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ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/oaef20

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To cite this article: Kelleb Mloyi & Edson Vengesai (2024) The impact of global risk aversion and domestic macroeconomic factors on the dynamic conditional correlations of South African financial markets, Cogent Economics & Finance, 12:1, 2431543, DOI: 10.1080/23322039.2024.2431543

To link to this article: https://doi.org/10.1080/23322039.2024.2431543

Published online: 25 Nov 2024.

COGENT ECONOMICS & FINANCE
2024, VOL. 12, NO. 1, 2431543
https://doi.org/10.1080/23322039.2024.2431543

FINANCIAL ECONOMICS | RESEARCH ARTICLE

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The impact of global risk aversion and domestic macroeconomic factors on the dynamic conditional correlations of South African financial markets

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ABSTRACT

This paper considers the impact of global risk aversion and domestic macroeconomic factors on the dynamic conditional correlations between the South African stock, bond, and foreign exchange markets. Our first stage findings using the DCC-GARCH model show that correlations between the selected markets are significantly dynamic over time. We further show that the correlations of asset pairs do not fall for extended periods during crisis periods, implying only short-lived increase in diversification benefits. Further analysis using the OLS regression model shows that global risk aversion and domestic macroeconomic factors have a heterogenous impact on the dynamic correlations of asset pairs. Consequent to these findings, this study advocates for the adoption of dynamic asset allocation and diversification strategies necessitating the periodic optimisation of portfolios as asset correlations, global risk aversion and domestic macroeconomics evolve. The study offers valuable insights and policy recommendations for investment practitioners, policymakers, and academics.

IMPACT STATEMENT

This research provides valuable insights into how global risk aversion and domestic macroeconomic factors influence the relationships between South African stock, bond, and foreign exchange markets. The study demonstrates that these correlations are highly dynamic, emphasising the need for investors to adopt responsive and flexible investment strategies. The findings offer crucial practical guidance for portfolio optimisation, risk management, and informed investment decisions in a volatile economic environment. This work is significant for its potential to inform investment practices and policy, ensuring they are aligned with the evolving financial landscape.

ARTICLE HISTORY
Received 20 August 2024
Revised 11 November 2024
Accepted 14 November 2024

KEYWORDS
Global risk aversion; dynamic conditional correlation; DCC GARCH; diversification; macroeconomic factors

SUBJECTS
Finance; Business, Management and Accounting; Economics

1. Introduction

Investors participate in financial markets to earn returns, Bodie et al. (2024) define returns as gains derived from taking risks and investing in financial markets. However, the entrenched volatility in financial market prices can result in financial losses. This risk of losses necessitates investors to implement robust portfolio risk management strategies. One such strategy is portfolio diversification, which involves investing in at least two financial assets with negative to low positive correlations. The diversification strategy reduces the idiosyncratic risk component, thereby minimising the overall portfolio risk. Crucial in diversification is the level and direction of asset correlation. The higher the asset correlation, the lower the diversification benefits; the lower the asset correlation, the greater the diversification benefits (Lin et al., 2018).

However, following Engle's Engle (2002) seminal work on conditional correlations, a lot of research has emerged documenting the dynamic nature of asset correlations. Katzke (2013), and McMillan (2021), among others, provide supporting evidence. Dynamic correlations entail asset correlations fluctuating and ever-

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changing over time. This complicates the portfolio risk management process by increasing the need for frequent portfolio rebalancing, which includes periodic recalibration of asset allocation and diversification strategies. Furthermore, as correlations vary over time, previously effective asset combinations may become ineffective, and vice versa, requiring a complete periodic restart of asset allocation and diversification.

Following this context, and as argued by Chiang et al. (2015), dynamic correlations mean that static asset allocation and diversification strategies do not effectively mitigate portfolio risk over time primarily due to assuming constant correlations and necessitating infrequent portfolio rebalancing which then renders resultant portfolio diversification ineffective as correlations change over time. Subsequently, this study aimed, firstly, at ascertaining whether correlations between the South African (SA) stock, bond, and foreign exchange markets (FX) are dynamic over time. Such understanding is crucial for driving the adoption of appropriate portfolio risk management strategies at all times, particularly whether investors must adopt static or dynamic asset allocation and diversification strategies.

