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Shadow banking interconnectedness in South Africa: Toda and Yamamoto (T-Y) Granger causality test

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Abstract

Purpose – Financial linkages are an important determinant of shock transmissions, and the risk of financial system instability is higher when financial institutions are closely connected. This paper aims to examine interconnectedness within the shadow banking system, a credit intermediation outside traditional banking, in South Africa.

Design/methodology/approach – The authors used the conditional value-at-risk (Co-VaR), using market returns of fixed-income funds, funds-of-funds, money market funds and multi-asset funds from January 2015 to December 2021, to identify funds with the highest contribution to systemic risk. The authors examined interconnectedness using the Toda and Yamamoto Granger causality test among the funds with the highest contribution to systemic risk.

Findings – The authors find a greater degree of interconnectedness in the shadow banking sector, and linkages are at an all-time high during COVID-19. The results also show that while money market funds are only receivers, multi-asset funds are both transmitters and receivers of systemic risk.

Practical implications – The regulator should strengthen monitoring of the linkages in shadow banking, particularly among multi-asset funds and money market funds, and during periods of financial turmoil.

Originality/value – The study contributes to the growing literature on systemic risk in shadow banking. Compared to prior literature, the authors use market returns data from an emerging African economy, South Africa.

Keywords CoVaR, Granger causality, Interconnectedness, Shadow banking

Paper type Research paper

1. Introduction

Shadow banking, a credit intermediation outside the traditional banking system, has attracted the interest of policymakers and regulators since the Global Financial Crisis (GFC). Before the crisis, financial regulation focused mostly on banks to prevent and manage idiosyncratic and systemic risk. However, the crisis revealed the depth of connections between shadow banking and the rest of the financial system, especially banks and insurers (Acharya *et al.*, 2009). In theory, financial linkages or interconnectedness are created through lending, borrowing and investment contracts; and exposures to common assets and markets (Allen and Gale, 2000; Zhou, 2010). Financial linkages create a channel for shock transmissions, and the risk of financial system instability is higher when financial institutions are closely connected (Battiston *et al.*, 2012). Most studies on the financial linkages focused on banks

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and insurers (Baumöhl *et al.*, 2022; Cai *et al.*, 2018; Malik and Xu, 2021; Roengpitya and Rungcharoenkitkul, 2012), and some included shadow banking entities, confirming the contribution of shadow banking to systemic risk through its linkages with other financial sectors (Abad *et al.*, 2022; Bakk-Simon *et al.*, 2012; Billio *et al.*, 2012; Chaturvedi and Singh, 2022; Gennaioli *et al.*, 2013; Kemp, 2017; Pozsar *et al.*, 2012). Nonetheless, there has been little attention to linkages within the shadow banking system, and the literature in this area focused on cross-border interconnectedness (Fong *et al.*, 2021; Girón and Matas-Mir, 2017; Hsu *et al.*, 2013). Policymakers and regulators underscore the importance of country case studies on shadow banking interconnectedness due to cross-country variation in the structure, composition and inherent risk, of the sector (FSB, 2020).

In this regard, South Africa makes an interesting case study for several reasons. Firstly, the country is among the emerging economies that reported rapid growth of shadow banking when compared to its global counterparts (FSB, 2020). The swift growth of shadow banking is mainly driven by multi-asset funds. Multi-asset funds that are compliant with the Pension Fund Act 24 of 1956, regulation 28, are popular for pension savings. Secondly, South Africa has a unique financial structure as the combined assets of Non-Bank Financial Institutions (NBFIs) are bigger than those of banks. Finally, there are growing overlaps in assets and liabilities between various types of shadow banks (Kemp, 2017). For example, R500bn worth of multi-asset fund assets and R205bn worth of funds-of-funds assets are held in collective investment schemes (CIS), including shadow banking entities (ASISA, 2021). This translates into 40% and 47% of multi-asset funds and funds-of-funds assets, respectively. Fixed-income funds have R62m in CIS, and the money market funds do not invest in other CIS but receive investments from them (ASISA, 2021). These connections within the shadow banking system create a channel for shock propagation and contagion (Allen and Gale, 2000).

The other channel for contagion is through indirect linkages due to exposures to common assets and markets (Brunnermeier and Pedersen, 2009; Giudici *et al.*, 2020). In South Africa, fixed-income, money market and multi-asset funds invest between 20% and 60% of their assets in banks, and government and corporate bonds (Figure 1). For instance, over 60% of the assets of money market funds, 48% of those of fixed-income funds and 11% of multi-asset funds' are invested in banks (Figure 1).

We use returns data of fixed-income funds, funds-of-funds, money market funds and multi-asset funds to measure shadow banking interconnectedness in South Africa from January 2015 to December 2021. Firstly, we measure systemic risk following the conditional value-at-risk (Co-VaR) methodology (Adrian and Brunnermeier, 2016), and we restrict the analysis of interconnectedness to funds that contribute the most to systemic risk – those with the highest Delta Co-VaR (ΔCo-VaR). Secondly, we analyse interconnectedness and the direction of linkages between fixed-income funds, funds-of-funds, money market funds and multi-asset funds in the whole study period and three sub-periods: January 2015 to April 2017, May 2017 to August 2019 and September 2019 to December 2021. The rest of this paper is organised as follows. Section 2 reviews the theoretical and empirical literature, Section 3 describes the research methodology, Section 4 presents empirical results, Section 5 presents the discussion of results, and Section 6 concludes.

