Source: Authors' own work

because sponsors have no legal obligations to bail out the failed entity. Therefore, regulators need to understand the variation in the size and systemic risk among shadow banking entities, and this will prompt regulators to monitor the growth of specific shadow banking entities to manage systemic risk.

Finally, the study tests the robustness of the findings by introducing the two potential moderating variables, interconnectedness among the shadow banking entities and the volatility of the returns of the individual shadow banking entities. Large financial institutions tend to have more connections (Cai *et al.*, 2018), and linkages create a channel for shock propagation within the financial system (Allen and Gale, 2000). Volatility increases systemic risk, particularly in small financial institutions (Yang *et al.*, 2023). The rest of this article is organized as follows. Section 2 reviews theoretical and empirical literature, Section 3 describes the research methodology, Section 4 presents empirical results, Section 5 presents the discussions and Section 6 concludes.

2. Literature

2.1 Theoretical concept

Shadow banking refers to "credit intermediation involving entities and activities outside the regular banking system" (FSB, 2011, P. 3). This includes all entities outside traditional banks that perform a core bank function of credit intermediation. Systemic risk is "a risk of disruption to financial services that is caused by an impairment of all parts of the financial system and has a potential to have serious negative consequences for the real economy" (IMF *et al.*, 2009, p. 5).

Theoretically, the relationship between the size of shadow banking and systemic risk is explained by the size of financial assets mobilized by large financial institutions and the extent of diversification (Zhou, 2010; Laeven *et al.*, 2014; Banwo *et al.*, 2019). Shadow banks become diversified through direct linkages created by investments, as well as through lending and borrowing between different entities in the financial system (Zhou, 2010). Diversification builds channels for shock transmission in the financial system (Allen and Gale, 2000; Wagner, 2010; Battiston *et al.*, 2012). Therefore, a large financial institution that is more diversified contributes more to systemic risk (Zhou, 2010). Systemic risk also arises when shadow banks create cash-like assets collateralised by illiquid assets during normal or quiet periods, and those assets become unavailable during uncertain periods, causing contraction in the supply of liquidity (Moreira and Savov, 2017). The decline in liquidity in the financial system will be significant in the event that the depressed entity is a sizeable shadow bank, and other entities may be forced to sell their assets on fire sale to meet the liquidity demands (Brunnermeier and Pedersen, 2009). Fire sales will depress asset prices, causing the failure of one or more financial entities (Brunnermeier and Pedersen, 2009). The failure of a shadow bank could further give rise to information contagion, leading to runs and higher costs of credit, because when information about a failed institution can trigger sudden withdrawals in other financial institutions, even if their business is sound (Acharya and Yorulmazer, 2008).

The size and systemic risk nexus is also discussed in numerous other theories. For example, Luck and Schempp (2015) created a model to highlight that panic-based runs become possible only if the shadow banking sector is large. In their bank model, Caccioli *et al*. (2012) argue that a large bank would increase systemic risk in a highly connected financial system. Otherwise, a large bank would only affect a few institutions in a loosely connected financial system. This argument may be applied in shadow banking, highlighting that systemic risk is conditional on properties of the shadow banking system or the financial system at large. However, following the banking sector results by Krause and Giansante (2012), large shadow banks would still cause more widespread instability even in a loosely connected financial system than a smaller shadow bank. Besides direct linkages, a large shadow would also transmit shocks through indirect connections such as common assets and market exposures (Chen, 1999; Acharya and Yorulmazer, 2008; Brunnermeier and Pedersen, 2009; Giudici *et al*., 2020).

2.2 Empirical literature

The majority of studies on the relationship between size and systemic risk focus on banks (Roengiptya and Rungcharoenkitkul, 2011; Kleinow *et al*., 2017; Mensah and Premaratne, 2017; Varotto and Zhao, 2018; Leukes and Mensah, 2019; Manguzvane and Mwamba, 2019; Borri and Giorgio, 2022), and as a result, this review builds on literature from the banking sector. The literature suggests that size has a positive effect on systemic risk (Moch, 2018). The positive effect was also reported in another study using global data, and the study highlighted that large banks create more systemic risk than smaller banks, especially when they have insufficient capital or unstable funding and engage in market-based activities (Laeven *et al*., 2014). The positive relationship between the size of a bank and systemic risk is also reported in several other studies (Borri and Giorgio, 2022; Kleinow *et al*., 2017; Mensah and Premaratne, 2017; Roengiptya and Rungcharoenkitkul, 2011; Varotto and Zhao, 2018). In South Africa, four large banks are found to contribute more to systemic risk than smaller banks (Manguzvane and Mwamba, 2019).