Secondly, this study sought to probe the impact of global risk aversion and domestic macroeconomic factors on these dynamic conditional correlations. Several reasons underpin the significance of this investigation in SA. Firstly, and as argued by García-Herrero and Saravia (2007), global risk aversion is at the centre of portfolio flows globally. Changes in global investor fear and uncertainty cause flight to quality and flight from quality phenomenon that changes the level and direction of asset correlations globally (Connolly et al., 2005). As detailed earlier, these changes in correlations have positive and negative implications on the effectiveness of portfolio diversification strategies. Secondly, due to the openness of SA financial markets, asset prices and, consequently, asset correlations are subject to the turbulences of global risk aversion. Resultantly, SA financial markets continue to tumble significantly in line with global markets during episodes of crisis. Vengesai (2022) highlights the 2007-2009 Global Financial Crisis (GFC) and the COVID-19-induced crisis as supporting evidence. Hence, understanding the impact of global risk aversion is crucial for SA as it enhances investors' understanding of how changes in global risk aversion affect dynamic correlations and, ultimately, the effectiveness of their portfolio diversification strategies. Drawing from the preceding context, these insights can also be used in tailoring robust asset allocation and diversification strategies that are responsive and adaptive to changes in global risk aversion regimes across selected asset classes in SA to ensure effective diversification at all times.

Furthermore, macroeconomic variables such as inflation, Gross Domestic Product (GDP), interest rates, savings, and money supply play a crucial role in determining the profitability and economic prospects of a country. Additionally, they enable investors to assess the economic environment in which businesses, households, and government operate, which is crucial for informing investment decisions (Bodie et al., 2024). As Baele et al. (2010) argue, fluctuations in these variables trigger simultaneous fluctuations in asset prices, which consequently lead to fluctuations in asset correlations. As noted earlier, fluctuations in asset correlations have implications for asset allocation and diversification strategies. Hence, understanding the impact of these factors is relevant and crucial for SA because, firstly, SA has had significant macroeconomic challenges which puts it on the backfoot when it comes to economic growth. These domestic macroeconomic challenges make SA an appropriate case study. These challenges include low GDP growth rates, sitting at 0.1% as of the first quarter of 2024, high unemployment rate, which is sitting at 32.9% as of the first quarter of 2024, and high interest rates (Hausmann et al., 2022; Stats SA, 2024). Thus, understanding the impact of domestic macroeconomic factors provides valuable insights to SA investors, allowing them to effectively adapt their asset allocation and diversification strategies amid a turbulent and challenging domestic macroeconomic environment.

Furthermore, SA's financial markets are globally integrated, making them increasingly susceptible to global factors. For example, during the height of the COVID-19-induced crisis, the Rand depreciated by a whopping 17% against the US dollar, the SA government bonds yields fell by over 9%, while the JSE all-share index plunged by more than 24.1% year to date leading up to the end of March 2020 (South African Reserve Bank (SARB), 2023). However, due to openness, SA continues to receive a significant amount of portfolio flows. Fast forward to 2023, SARB (2023) estimated the inward foreign portfolio flows at R47.7 billion as of the first quarter of 2023. Hence, the combination of SA's challenging domestic economic landscape and its openness to global financial markets makes it a significantly complex and volatile environment in which to invest, thus making a compelling case for studying the dynamics of its financial markets. Additionally, JS's dual status as both an emerging and semi-advanced market offers a unique lens through which to examine financial dynamics that are applicable to both developing and more established economies. The Johannesburg Stock Exchange (JSE) is the largest stock exchange in Africa and one of the top 20 globally by market capitalisation (JSE, 2024). Thus, it provides a well-diversified platform that captures the behaviour of a broad range of asset classes. This depth and liquidity make it an excellent proxy for studying asset correlations in the context of broader global financial systems. The analysis of multiple asset classes in this study is crucial and relevant because it provides additional insights not covered in the current body of literature, thus giving investors an opportunity to navigate the dynamics of not only the SA stock-bond but the stock-FX and bond-FX correlations for guiding effective asset allocation and diversification strategies across different periods, asset classes, levels of global risk aversion and domestic macroeconomic regimes.