2. Literature

2.1 Theoretical background

We begin by explaining the concepts of systemic risk and shadow banking. Systemic risk is a risk of disruption to the financial services caused by an impairment of all parts of the financial system and has the potential to have serious negative consequences for the real

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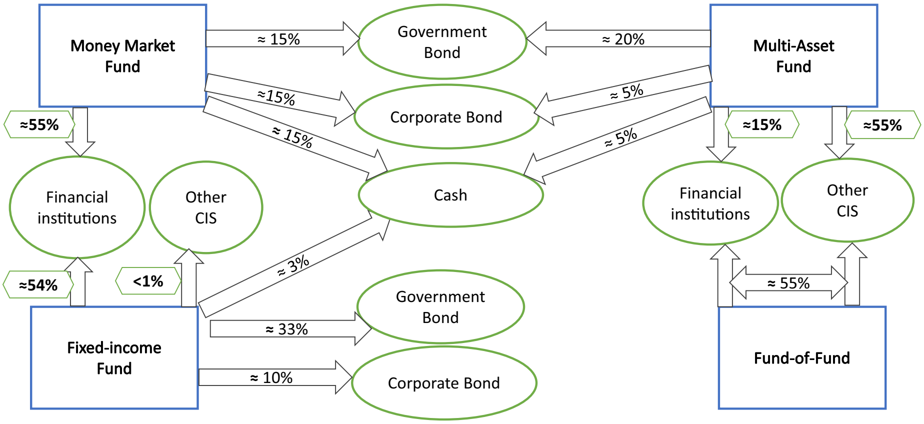

Note: Resources in financial institutions are predominantly in banks
Source: Authors' own work using data from ASISA

Figure 1. Shadow banking network in South Africa

economy (International Monetary Fund, Bank for International Settlements, and Financial Stability Board, 2009), and shadow banking broadly refers to "credit intermediation involving entities and activities outside the regular banking system" (FSB, 2011). The narrower definition of shadow banking focuses on NBFIs involved in credit intermediation activities that may pose bank-like financial stability risks (FSB, 2020). Shadow banks perform the core bank function, credit intermediation, but with limited or no macro-prudential regulation, and without access to liquidity backstop from the central bank. Shadow banking in South Africa refers to brokers, credit insurance, finance companies, fixed-income funds, fund-of-funds, hedge funds, securitization schemes (excluding securitization that banks invest in), money market funds and multi-asset funds (Kemp, 2017).

The shadow banking entities in South Africa are involved in credit intermediation, and maturity and liquidity transformation. Maturity transformation occurs when short-term funds are used to secure long-term investments (Adrian and Ashcraft, 2016), which includes mobilising funds from individual and wholesale funders to invest in securitised assets, government and corporate bonds, and other money market instruments. In other words, shadow banking intermediation uses liquid depositors' investments to fund illiquid assets; therefore, they are also involved in liquidity transformation (Adrian and Ashcraft, 2016). The risk to the stability of the financial system arises when the short-term liquid deposits that are collateralised on illiquid assets become unavailable, especially during uncertain periods, causing a contraction in the supply of liquidity (Moreira and Savov, 2017). Liquidity shortages may trigger fire sales and therefore depress asset prices causing the failure of one or more financial entities (Brunnermeier and Pedersen, 2009).

The collapse of financial entities could spill over when the failed institutions cannot honour their contracts, leading to a decline in the assets of their counterparties (Allen and Gale, 2000). Shadow banking entities create counterparty contracts, and if those counterparties have similar contracts with other financial institutions, a network is created. The network determines the extent and speed at which shocks are transmitted from one

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institution to the other in the system, and this is a key feature of systemic risk. The shock propagation between connected institutions is also elaborated through the three-bank model by Zhou (2010), showing that common exposures to investment portfolios expose an institution to risks. Battiston *et al.* (2012) further highlight that exposure to diverse portfolios and a high level of interconnectedness increases systemic risk. Besides direct connections, failures in the financial system could also be due to information contagion, macroeconomic feedback and common asset and market exposure channels (Acharya and Richardson, 2009; Brunnermeier and Pedersen, 2009; Giudici *et al.*, 2020).

The failure of one or more shadow banks could spill over to other financial sectors because of financial linkages (Billio *et al.*, 2012; Chaturvedi and Singh, 2022; Kemp, 2017). For example, Banks participate in shadow banking through off-balance sheet activities (Huang, 2018), which also involves securitisation and selling of bundled loans to Special Purpose Vehicles (SPVs). Banks and shadow banking are also connected through sponsor arrangements whereby a bank owns a money market or multi-asset fund. Similarly, insurers and asset managers establish their funds, and those funds invest in bank deposits or loans, equity, money markets, bonds or other funds. Altogether, the advent of shadow banking has increased linkages and interdependencies in the whole financial system (Bakk-Simon *et al.*, 2012; Billio *et al.*, 2012; Hautsch *et al.*, 2014; Wang *et al.*, 2018), and the collapse of connected shadow banking entities could propagate shocks to all sectors in the financial system.

2.2 Empirical literature

The empirical review draws insights from systemic risk literature, with a focus on interconnectedness. Financial linkages are an important determinant of shock transmissions, and the risk of financial system instability is higher when financial institutions are closely connected (Battiston *et al.*, 2012). Evidence from several countries, including South Africa, shows linkages between financial institutions, and the degree of interconnections is mostly below 25% of all possible connections between the financial entities studied (Billio *et al.*, 2012; Chaturvedi and Singh, 2022; Leukes and Mensah, 2019; Mensah and Premaratne, 2017). However, in some countries, interconnectedness reached a peak of 60% of all possible connections during COVID-19 (Baumöhl *et al.*, 2022).

Generally, literature on interconnectedness and systemic risk could be disaggregated into system-wide, sectoral and institutional-level connections. More studies focus on sectoral and institutional-level linkages than system-wide connectedness. The few studies on system-wide linkages highlight an increase in financial system interconnectedness following the rapid growth of shadow banking in several countries (Bakk-Simon *et al.*, 2012; Billio *et al.*, 2012; Hautsch *et al.*, 2014; Wang *et al.*, 2018). For example, Wang *et al.* (2018) studied linkages and systemic risk among banks, securities and insurers in China, and conclude that the swift growth of shadow banking is the basis for an increase in interconnectedness and systemic risk. Other studies show similar results, highlighting that traditional banks are increasingly reliant on funding from the NBFIs (Abad *et al.*, 2022; Bakk-Simon *et al.*, 2012; Kemp, 2017).

Sectoral interconnectedness studies mainly focus on banks and insurers. Globally Systemic Important Banks (GSIBs) and Globally Systemic Important Insurers (GSIIs) are reported to be more connected, especially during financial stress (Malik and Xu, 2021). A multi-country data from 16 developed markets in America, Europe and Asia reports that the interconnectedness between insurers and the other sectors – financial and non-financial firms – has strengthened in the past four decades (Jourde, 2022). The study also shows that banks are more connected with the financial system, whereas major insurers are exposed to the non-financial sector (Jourde, 2022). These results are unique; however, they are attributed to the investment channel whereby major insurers are significant sources of funding for non-financial firms.