Despite evidence of the positive relationship between size and systemic risk, a review of international crises shows that size does not cause systemic risk, but systemic risk is driven by the characteristics of the regulatory regime (Weiß *et al*., 2014). The regulatory regime includes funding for deposit insurance and regulatory capital stringency. Other studies also conclude that size alone is not a predictor of systemic risk, but the relationship is compounded by interconnectedness, the country's debt ratio, equity capital and changes in financial markets (Barth and Schnabel, 2013; Gauthier *et al*., 2012; Foggitt *et al*., 2017; Lehar, 2005; Zhou, 2010). In South Africa, Foggitt *et al*. (2017) reveal that the relationship between size and systemic risk may vary during normal and turbulent periods. Their study concludes that the small banks in the sample, in terms of market capitalization, contribute more to systemic risk during the quiet period, whereas large banks increase systemic risk during turbulent times.

In the European shadow banking literature, an analysis that included 183 money market funds and 79 finance services shows a positive relationship between size and systemic risk (Pellegrini *et al*., 2022b). Systemic risk increases when the size of large money market funds increases, but not in finance services (Pellegrini *et al*., 2022b). The relationship between size and systemic risk is also reported in other shadow banking studies from China and Europe (Delawar and Sagi, 2024; Pellegrini *et al*., 2022a, b). The studies also show that higher volatility in equity returns increases systemic risk (Delawar and Sagi, 2024; Meher *et al*., 2024). The other important factor in the relationship between size and systemic risk is diversification, which creates linkages and channels for shock propagation through counterparty contracts or common asset and market exposures (Allen and Gale, 2000; Wagner, 2010; Zhou, 2010; Battiston *et al*., 2012). The linkages between sponsors and their shadow banks increase the fragility of the financial system (Bengtsson, 2014).

3. Methodology

3.1 Data

We obtained the funds' monthly market returns data from Morningstar for the period from January 2015 to December 2021. We restricted the analysis to this period due to significant missing data from the prior years. The dataset has 236 multi-asset funds, 164 funds-of-funds, 43 fixed-income funds and 23 money market funds, and this data represents approximately 60% of the shadow banking in South Africa.

We retrieved monthly closing prices of JSE Top40 Returns, the South African Volatility Index (SAVI) and financial sector returns from iress website and accessed 10-year government bond and 3-month T-bills data from the South African Reserve Bank. The state variables data were converted using the formula below:

$$X_{it} = \left[\ln\left(\frac{P_{it}}{P_{it-1}}\right)\right] * 100 \quad (1)$$

where X_{it} is the change in price, P_{it} is the closing price of state variable i on month t and P_{t-1} is the previous price.

3.2 Measuring systemic risk and size

Several approaches are followed in measuring systemic risk (Benoit *et al.*, 2017; Dičpinigaitienė and Novickytė, 2018; Ellis *et al.*, 2022; Lehar, 2005). However, we use CoVaR methodology (S to assess the overall risk spread (CoVaR) and the breakdown of the marginal risk from all risks (ΔCoVaR). CoVaR uses publicly available market returns data and can act as an early warning signal for future systemic risk threats. We measure the size of shadow banking entities using the log of total assets.

3.3 CoVaR/ΔCoVaR estimation

We estimate CoVaR using quantile regression, with the financial sector returns as the dependent variable and the returns of the individual funds as independent variables (Adrian and Brunnermeier, 2016). We included a set of state variables as independent variables to produce the time-varying CoVaR. The state variables are equity market return, an indirect proxy for intrinsic financial system risk, the SAVI measuring risk within the equity market and yield spread capturing changes in the business cycle (Table 1). The yield spread is the difference between the 10-year South African government bond and the 3-month T-bill rate. We follow Adrian and Brunnermeier (2016) by introducing one-month lags on state variables to capture time variation. The quantile regression model is specified as follows:

$$VaR^{s|i}_{t,q} = \widehat{\alpha^{s}_{0,q}} + \widehat{\alpha^{s}_{1,q}} X^{i}_{t,} + \widehat{\beta^{s}_{q}} N_{t}. \quad (2)$$