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Nevertheless, the other results on banks' connection with the financial system highlight that banks are significant in the propagation of financial shocks. On interconnectedness between banks and shadow banking, linkages are reported with the finance companies in India (Chaturvedi and Singh, 2022), hedge funds in the USA (Billio *et al.*, 2012), and money market funds in South Africa (Kemp, 2017).

At the institutional level, evidence focused mostly on interconnectedness and systemic risk in the banking sector. Several studies reported interconnectedness between banks using either a single country or multi-country data (Baumöhl *et al.*, 2022; Cai *et al.*, 2018; Roengpitya and Rungcharoenkitkul, 2012). In Thailand, bank interconnectedness was found to be constant during both the quiet and financial stress periods, and the interconnectedness between large banks was the same as the linkages between large and small banks (Roengpitya and Rungcharoenkitkul, 2012). In contrast, Cai *et al.* (2018) report that large banks contribute more to aggregate interconnectedness, and equally, contribute more to systemic risk during a recession.

Notwithstanding, there are few studies on the interconnectedness between shadow banking entities. In the analysis of financial sector linkages, Billio *et al.* (2012) turn to a particular focus on interconnections between hedge funds and brokers, and Chaturvedi and Singh (2022) on finance companies and mutual funds. In the specific shadow banking studies, Hsu *et al.* (2013) and Girón and Matas-Mir (2017) examined interconnectedness in Europe, and Fong *et al.* (2021) focused on other financial intermediaries (OFIs) in 27 developed and emerging economies. They used balance sheet data, assets and liabilities of OFIs, and concluded that there is interconnectedness in shadow banking (Fong *et al.*, 2021; Girón and Matas-Mir, 2017; Hsu *et al.*, 2013). Overall, this points to a growing literature on cross-border linkages, but limited evidence on the country-level analysis of shadow banking interconnectedness, particularly in emerging economies. This limitation is primarily due to data unavailability. However, other financial sector studies, including Billio *et al.* (2012) and Chaturvedi and Singh (2022) turned to market returns data to overcome this challenge.

Evidence suggests that interconnectedness increases during periods of financial distress (Billio *et al.*, 2012; Drakos and Kouretas, 2015; Leukes and Mensah, 2019; Malik and Xu, 2021; Mensah and Premaratne, 2017; Wang *et al.*, 2018; Xu *et al.*, 2019). The interconnectedness between banks, insurers, securities and trust institutions was high in China during the GFC compared to the period before and after the crisis (Wu *et al.*, 2021). Similar results were reported by Leukes and Mensah (2019) in South Africa. The interconnectedness also increased during systemic stress in China (Wang *et al.*, 2018), and during COVID-19 in various countries (Baumöhl *et al.*, 2022). Overall, the degree of interconnectedness rises during various periods of financial distress, and the analysis that included shadow banking data reached a similar conclusion (Billio *et al.*, 2012; Fong *et al.*, 2021).

Interconnectedness engenders vulnerabilities of shock spill overs in the financial system, and shadow banking regulation focuses on reducing interdependencies. In the USA, the Volcker rule prevents banks from sponsoring private funds. The European region developed guidelines recommending tighter limits on banks' exposure to shadow banking at industry and individual institution levels (EBA, 2015). The regulatory shifts in the USA and Europe aim to have investors provide credit and liquidity backstops to shadow banking, and being responsible for the ex-ante economic cost of maturity transformation (Adrian and Ashcraft, 2012). In South Africa, regulation limit banks' exposures to shadow banking entities or activities that are susceptible to runs. CISCA Notice 90 of 2014 in South Africa limits the exposure of money market funds and funds of funds to their counterparties and banks. Besides interconnectedness, the global shift in the regulation of shadow banking focuses on liquidity risk, excessive leverage and procyclicality and the opaqueness and complexity of shadow banking.

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3. Methodology

The critical issue in the studies of linkages between financial institutions is the measures of interconnectedness applied. Generally, studies follow two approaches. They either use balance sheets or market data. Due to limitations with access to balance sheet data, we examine interconnectedness using the market returns data and follow the Granger causality test to estimate the degree of interconnectedness and the direction of the relationship (Granger, 1969). The standard Granger is modified into the Toda and Yamamoto approach as the series have different orders of integration (Toda and Yamamoto, 1995).

The alternative measures of interconnectedness that use market returns data are TENET (Härdle *et al.*, 2016), and Cross-quantilogram (Han *et al.*, 2016). TENET is the semiparametric technique and it is an extension of Co-VaR (Härdle *et al.*, 2016). Cross-quantilogram measures interconnectedness, spillover effects and the directionality of shock transmission in all parts of the series distribution or quantiles (Han *et al.*, 2016). These measures are, equally robust; nonetheless, we disregard cross-quantilogram and TENET because the objective is to test the relationship and direction of linkage and not relationships within quantiles or tail dependencies. We only use a tail-dependent analysis method, Co-VaR and *Δ*Co-VaR, to select 20 funds with high systemic risk, for inclusion in the Granger causality test.

3.1 Data

We received funds' monthly performance data from Morningstar for the period January 2015 to December 2021, and the series provides 84 months, which is sufficient for statistical analysis when considering annual seasonality (MacCleary *et al.*, 2017). The data set has 466 funds – 236 multi-asset funds, 164 funds-of-funds, 43 fixed-income funds and 23 money market funds. This represents 49% of multi-asset funds and funds-of-funds, 53% of fixed-income, and 60% of money market funds that are classified as shadow banking under the narrow definition of shadow banking. We excluded the funds with incomplete data those funds that have been active for less than 6 years.

We retrieved monthly closing prices of JSE Top40 Returns, South African Volatility Index (SAVI), and financial sector returns from iress.co.za. We 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:

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

where X_{it} is the change in price, P_{it} is the closing price of state variable i on month t and $P_{t\text{-}1}$ is the previous price. State variables are equity market return, market volatility and yield spread. Equity market return is measured using the JSE Top40 Tradeable returns, market volatility through the JSE SA Volatility Index (SAVI), and yield spread is a change in the yield spread – taking the difference between the yield of 10-year South African government bond and 3-month treasury bills (T-bills) rate.

3.2 Quantile regression

We used quantile regression to estimate systemic risk, Co-VaR and *Δ*Co-VaR (Adrian and Brunnermeier, 2016). The systemic risk could also be estimated using autoregressive conditional heteroscedasticity (ARCH) family models (Bollerslev, 2008). However, quantile and ARCH family models show similar patterns of results when measuring systemic risk following the CoVaR methodology (Adrian and Brunnermeier, 2016). The advantage of

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quantile regression is its efficient use of data, and that it produces conditional quantiles without the distributional assumptions (Adrian and Brunnermeier, 2016). The regression models had the financial sector returns as the dependent variable and the returns of the individual funds as independent variables. We included a set of state variables as independent variables to produce the time-varying Co-VaR and ΔCo-VaR. 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. A one-month lag was applied in all state variables. The quantile regression model is specified as follows:

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

where $VaR_{t,q}^{s|i}$ 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:

$$VaR_{t,q}^{s|i=distress} = \widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} X_{t,q}^{i} + \widehat{\beta_{q}^{s}} N_t \tag{2}$$

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 Co-VaR conditioned on fund i in distress from Co-VaR conditioned on fund i in a normal state. Co-VaR conditioned on fund i in the normal state is denoted by:

$$VaR_{t,q}^{s|i=normal\ state} = \widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} + \widehat{\beta_{q}^{s}} N_t \tag{3}$$

$VaR_{t,q=0.50}^{i}$ 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:

$$\Delta Co\text{–}VaR_{t,q}^{s|i} = \left(\widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q}^{i} + \widehat{\beta_{q}^{s}} N_t\right) - \left(\widehat{\alpha_{0,q}^{s}} + \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} + \widehat{\beta_{q}^{s}} N_t\right) \tag{4}$$

(4)

or

$$\Delta Co\text{–}VaR_{t,q}^{s|i} = \widehat{\alpha_{1,q}^{s}} VaR_{t,q}^{i} - \widehat{\alpha_{1,q}^{s}} VaR_{t,q=0.50}^{i} \tag{5}$$

where $\Delta Co\text{–}VaR_{t,q}^{s|i}$ is the marginal contribution of an institution i to systemic risk. We restrict our analysis of interconnectedness to 20 funds, that is five funds in each fund class. We use the five largest contributors to systemic risk among fixed-income funds, funds-of-funds, money market funds, and multi-asset funds. We analyse interconnectedness and the direction of linkages in the whole study period and three sub-periods.

3.3 Granger causality

We measured interconnectedness using the Granger causality test (Granger, 1969). Granger causality measures the degree of interconnectedness and the direction of the relationship between institutions. It is founded on the concept that causes occur before effects and knowing the status of a cause at an earlier period could enhance the prediction of the effect at a later period (Granger, 1969). In the Granger causality test, X is said to be Granger-cause Y if previous values of X contain information that helps predict Y above and beyond that

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contained in past values of Y alone (Granger, 1969). The Granger causality test involves estimating the vector autoregressive (VAR) model:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \tag{6}$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \omega_t \tag{7}$$

where m denotes the maximum lag length and ε_t and ω_t are two uncorrelated white noise processes. In equation (1), Y is said to cause X when b_j is not equal to zero. Similarly, in equation (2), X causes Y when c_j is significantly different from zero; if the ρ-value is less than 5%. Granger causality is sensitive to the order of cointegration and lag length. Therefore, we first tested all series for unit root using augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. ADF and KPSS provide a complementary approach to unit root testing. ADF test the null hypothesis that the series is non-stationary, whereas KPSS tests that the series is stationary around the deterministic trend. The series were found to have either cointegration order I (0) or I (1), and we applied the Toda and Yamamoto (1995) approach since the series are cointegrated with different orders of integration (Appendix 1). The technique estimates the vector autoregressive (VAR) model at levels, and it is robust to the integration and cointegration of the process. Toda and Yamamoto (1995) adopts a revised Wald test for restriction on each parameter of the VAR (k), where the lag length is k, and the actual order of the system (k) is supplemented by the highest order of integration (dmax). However, the VAR (k + dmax) is estimated without the coefficients of the lagged (dmax) vector. The Wald statistic adopts a chi-square allocation of a function with degrees of freedom that corresponds to the number of eliminated lagged variables. The empirical model in the VAR (k + dmax) system to execute the Toda and Yamamoto Granger Causality approach is as follows:

$$X_t = \omega + \sum_{i=1}^{m} \theta_i X_{t-i} + \sum_{i=m+1}^{m+dmax} \theta_i X_{t-i} + \sum_{i=1}^{\mathrm{m}} \delta_i Y_{t-1} + \sum_{i=m+1}^{m+dmax} \delta_i Y_{t-i} + v_1 \tag{8}$$

$$Y_t = \varphi + \sum_{i=1}^{m} \varnothing_i Y_{t-i} + \sum_{i=m+1}^{m+dmax} \varnothing_i Y_{t-i} + \sum_{i=1}^{m} \beta_i X_{t-1} + \sum_{i=m+1}^{m+dmax} \beta_i X_{t-i} + v_{2t} \tag{9}$$

where X and Y are returns of two different funds, and ω, θ, δ, φ, $\varnothing$, β are parameters of the model. *dmax* is the maximum order of cointegration.

We selected lag length using the Akaike Information Criterion (AIC), and tested for serial correlation using Durbin–Watson (DW) statistic and Lagrange-multiplier (LM) test. Where serial correlation is detected, more lags are added to produce the maximum lag length (k), and the procedure is a correction for serial correlation, but the downside is that it reduces the degrees of freedom. We adopted the Lutkepohl (2005) procedure by adding the maximum order of integration (dmax) and maximum lag length (k) to determine the lag length of the series. The results of causality are interpreted at a 5% significance level.

We interpret our results using the Dynamic Causality Index (DCI). We compute DCI in line with Billio *et al.* (2012), and use the 28-month rolling window to split the sample period into three equal sub-periods: January 2015 to April 2017, May 2017 to August 2019 and September 2019 to December 2021. DCI is computed as follows:

$$DCI_t = \frac{\textit{number of causal relationships in window}}{\textit{total possible number of causal relationships}} \tag{10}$$

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where the magnitude of the DCI directly indicates the level of interconnectedness. A higher DCI value suggests high interconnections and a lower value means fewer interconnections. While this analysis establishes linkages between financial institutions, it does not distinguish whether the linkage is contagion effects or due to exposures to the common factor. Nonetheless, our focus is primarily on interconnectedness and the direction of linkages between shadow banking entities, regardless of the nature of connectedness.