Where $VaR^{s|i}_{t,q}$ is the q percent VaR of the financial system conditioned on the returns of fund i. Therefore, the quantile regression of the VaR of the financial system conditional on fund i being in distress is specified as follows:

Table 1. List of study variables

Variable	Proxy	Variable type
Systemic Risk	CoVaR/ΔCoVaR	Dependent
Size	Log of total assets	Independent (Primary)
Shadow banking class	Fixed-income funds/fund-of-funds/money market funds/ multi-asset funds	Independent (Secondary)
Sponsor	Bank/insurance/asset managers	Independent (Secondary)
Investor	Institutional/retail	Independent (Secondary)
Interconnectedness	The total number of in–ward and out-ward connections for individual funds	Control variable
Volatility	Returns standard deviation	Control variable

Source(s): Authors' own work

$$VaR_{t,q}^{s|i=distress} = \widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} X_{t,q}^{i} + \widehat{\beta_{q}^{s}} N_t \quad (3)$$

Where $VaR_{t,q}^{s|i=distress}$ is the VaR of the system when fund i is in distress. The marginal contribution of individual fund i to systemic risk was calculated as the difference between CoVaR conditioned on fund i in distress from CoVaR conditioned on fund i in a normal state. CoVaR conditioned on fund i in the normal state is denoted by:

$$VaR_{t,q}^{s|i=normal\ state} = \widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} + \widehat{\beta_{q}^{s}} N_t \quad (4)$$

$VaR_{t,q=0.50}^{i}$ is the 50% VaR of institution i and was used to represent an institution that is operating in a normal state. The marginal contribution to systemic risk is as follows:

$$\Delta CoVaR_{t,q}^{s|i} = \left(\widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q}^{i} + \widehat{\beta_{q}^{s}} N_t\right) - \left(\widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} + \widehat{\beta_{q}^{s}} N_t\right) \quad (5)$$

or

$$\Delta CoVaR_{t,q}^{s|i} = \widehat{\alpha_{1,q}^{s}} VaR_{t,q}^{i} - \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} \quad (6)$$

Where $\Delta\ CoVaR_{t,q}^{s|i}$ is the marginal contribution of an institution i to systemic risk. $\Delta\ CoVaR_{t,q}^{s|i}$ is the change in the value-at-risk of the financial system conditional on an institution being under distress relative to its median state (Adrian and Brunnermeier, 2016).

3.4 Correlation analysis

We test for the association between size and systemic risk using Pearson and Spearman correlation tests. Pearson measures linear correlation, and Spearman assesses both linear and non-linear relationships. We set the significance level at 5%, and interpret the correlation results following Ratner (2009), where coefficient values < 3 represent weak, >3–<7 moderate and >7 strong association.

3.5 Regression models

3.5.1 Ordinary least squares regression. We estimate the ordinary least squares (OLS) regression with the dependent variables, CoVaR and ΔCoVaR and the independent variable, log of total assets as a proxy for size. We also include shadow banking class, and sponsor and investor types (Table 1). In other models, we include interconnectedness and volatility as dependent variables. However, the primary OLS model is denoted by:

$$Systemic\ risk = \beta_0 + \beta_1 \text{Size} + \beta_2 \text{shadow banking class} + \beta_3 \text{Sponsor} + \beta_4 \text{Investor} + \mu \quad (7)$$

Where β_0, and intercept term represents the mean response when all the predictors are equal to zero. β_1 to β_4 are regression coefficients representing a change in the mean response per unit increase in the associated predictor variable when all other predictors are held constant. μ is a composite error term, the difference between the predicted and actual values. The assumptions of multivariate regression analysis are linearity, normality, homoskedasticity, and having no multiple ties between independent variables (Osborne and Waters, 2002). We draw scatter plots to test for linearity and use the Shapiro–Wilk for normality assumptions. Shapiro–Wilk tests the null hypothesis that the variable, error term, is normally distributed. We apply the Langrage Multiplier test for the null hypothesis that the process is homoscedastic. We calculate the variance inflation factor to test multicollinearity among independent variables. We run several multiple regression models and test for violations of model assumptions. The results of OLS regressions and tests of the assumptions are presented in Annexes 1 and 2, respectively.