4. Results

4.1 ΔCo-VaR results

We begin the section with Co-VaR and ΔCo-VaR results which are used to measure the contribution of shadow banking to systemic risk and to determine the 20 funds with the highest contribution to systemic risk for inclusion in the interconnectedness analysis. We interpret all results at 5% significance level. Co-VaR and ΔCo-VaR results encompass the full sample, 466 funds for the period from January 2015 to December 2021, and we begin with descriptive statistics of the variables used in the analysis – state variables, and returns of both financial services and the individual funds.

Descriptive statistics of the state variables and financial sector returns are summarised in Table 1. The changes in equity market returns and 10-year government bonds are symmetrical, with the mean and median values within a close range. Equity market returns follow a normal distribution with a kurtosis of 3.2 and skewness close to zero. Financial sector returns and 3-month T-bills are skewed to the left, whereas SAVI has a tail on the right side. SAVI and yield are more dispersed.

The tables on the descriptive statistics of all funds is available from the authors on request. The descriptive statistics show that money market funds have the lowest returns, and multi-asset funds have the highest. Similarly and as expected, the maximum returns of multi-asset funds, fixed-income funds and funds-of-funds are higher compared to that of money market funds. Multi-asset funds have a higher standard deviation which means their returns are the most volatile, whereas money market funds are the least volatile as their standard deviations are lower than those of all other funds.

We estimate Co-VaR and ΔCo-VaR using quantile regression, and the full set of results is available on request from the authors. We ran a quantile regression with the financial sector returns as the dependent variable, and fund returns and lags of state variables as independent variables. We included lags of state variables to adjust for the changes in tail dependence over time. We interpret the absolute values without consideration of their signs – whether negative or positive. Therefore, the highest absolute percentage implies the highest

Table 1. Descriptive statistics of state variables

Variable	*N*	Mean	Median	SD	Kurtosis	Skewness	Min	Max
EMR	84	0.50	0.39	4.30	3.21	0.01	−11.82	12.90
FSR	84	−0.11	0.45	5.03	15.03	−2.35	−29.31	10.28
SAVI	84	−0.16	0.12	12.14	7.83	1.27	−25.19	56.91
10-year gov bonds	83	0.30	0.00	3.41	8.63	1.05	−10.57	16.27
3-month T-bills	84	−0.54	0.28	4.41	19.26	−3.15	−27.82	6.4
Yield	83	1.51	−0.67	12.73	5.56	0.98	−27.50	54.65

Notes: *EMR = equity market returns; *FSR = financial sector returns; *SAVI = South African volatility index; *Yield = yield spread [(10-year gov bonds) – (3-month T-bills)]
Source: Authors' own work

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contributor to systemic risk. The highest contributor to systemic risk is a fund-of-fund. However, most multi-asset funds and fixed-income funds are among the highest contributors to systemic risk. We performed further analysis to produce ΔCo-VaR for all funds. Thereafter, we focus narrowly, but in-depth on the 20 funds with the largest ΔCo-VaR.

We provide in Table 2 summaries of the ΔCo-VaR of 20 funds with the highest marginal contribution to systemic risk. Multi-asset funds are the largest contributors to systemic risk. A multi-asset fund with the highest marginal contribution to systemic risk has an average ΔCo-VaR of negative 10.07%. The average and minimum ΔCo-VaR also point to multi-asset funds as the largest contributors to systemic risk. Funds-of-funds and fixed-income funds are the second and third largest contributors to systemic risk while money market funds have lower ΔCo-VaR compared to all funds. Similarly, money market funds have a lower standard deviation compared to all other funds, which shows that money market funds have the least volatile marginal contribution to systemic risk. A fund-of-fund has the most volatile ΔCo-VaR followed by a fixed-income fund and multi-asset funds.

4.2 Granger causality results

Table 3 provides summary statistics of the monthly returns for the 20 funds selected for interconnectedness analysis. The average returns of funds-of-funds are higher, followed by fixed-income funds and multi-asset funds. A normal distribution has a kurtosis of 3 and

Table 2. Marginal contribution to systemic risk (ΔCo-VaR) of funds

Fund	N	Mean	SD	Min	Max
Multi-asset funds					
MAF-22	84	−9.49	5.48	−32.30	0.88
MAF-48	84	−10.06	5.01	−31.53	0.00
MAF-86	84	−9.73	4.60	−26.13	0.67
MAF-87	84	−9.98	5.01	−29.24	0.96
MAF-111	84	−10.07	4.32	−27.84	0.10
Fixed-income funds					
FIF-12	84	−8.38	4.13	−27.97	−0.18
FIF-11	84	−8.86	4.85	−27.35	0.37
FIF-31	84	−9.17	4.63	−31.23	0.35
FIF-39	84	−9.21	3.18	−21.99	−1.59
FIF-43	84	−9.35	5.82	−27.70	2.84
Funds of funds					
FOF-134	84	−10.06	6.03	−27.50	3.55
FOF-156	84	−9.06	4.29	−25.00	−0.10
FOF-117	84	−9.06	4.11	−25.33	−0.41
FOF-41	84	−9.27	3.34	−22.09	−1.48
FOF-141	84	−9.30	3.93	−24.92	0.04
Money market funds					
MMF-18	84	−7.72	3.81	−24.63	0.00
MMF-11	84	−7.74	3.94	−25.67	0.00
MMF-7	84	−7.76	3.80	−24.42	0.00
MMF-4	84	−7.76	3.82	−24.79	0.02
MMF-13	84	−7.82	3.82	−24.92	0.00

Note: Funds with the highest ΔCoVaR among the funds classes
Source: Authors' own work

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values greater than this represent fatter tails than a normal distribution. Most funds-of-funds, fixed-income funds, and multi-asset funds are leptokurtic, meaning they have fat fails, whereas money market funds are platykurtic. Funds-of-funds and multi-asset funds have the most volatile returns, as their standard deviations are higher. In contrast and as expected, money market funds provide positive, moderate and least volatile returns. Their maximum returns are almost steady. Fixed-income funds and money market funds are low-risk as their returns are left-skewed. In contrast, multi-asset funds and funds-of-funds are right-skewed and are therefore high-risk.

We examine linkages between funds using the Granger Causality Toda and Yamamoto approach (Toda and Yamamoto, 1995). The selection of the T-Y Granger causality approach is motivated by that the series had cointegration of different order, I(0) and I(1). The results of the T-Y Granger causality analysis are in Table 4, showing interconnectedness among funds at a 5% significance level for the three subsamples, and the full sample. In the full sample period, linkages are 28.42% of all possible connections, and this shows the degree of interdependencies between funds. Interconnections are higher among multi-asset funds, followed by money market funds. Multi-asset funds linkages are 7.89% of total possible interconnections.

Table 3. Descriptive statistics of the funds returns data

Fund	N	Mean	SD	Min	Max	Skewness	Kurtosis
Multi-asset funds							
MAF-22	84	0.60	0.13	0.22	0.79	−0.89	2.97
MAF-48	84	0.63	0.34	−0.43	1.96	0.47	6.39
MAF-86	84	0.55	2.64	−5.68	10.61	0.38	4.72
MAF-87	84	0.60	2.11	−5.29	9.36	0.59	5.89
MAF-111	84	0.58	0.30	−0.59	1.76	−0.69	9.87
Fixed-income funds							
FIF-12	84	0.56	0.18	−0.03	1.31	0.61	7.77
FIF-11	84	0.58	0.17	0.00	0.90	−1.47	5.83
FIF-31	84	0.64	0.48	−1.65	2.59	−0.59	10.39
FIF-39	84	0.59	1.50	−7.22	4.14	−1.48	10.27
FIF-43	84	0.61	0.18	−0.16	0.86	−1.60	6.62
Funds-of-funds							
FOF-134	84	0.44	0.11	0.16	0.66	−0.60	2.59
FOF-156	84	0.73	2.47	−6.37	9.03	0.03	3.95
FOF-117	84	0.81	3.26	−10.06	12.64	0.16	4.88
FOF-41	84	0.59	2.76	−8.58	11.91	0.22	6.16
FOF-141	84	0.57	1.41	−4.79	6.17	0.11	6.64
Money market funds							
MMF-18	84	0.53	0.12	0.28	0.68	−0.98	2.51
MMF-11	84	0.52	0.12	0.23	0.64	−0.97	2.44
MMF-7	84	0.52	0.11	0.28	0.64	−1.04	2.51
MMF-4	84	0.56	0.11	0.27	0.67	−1.14	3.04
MMF-13	84	0.51	0.13	0.00	0.66	−1.60	5.47

Notes: Descriptive statistics of the returns of 20 funds with the highest *Δ*CoVaR among the fund classes; five funds each from fixed-income funds, funds-of-funds and multi-asset funds; descriptive statistics of all funds, 466, are available on request
Source: Authors' own work

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Connectedness between funds varies considerably over time, and funds become highly connected during periods of systemic shocks. DCI is 24.47% during the period from September 2019 to December 2021 compared to 12.37% and 17.37% in the periods May 2017 to August 2019 and January 2015 to April 2017, respectively (Table 4). Overall, interconnections are higher during the interval that includes the COVID-19 period. The pandemic created shock waves in the financial markets. In the same period, linkages are highest among multi-asset funds at 7.63%, and funds-of-funds at 7.37% (Table 4). Between January 2015 and April 2017, linkages are highest among fixed-income funds. Interconnections are almost equal across all funds from May 2017 to August 2019, but slightly higher among multi-asset funds and money market funds.

Figures 2 and 3 provide network visualization for the full sample and three subsamples. These linkages among funds are also summarized in Appendix 2. During the whole sample period, more connections are from multi-asset funds to all other funds. There are 10 connections to fixed-income funds and 9 to money market funds. Similarly, there are more inbound connections to multi-asset funds, especially from money market funds. Altogether, this shows that multi-asset funds have greater linkages than all other funds. These linkages explain the systemic importance of multi-asset funds as their diversified portfolios create direct and indirect exposure to shocks.

Despite this, it is also important to note that money market funds have more inbound connections, even more than multi-asset funds. Most of these linkages are from fixed-income funds. This is also observed in the subsample period, particularly from January 2015 to April 2017. There are no linkages from multi-asset funds to funds-of-funds from January 2015 to April 2017. However, connections from multi-asset funds to funds-of-funds increases significantly between September 2019 and December 2021. Network density is higher among fixed-income funds from January 2015 to April 2019. However, during September 2019 and December 2021, connections increase for multi-asset funds, funds-of-funds and money market funds. The period coincides with COVID-19 and therefore shows growing networks during financial distress among all funds except for fixed-income funds.

5. Discussion

Financial linkages are an important determinant of shock transmissions, and systemic risk is high when financial institutions are closely connected (Battiston *et al.*, 2012). There are several studies on linkages between shadow banking and other financial sectors (Abad *et al.*,

Table 4. Number of Granger-causal relationships from funds

	Full Sample: January 2015 to December 2021		January 2015 to April 2017		May 2017 to August 2019		September 2019 to December 2021	
Fund	No.	% of total	No.	% of total	No.	% of total	No.	% of total
MAF	30	7.89	12	3.16	13	3.42	29	7.63
FIF	24	6.32	25	6.58	11	2.89	17	4.47
FOF	26	6.84	13	3.42	10	2.63	28	7.37
MMF	28	7.37	16	4.21	13	3.42	19	5.00
Total	108	28.42	66	17.37	47	12.37	93	24.47

Notes: Toda and Yamamoto Granger causality relationships that are statistically significant at a 5% level among the monthly returns of 20 funds
Source: Authors' own work