3.5.2 Quantile regression. We also examine the relationship between the size of shadow banking and systemic risk using quantile regression (Koenker and Bassett, 1978). Quantile regression provides an alternative to OLS regression based on the conditional median. Whereas least-squares regression is concerned with modelling the conditional mean of the response variable, quantile regression models the conditional τth quantile of the response variable, for some value of $\tau \in (0, 1)$. Quantile regression produces conditional quantiles without the distributional assumptions (Koenker and Bassett, 1978). Therefore, it's suited for non-linear or non-normally distributed data. Meaning that the model does not have to satisfy the assumptions required for OLS. The conditional quantile model is written as

$$Q_q\left(y_i \mid x_i\right) = x_i'\beta_q, i = 1, \ldots.., n \tag{8}$$

Where Q_q and x_i are K X 1 vectors and $x_{i1}' \equiv 1$. The error $\mu_q \equiv y - x'\beta_q$ is assumed to have a continuously differentiable cumulative distribution function, $F_{\mu q}(\cdot|X)$ and density function, $F_{\mu q}(\cdot|X)$. For the Kth regressor, the marginal coefficient for the qth quantile is expressed as:

$$\frac{\partial Q_q(y|x)}{\partial x_k} = \beta_{qk} \tag{9}$$

A quantile regression parameter, β_{qk} represents the change in a specified quantile q of the outcome variable y (systemic risk) from a one-unit change in the regressor x_k (size, shadow banking class, sponsor, investor). Quantile regression minimizes, $\sum_i q|e_1| + \sum_i (1-q)|e_1|$, a sum that gives the asymmetric penalties, $q|e_1|$ for underprediction and $(1-q)|e_1|$ for overprediction. The qth quantile regression estimator $\widehat{\beta}_q$ minimizes over $\widehat{\beta}$ the objective function:

$$Q\left(\beta_q\right) = \sum_{i:y_i \geqslant x_i'\beta}^{N} q|y_i - x_i'\beta_q| + \sum_{i:y_i < x_i'\beta}^{N} (1-q)|y_i - x_i'\beta_q| \tag{10}$$

Where $0 < q < 1$. We implement the restricted regression quantiles to overcome the plane crossing problem, common models with finite observations (Zhao, 2000). All models are restricted to 50 replications. We define τ^{th} quantile at lower (25th percentile) and upper (75th percentile) quartiles and median (50th percentile), and interpret the results at a 5% statistical significance level.

4. Empirical results

We estimated the relationship between the size of shadow banks and systemic risk. The independent variable is size proxied by the log of total assets, and the dependent variables are CoVaR and ΔCoVaR. The summary statistics of dependent variables are shown in Table 2. The dependent variables are estimated using market returns summarised in Table 2, showing higher returns and volatility in multi-asset funds.

The mean CoVaR or average contribution to systemic risk is 0.619%, and the marginal contribution, ΔCoVaR, is −7.812%. The highest contributors to systemic risk (CoVaR) are multi-asset funds, whereas money market funds contribute the least (Table 2). CoVaR volatility is higher in multi-asset funds and lower in money market funds, with standard deviations of 0.182% and 0.016%, respectively. Funds-of-funds have the highest marginal contribution to systemic risk (ΔCoVaR) at −7.990%, followed by multi-asset funds at

Table 2. Descriptive statistics – CoVaR/ΔCoVaR

Variable	Mean	Std. Dev	Min	Max	Obs
Market returns					
Fixed-income fund	0.589	0.0816	0.264	0.704	43
Fund-of-fund	0.598	0.132	0.240	1.228	164
Money market fund	0.532	0.015	0.499	0.561	23
Multi-asset fund	0.648	0.182	0.106	1.540	236
Systemic Risk					
CoVaR	0.619	0.157	0.106	1.540	466
ΔCoVaR	−7.812	0.820	−10.069	−4.601	466
CoVaR by shadow banking class					
Fixed-income fund	0.589	0.082	0.264	0.704	43
Fund-of-funds	0.599	0.132	0.240	1.228	164
Money market fund	0.532	0.016	0.499	0.561	23
Multi-asset fund	0.648	0.182	0.106	1.540	236
CoVaR by sponsor					
Bank	0.604	0.136	0.337	1.006	42
Insurer	0.599	0.099	0.350	0.892	67
Asset manager	0.625	0.167	0.106	1.540	357
CoVaR by investor					
Institutional	0.589	0.152	0.106	0.868	23
Retail	0.619	0.157	0.165	1.540	417
ΔCoVaR by shadow banking class					
Fixed-income fund	−7.554	0.768	−9.350	−5.611	43
Fund-of-funds	−7.990	0.706	−10.064	−4.601	164
Money market fund	−7.627	0.099	−7.818	−7.383	23
Multi-asset fund	−7.753	0.915	−10.069	−5.110	236
ΔCoVaR by sponsor					
Bank	−7.697	0.943	−9.492	−4.601	42
Insurer	−7.828	0.817	−10.064	−5.530	67
Asset manager	−7.822	0.806	−10.069	−5.110	357
ΔCoVaR by investor					
Institutional	−8.233	0.589	−10.060	−7.398	23
Retail	−7.793	0.823	−10.069	−4.601	417