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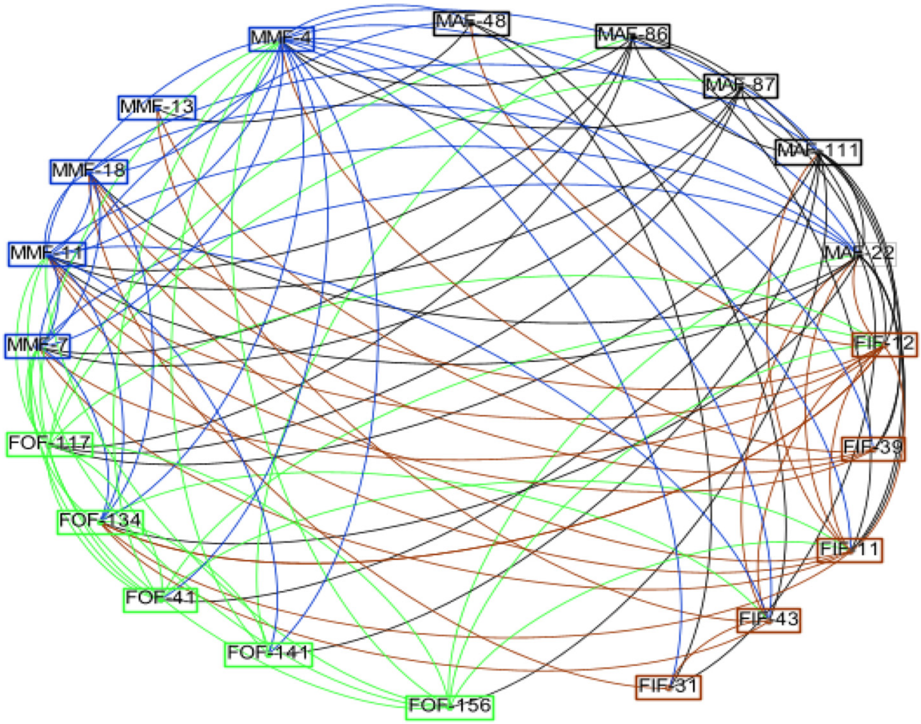

Notes: The network diagram represents the granger-causal relationships at the 5% significance level; there are 108 significant granger-causal relationships for the period
Source: Authors' own work

Figure 2. Network diagram of Granger-causal relations: full sample

2022; Bakk-Simon *et al.*, 2012; Billio *et al.*, 2012; Chaturvedi and Singh, 2022; Gennaioli *et al.*, 2013; Kemp, 2017; Pozsar *et al.*, 2012). However, there are limited studies on interconnectedness within shadow banking, particularly in emerging economies. We measure linkages within shadow banking in South Africa using market returns of multi-asset funds, funds-of-funds, fixed-income funds and money market funds from January 2015 to December 2021. We us Toda and Yamamoto Granger causality test (Toda and Yamamoto, 1995) to estimate linkages and the direction of relationships.

Our results show interconnectedness within shadow banking in South Africa. The degree of interconnectedness, measured by DCI, is 28.42%. This represents a proportion of all possible total causal relations. In this regard, our results show higher linkages compared to previous studies. DCI was reported to be less than 13% by Billio *et al.* (2012) among banks, insurers, brokers and hedge funds in the USA. Similarly, the linkage is greater than the DCI in the banking sector studies in India and other several Asian countries (Chaturvedi and Singh, 2022; Mensah and Premaratne, 2017). Furthermore, interconnectedness in our results is also higher compared to the degree of linkage in the South African banking, insurance and financial services sectors, where DCI reaches a peak of 21% (Leukes and Mensah, 2019). Overall, this shows a high level of interconnectedness within the South African financial

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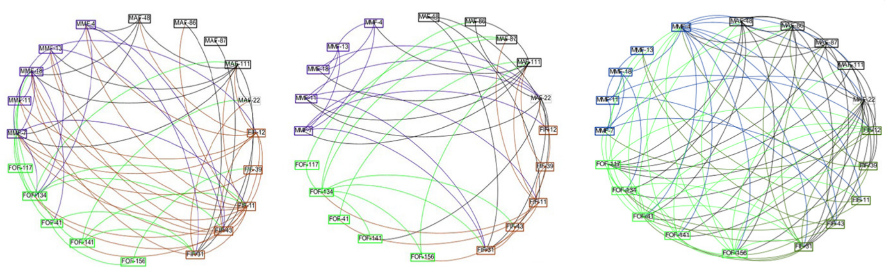

(a) (b) (c)

Notes: The network diagram represents the granger-causal relationships at the 5% significance level; the number of significant granger-causal relationships for the period are included below each figure; (a) january 2015–april 2017, 66 significant granger casual relationships; (b) may 2017–august 2019, 47 significant granger casual relationships; (c) september 2019–december 2021, 93 significant granger casual relationships
Source: Authors' own work

Figure 3. Network diagram of Granger-causal relations: sub-samples

system, but even higher linkages in shadow banking. Our results are consistent with previous studies that reported interconnectedness in shadow banking (Chaturvedi and Singh, 2022; Fong *et al.*, 2021; Girón and Matas-Mir, 2017; Hsu *et al.*, 2013). In South Africa, interconnectedness arises from investments between shadow banking entities as multi-asset funds and funds-of-funds invest almost half of their assets in other funds (ASISA, 2021). The common market exposure could be another channel of shock transmission as almost 30% of money market and fixed-income funds assets, and 16% of multi-asset funds are invested in government bonds (ASISA, 2021).

When we disaggregate the analysis into three sub-periods, our results show that interconnectedness is all-time high during COVID-19. DCI reaches 24.27% between September 2019 and December 2021, and this is higher than in any other period. Our results are in line with strong evidence of the high degree of interconnectedness during periods of financial distress (Baumöhl *et al.*, 2022; Billio *et al.*, 2012; Chaturvedi and Singh, 2022; Fong *et al.*, 2021; Leukes and Mensah, 2019; Mensah and Premaratne, 2017). Shadow banking interconnectedness during COVID-19 is higher than the 21% peak reported in banking, insurance and financial services during the global financial crisis in South Africa (Leukes and Mensah, 2019). However, the impact of COVID-19 is greater in Europe, Asia and the USA where DCI reached a peak of 60% in the banking sector (Baumöhl *et al.*, 2022). COVID-19 instigated a significant negative shock in the real sector economy and that cascaded to the financial markets through various mechanisms, including a decline in aggregate assets and investment leading to credit constraints.