Note(s): This table provides a summary of descriptive statistics of equity returns and systemic risk (CoVaR and ΔCoVaR). Multi-asset funds have the highest returns, followed by fixed-income funds and funds-of-funds. Multi-asset funds and funds-of-funds are more volatile, as they have higher standard deviation. Multi-asset funds, retail funds, and funds owned by asset managers have a higher contribution to systemic risk (CoVaR). Funds-of-funds and institutional funds have a higher marginal contribution to systemic risk (ΔCoVaR)

Source(s): Authors' own work

−7.753% (Table 2). Funds sponsored by asset managers display higher and more volatile systemic risk compared to those owned by banks and insurers (Table 2).

The summary statistics of the independent variable, the total assets and the transformed variable, the log of total assets is shown in Table 3. The mean or average fund size is R3.7 billion. The largest fund has R155 billion in assets and the smallest has R11 million. The largest fund is a retail multi-asset fund owned by asset managers. The largest fund-of-fund and money market fund have R27 billion and R39 billion assets, respectively. The assets of bank-sponsored funds range from R34 million to R58 billion, and those of funds owned by insurers total between R53 million and R37 billion.

Table 3. Descriptive statistics – total assets/Log assets

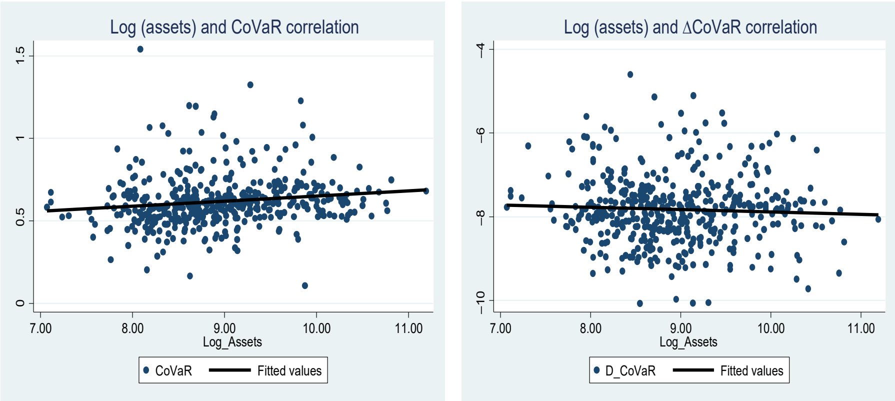
Variable	Mean	Std. dev	Min	Max	Obs
Log (total assets)	8.931	0.729	7.070	11.192	455
Total Assets (ZAR Million)	3,718	10,498	11	155,888	455
Log (total asset) by shadow banking class					
Fixed-income Fund	9.167	0.892	7.112	10.769	42
Funds-of-Funds	8.643	0.567	7.070	10.442	158
Money Market Fund	9.397	0.791	7.554	10.599	23
Multi-asset Fund	9.043	0.724	7.114	11.193	222
Log (total asset) by sponsor					
Bank	9.266	0.733	7.532	10.769	41
Insurer	9.145	0.713	7.728	10.570	65
Asset Managers	8.849	0.713	7.070	11.193	339
Log (total asset) by investor					
Institutional	9.264	0.562	8.108	10.259	22
Retail	8.924	0.735	7.070	11.193	410
Total asset by shadow banking class (ZAR Million)					
Fixed-income Fund	6,262	12,551	12	58,877	42
Funds-of-Funds	1,270	3,131	11	27,687	158
Money Market Fund	7,711	10,216	35	39,781	23
Multi-asset Fund	4,565	12,920	12	155,888	222
Total assets by sponsor (ZAR Million)					
Bank	5,842	10,401	34	58,877	41
Insurer	4,046	6,199	53	37,169	65
Asset Managers	3,398	11,136	11	155,888	339
Total asset by investor (ZAR Million)					
Institutional	3,650	4,518	122	18,137	22
Retail	3,817	10,875	11	155,888	410

Note(s): This table provides a summary of descriptive statistics of total assets. The largest shadow bank is a retail multi-asset fund with R155 billion in assets under management. Retail and multi-asset funds are more volatile because they have a higher standard deviation

Source(s): Authors' own work

Figure 2 shows the results of Pearson and Spearman rank correlation. There is a positive correlation between size and CoVaR. This means funds' contribution to systemic risk tends to increase with the growth in the size of shadow banks. However, the association is weak, with a Pearson correlation coefficient of 0.144 and a Spearman rank coefficient of 0.2316. Since both Pearson and Spearman correlation coefficients are statistically significant at a 5% level, it means the relationship is linear. In contrast, the Pearson and Spearman correlation tests are insignificant for the relationship between size and ΔCoVaR.

The OLS results are presented in Table 4 and Annex 1, and interpreted at 5% significance level. There is a statistically significant relationship between size and systemic risk. A percentage point increase in size will increase systemic risk (CoVaR) by 0.039% (p = 0.001). A similar increase in size will increase shadow banking's marginal contribution to systemic risk, ΔCoVaR, by 0.133% (p = 0.022). However, the ΔCoVaR model violates the linearity assumption (Annex 1). We also estimate the OLS models with small, medium and large shadow banks and the results are statistically significant with medium-sized (p-value = 0.004) and large (p-value<0.001) funds, confirming the positive effect of size on CoVaR (Table 4).



Pearson = 0.144 (p = 0.002) Spearman = 0.2316 (P < 0.001)

Pearson = −0.049(p = 0.299) Spearman = −0.024 (P = 0.618)

Figure 2. Correlation between size and systemic risk. **Source(s):** Authors' own work

Table 4. OLS regression: Log (assets) and CoVaR/ΔCoVaR by shadow baking class, sponsor and investor

Variable		N	COVAR	ΔCOVAR
Full Sample		432	*0.039 (0.001)**	*−0.133 (0.022)**
Fund size	Small	112	0.030 (0.146)	−0.207 (0.061)
	Medium	111	*0.061 (0.004)**	*−0.281 (0.012)**
	Large	132	*0.083 (p < 0.001)**	−0.156 (0.167)
Shadow banking class	Fixed-income funds	42	*0.036 (0.012)**	*−0.362 (0.003)**
	Funds-of-funds	151	0.027 (0.141)	−0.109 (0.269)
	Money market funds	23	0.007 (0.148)	0.004 (0.897)
	Multi-asset funds	216	*0.054 (0.003)**	−0.030 (0.737)
Sponsor	Banks	41	0.032 (0.298)	−0.239 (0.258)
	Insurer	65	0.025 (0.157)	−0.102 (0.540)
	Asset manager	326	0.152 (0.272)	−0.111 (0.086)
Investor	Institutional	410	*0.041 (<0.001)**	*−0.142 (0.017)**
	Retail	32	0.005 (0.956)	0.389 (0.190)

Note(s): This table reports the OLS results. (*) indicates that the relationship between size and systemic risk is statistically significant at 5% significance level. The full sample model is statistically significant with both CoVaR and ΔCOVAR, but the model with ΔCOVAR violates the linearity assumption. Multi-asset funds and retail funds results are statistically significant and satisfy all OLS assumptions

Source(s): Authors' own work

We estimate various models with the size of fixed-income fund, fund-of-funds, money market funds and multi-asset funds as outcome variables. The size of a multi-asset fund has a positive effect on systemic risk. A percentage point increase in the size of the multi-asset fund will increase CoVaR by 0.054% (p = 0.003). The results of fixed-income funds are statistically significant with both CoVaR and ΔCoVaR (Table 4 and Annex II), however, the results are interpreted with caution because the model violates the linearity assumption (Annex II). There is no relationship between the size of funds-of-funds or money market funds with both CoVaR and ΔCoVaR as the results are statistically insignificant (Table 4 and Annex II).

The results of quantile regression are shown in Table 5 and Annex III. The quantile regression results confirm the OLS estimates that size has a positive relationship with CoVaR, and not ΔCoVaR. For the CoVaR model, the coefficients of OLS and quantile regression at mean and median are 0.039% and 0.037%, respectively (Tables 4 and 5). This means they are not significantly different. At the lowest quantile, the coefficient is 0.047%, and this means the effect of size is slightly elevated at the lower-than-average systemic risk levels. At the 75th quantile, there is no relationship between size and systemic risk and this shows that size has no effect when systemic risk is elevated beyond a certain level. Put differently, the effect of size diminishes as systemic risk increases beyond the 75th percentile.