Multi-asset funds are more interconnected with all other funds. They have more outbound connections and are second to money market funds in terms of inbound connections. This means multi-asset funds are the major transmitters of systemic risk, while money market funds are the main receivers. These results are explained by the structure of multi-asset funds, as they are more diversified and therefore their shocks, potentially, spill over to money markets, bonds, property, and equities markets where other funds also invest. Furthermore, the direct linkage arises from that multi-asset funds in South Africa invest a significant

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proportion of their assets in other funds (Figure 1). Our results are consistent with the systemic risk patterns, considering that multi-asset funds have a higher marginal contribution to systemic risk. In other words, whilst we did not examine the relationship between interconnectedness and systemic risk, we observe that a more connected fund class, a multi-asset fund, have a higher marginal contribution to systemic risk. Interconnectedness creates a channel transmission of shock between financial institutions (Allen and Gale, 2000).

Money market funds have more inbound connections and therefore are the most systemic risk receivers. This could be explained by that money market funds have a significant portion of their assets as "cash on call" mainly to meet the demands for liquidity, particularly for banks. The connections create liquidity pressures for money market funds whereby excess demand for liquidity in the short term, especially during uncertain periods, leads to the liquidation of long-term assets in the financial system (Moreira and Savov, 2017). The other channel for systemic risk to money market funds could be through exposure to common assets and markets as discussed in the model by Allen and Gale (2000). Money market funds do not invest in other funds in South Africa but are predominantly exposed to banks, government bonds, and corporate debt. Over 60% of money market funds assets are invested in banks, 14% in government bonds, and 4% in corporate debt (Figure 1). Therefore, a systemic event that affects banks and the bond market will likely have an impact on money market funds.

6. Conclusion

In conclusion, we measure interconnectedness in South African shadow banking between January 2015 and December 2021. We report interconnectedness in shadow banking in line with the linkages reported in other countries (Chaturvedi and Singh, 2022; Fong *et al.*, 2021; Girón and Matas-Mir, 2017; Hsu *et al.*, 2013), and shadow banking linkages reach a peak during COVID-19 showing the impact of the pandemic in the financial sector. Multi-asset funds are more interconnected than all other funds and have more outbound connections than any other funds. However, money market funds have more inbound connections. Altogether, multi-asset funds are significant transmitters and receivers of systemic risk whereas money market funds are receivers.

Our results point to multi-asset funds as a central interlink in the shadow banking system, and therefore requiring regulatory attention to limit interdependencies, especially during periods of financial distress. Regulators should limit the exposures of multi-asset funds to other funds and should develop a tailored tool for monitoring money market funds, to inform appropriate interventions for strengthening their resilience. Investors should monitor money market funds' exposure to other funds and sectors to minimize losses in investment.

This study contributes to the literature on shadow banking and systemic risk, particularly in emerging economies. However, it has some limitations. We focused on single-country data, and this leaves a gap for more in-depth analysis focusing on other emerging countries, particularly those experiencing a rapid growth of shadow banking. We used market returns data and future studies with detailed balance sheet data could explore overlaps on assets and liabilities from both individual funds and sectoral levels perspectives. This could help reveal specific network patterns that could threaten the stability of the financial system. Finally, future studies could focus on measuring interconnectedness during specific periods of financial and economic turbulences to explain the linkages trends and to provide further policy recommendations.

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Appendix 1

Table A1. Unit root test results

Fund	Optimal lag	Order of co-integration	ADF Constant		ADF Trend		KPSS	Conclusion
MAF-22	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0165*	Stationary
MAF-48	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0517*	Stationary
MAF-86	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0461*	Stationary
MAF-87	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0264*	Stationary
MAF-111	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0153*	Stationary
FIF-12	1	First difference	−2.905	0.0042	−3.469	<0.001	*0.0537*	Stationary
FIF-11	1	First difference	−2.905	0.0001	−3.469	<0.001	*0.015*	Stationary
FIF-31	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0443*	Stationary
FIF-39	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0552*	Stationary
FIF-43	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0147*	Stationary
FOF-134	1	First difference	−2.905	0.0547	−3.469	0.0193	*0.0247*	Stationary
FOF-156	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0712*	Stationary
FOF-117	1	Level	−2.904	<0.001	−3.468	<0.001	*0.031*	Stationary
FOF-41	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0556*	Stationary
FOF-141	1	Level	−2.904	<0.001	−3.468	<0.001	*0.0352*	Stationary
MMF-18	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0641*	Stationary
MMF-11	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0876*	Stationary
MMF-7	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0983*	Stationary
MMF-4	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0326*	Stationary
MMF-13	1	First difference	−2.905	<0.001	−3.469	<0.001	*0.0326*	Stationary

Source: Authors' computation

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Appendix 2

Table A2. Linkages between funds at 5% significance level

Fund	MAF (%)	FIF (%)	FOF (%)	MMF (%)
Full Sample: January 2015 to December 2021				
MAF	4 (3.70)	10 (9.26)	7 (6.48)	9 (8.33)
FIF	5 (4.63)	4 (3.70)	3 (2.78)	12 (11.11)
FOF	6 (5.56)	4 (3.70)	5 (4.63)	11 (10.19)
MMF	8 (7.41)	5 (4.63)	7 (6.48)	8 (7.41)
January 2015 to April 2017				
MAF	2 (3.03)	4 (6.06)	0 (0.00)	6 (9.09)
FIF	5 (7.58)	5 (7.58)	3 (4.55)	12 (18.18)
FOF	2 (3.03)	6 (9.09)	1 (1.52)	4 (6.06)
MMF	0 (0.00)	5 (7.58)	4 (6.06)	7 (10.61)
May 2017 to August 2019				
MAF	2 (4.26)	5 (10.64)	1 (2.13)	5 (10.64)
FIF	5 (10.64)	3 (6.38)	3 (6.38)	0 (0.00)
FOF	5 (10.64)	2 (4.26)	3 (6.38)	0 (0.00)
MMF	3 (6.38)	4 (8.51)	0 (0.00)	6 (12.77)
September 2019 to December 2021				
MAF	6 (6.45)	8 (8.60)	13 (13.98)	2 (2.15)
FIF	5 (5.38)	1 (1.08)	7 (7.53)	4 (4.30)
FOF	5 (5.38)	9 (9.68)	8 (8.60)	6 (6.45)
MMF	4 (4.30)	6 (6.45)	4 (4.30)	5 (5.38)

Notes: Summarized results of Toda and Yamamoto granger causality relationships that are statistically significant at 5% level; *Multi-asset Fund (MAF); *Fixed-income Funds (FIF); *Funds-of-Funds (FOF); *Money Market Fund (MMF)
Source: Authors' computation

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