Across all quantiles, multi-asset funds have a positive relationship with CoVaR. The relationship is slightly stronger at the 50th percentile. At the median, a percentage point increase in the size of the multi-asset fund will increase systemic risk by 0.068% (Table 5), whereas a unit increase in size will increase CoVaR by 0.059% at the 25th percentile and 0.047% at the 75th percentile (Table 5). Other significant results are for funds sponsored by insurers and asset managers, and retail funds at the 25th percentile. Funds owned by asset managers are statistically significant at the 50th percentile ($p < 0.001$), and retail funds at the 25th percentile ($p < 0.001$), and this means the size of funds owned by asset managers and retail funds increases the contribution to systemic risk when systemic risk is at the median and lower levels, respectively (Annex 3).

We estimate two quantile regression models combining variables where size has a statistically significant relationship with CoVaR. Firstly, we combine multi-asset funds, funds owned by asset managers and retail funds. The results are statistically significant at 25th (Coeff = 0.05; $p < 0.001$) and 50th (Coeff = 0.073; $p = 0.002$) percentiles. The results point to

Table 5. Quantile regression: Log (assets) and CoVaR by shadow banking class, sponsor, and investor

		N	COVAR q25	Q50	Q75
Full Sample		432	*0.047 (<0.001)**	*0.037 (<0.001)**	0.015 (0.133)
Shadow banking class	Fixed-income funds	42	0.024 (0.520)	0.013 (0.521)	0.013 (0.585)
	Funds-of-funds	151	0.028 (0.210)	0.018 (0.189)	0.012 (0.279)
	Money market funds	23	0.007 (0.137)	0.003 (0.619)	0.005 (0.535)
	Multi-asset funds	216	*0.059 (<0.001)**	*0.068 (<0.001)**	*0.047 (0.025)**
Sponsor	Banks	41	0.017 (0.189)	0.013 (0.529)	0.012 (0.653)
	Insurer	65	*0.055 (0.046)**	0.011 (0.338)	0.003 (0.850)
	Asset manager	326	*0.047 (p < 0.001)**	*0.039 (p < 0.001)**	0.021 (0.097)
Investor	Institutional	32	0.028 (0.905)	0.043 (0.593)	0.057 (0.835)
	Retail	410	*0.049 (p < 0.001)**	0.013 (0.269)	0.013 (0.269)
Retail multi-asset funds sponsored by asset managers		161	*0.059 (p < 0.001)**	*0.073 (p = 0.002)**	0.062 (0.090)
Retail multi-asset funds sponsored by insurers		25	0.064 (0.123)	0.052 (0.078)	0.048 (0.066)

Note(s): This table reports the quantile regression results. (*) indicates that the relationship between size and systemic risk is statistically significant at 5% significance level. The full sample size model is statistically significant at 25th and 50th percentiles, lower and median levels of systemic risk, respectively. The multi-asset funds model is significant at lower, median and higher systemic risk levels. Other significant results are those of insurers, asset managers, and retail funds at 25th percentile. The asset manager model is also significant at 50th percentile

Source(s): Authors' own work * denotes a statistically significant relationship a positive relationship between the size of retail multi-asset funds owned by asset managers and CoVaR. However, it is important to note that the relationship is pronounced at low and medium systemic risk levels, and not when systemic risk is high. Secondly, we model multi-asset funds, insurer-sponsored funds and retail funds, and the results are insignificant across all quantiles.

4.1 Robustness tests

We run a number of robustness tests. Firstly, we run OLS and quantile regressions with interconnectedness and volatility as control variables. The relationship between size and CoVaR is significant in the model with volatility ($p < 0.001$). When we add the interaction term for size and volatility, the results for size remain significant ($p = 0.007$). In the analysis across fund classes and types, the results are significant in the models with multi-asset funds ($p < 0.001$) and retail funds ($p < 0.001$).

Secondly, we control for interconnectedness, measured as the number of connections between funds. We run models with interconnectedness among 20 funds, five (with the highest (ΔCoVaR)) from each of the four fund classes, 20 funds with the lowest (ΔCoVaR) and 40 funds combining funds with the highest and lowest CoVaR. The relationship between size and CoVaR is significant ($p = 0.040$) in the model with 40 funds, and insignificant in the model of 20 funds with the highest ΔCoVaR ($p = 0.645$) and 20 funds with the lowest ΔCoVaR ($p = 0.124$).

Finally, we run a quantile regression of the size of retail multi-asset funds owned by asset managers and CoVaR in two subperiods, tranquil (January 2015 to February 2020) and financial turmoil – COVID-19 (March 2020 to December 2021) intervals. The results for the two subperiods are statistically insignificant across all quantiles. The insignificant results could be due to a shorter time series after splitting the study interval into two subperiods.

5. Discussion of findings

The results of OLS and quantile regression models reveal a positive linear relationship between the size of shadow banking and systemic risk in South Africa. This result is consistent with the findings of Pellegrini *et al*. (2022a, b) in China and Europe, who reported that systemic risk increases with the size of large shadow banks. The result is also in line with the majority of the banking sector studies summarised by Moch (2018), which concluded that size has a positive effect on systemic risk. The result is likely due to herding behaviour and diversification. Herding increases systemic risk, particularly in large institutions (Cai, 2022). Furthermore, large institutions tend to be diversified, and diversification amplifies systemic risk by creating linkages through counterparty contracts and common assets and market exposure (Allen and Gale, 2000; Wagner, 2010; Zhou, 2010; Battiston *et al*., 2012).

The results of quantile regressions with the different shadow banking classes show that the size of multi-asset funds has a positive effect on systemic risk, and the results are significant across all quantiles of systemic risk. The result is consistent with the asset size of multi-asset funds and their diversification strategy. Multi-asset funds control large assets in South Africa, and their assets are more than double that of all other funds (Figure 1). The funds combine different assets such as stock, bonds, real estate and cash to achieve stable long-term positive returns. The multi-asset funds are highly connected to the shadow banking system, and they are the main transmitters and receivers of systemic risk in South Africa (Mashimbye and Fanta, 2025). Despite their diversified portfolios, returns and systemic risk of multi-asset funds are most volatile compared to other funds. In this case, the broader economic fluctuations may be the cause of volatility and therefore, increasing systemic risk (Mieg, 2022; Delawar and Sagi, 2024).

Other noticeable results are those of money market funds. The size of money market funds does not influence systemic risk. This result is different from that of Pellegrini *et al*. (2022a), who found that the size of money market funds and not finance services firms was a predictor of systemic risk. The results could be explained by the size of money market funds and their economic functions in different economies. In Europe, shadow banking is more market-based and operates in parallel with traditional banking (Huang, 2015), whereas South Africa's shadow banking is dominated by multi-asset funds targeting retail depositors (Kemp, 2017). Money market funds in South Africa are significantly smaller compared to multi-asset funds, and they mostly serve as liquidity reserves for banks. As such, the contribution of money market funds to systemic risk in South Africa is insignificant and only evident during turbulent periods (Mashimbye and Fanta, 2024).

The result of models that combines fund class and type reveals a positive relationship between retail multi-asset funds sponsored by asset managers and systemic risk. The result is not surprising because retail multi-asset funds sponsored by asset managers control large financial assets, and multi-asset funds are the largest contributors to systemic risk. Retail multi-asset funds sponsored by asset managers may cause systemic risk through insufficient credit risk transfer to asset managers, runs on funds that cause sudden reductions in funding to banks and other financial entities and contagion through common asset and market exposure between funds and their sponsors (Bengtsson, 2014).

6. Conclusions

The study examined the relationship between the size of shadow banking and systemic risk in South Africa and concluded that a positive relationship exists, indicating that larger shadow banks contribute more to systemic risk. The size and systemic risk nexus is more pronounced in multi-asset funds and the relationship is stronger for retail multi-assets sponsored by asset managers. The findings point to retail multi-asset funds as a source of systemic risk in the South African shadow banking and, therefore, require regulation and supervision. Regulators should reconsider the regulations that encourage diversification, while monitoring systemic risk following the rapid growth of multi-asset funds. Asset managers should shift their attention from idiosyncratic risk to systemic risk and monitor the implications of their large asset portfolios and diversification strategies on the stability of the financial system. Future research could focus on other emerging economies using different measures of systemic risk and test the size and systemic risk nexus during various economic and financial cycles.

Supplementary material

The supplementary material for this article can be found online.

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