However, despite the clear importance of understanding the nexus between global risk aversion, domestic macroeconomic factors, and dynamic conditional correlations in SA, no studies have focused on SA equity, bond, and FX markets. A handful of studies concentrating on SA have only focused on stock-bond market correlations and correlations of JSE equity sectoral index pairs. The lack of evidence and insights within the broader SA financial markets hinders the formulation of informed portfolio risk management strategies. Strategies that are adaptive and aligned to the prevailing nature of asset correlations and everchanging levels of global risk aversion and domestic macroeconomic factors. Consequently, this subjects investment portfolios to elevated levels of market risk and hinders the development of robust investment approaches that are resilient and adaptive to ever-changing global and domestic macroeconomic environments. As a result, this paper provides evidence and policy implications of the impact of global risk aversion and domestic macroeconomic factors on dynamic conditional correlations from an emerging market (SA) perspective. The findings of this study contribute to the current discourse in the domain of portfolio risk management and, broadly, in the field of financial economics. This paper is organised as follows this section discusses the introduction of the study, the 2nd section unpacks the theoretical and empirical literature, the 3rd section delineates the research methodology, the 4th section discusses the results, and the 5th section documents the conclusions of the study.

2. Literature review

The Markowitz portfolio selection theory is one of the most significant contributions ever in financial economics. Markowitz (1952) documented the concept of diversification in his theory, particularly how a mix of assets with low correlations can minimise risk while maximising returns at every risk level. Crucially, Markowitz (1952) demonstrated that the level and direction of asset correlations have a determining role in the effectiveness of diversification strategies by proving that diversification benefits or effectiveness fall as asset correlations rise from negative to positive. These findings imply that investors need to carefully consider investing in assets with low correlations as this provides a higher risk-return tradeoff than investing otherwise. These findings also suggest that during periods of heightened asset correlations, the benefits of diversification can diminish, leading to high portfolio exposure. These implications fuel the need to explore the behaviour of asset correlations and stay up to date as changes in asset correlations may affect the effectiveness of diversification strategies. The relevance of the Markowitz portfolio theory to this study hinges on its very emphasis on portfolio diversification as a panacea to portfolio risk. This study uses the Markowitz theory as a baseline to guide the analysis of the level and direction of stock, bond, and FX market correlations and uncover diversification opportunities across selected markets in SA. However, this study inches further by carrying out multiple period assessments to ascertain, firstly, whether asset correlations are dynamic and, secondly, whether global risk aversion and domestic macroeconomic factors have any impact on these correlations. Such understanding is crucial for adopting appropriate asset allocation and diversification strategies across different time periods, asset classes, levels of global risk aversion, and domestic macroeconomic regimes.

Sharpe (1964) came up with the single index model by capitalising on the mathematical complexities associated with the Markowitz portfolio selection theory. In particular, the computations of variance and covariances between large bodies of assets which are tedious and time-consuming (Van Wyk et al., 2015). In this model, each price movement can be computed against the market index as opposed to all the individual securities in the market. The single index model was later referred to as the Capital Asset

Pricing Model (CAPM), which brought in the work of Lintner (1965) and Mossin (1966). Following the CAPM, Ross (1976) proposed the arbitrage pricing theory (APT) by arguing that multiple systematic factors affect the long-run returns of assets and that these systematic factors represent the fundamental macroeconomic risks (Bodie et al., 2024). While the CAPM implies that returns are solely determined by market risk, the APT implies that returns are determined by multiple macroeconomic factors (Van Wyk et al., 2015). Hence, the combined relevance of these theories to this investigation stems from their appreciation of the fact that returns are affected by market and fundamental macroeconomic factors. However, as argued by Vengesai (2022), the opening up of SA financial markets to the global environment has led to the configuration of earlier standard versions of the CAPM and the APT to reflect international variables and international diversification. Rightfully so, as the standard theories were biased towards the local economies and markets. Hence, this study stretches further by considering both global risk aversion and domestic macroeconomic factors in examining the dynamics between stock, bond, and FX market correlations, thus reflecting the realities of SA's open economy.

As we transition from the theoretical literature to the empirical literature, the past two decades have seen a proliferation of Multivariate Generalised Autoregressive Conditional Heteroskedasticity (MV-GARCH) models. Partly because of the elevated need to understand global financial market contagion and comovement as necessitated by the 2007-2009 GFC, and international diversification analysis as necessitated by the globalisation of financial markets. Subsequently, MV-GARCH models such as the VECH model introduced by Bollerslev et al. (1988), the BEKK model proposed by Engle and Kroner (1995), and the Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990), have been used widely. In particular, the CCC model has been widely used to estimate correlations between assets. Though parsimonious in modelling conditional correlations compared to the above models, the CCC model's assumption of constant correlations has been flagged as too restrictive due to the time-varying nature of correlations in real life (Margani & Husodo, 2022). As a result, Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model by relaxing the constant correlation assumption in the CCC model and allowing the correlations to vary. This study utilizes the DCC model in modelling dynamic correlations following leading studies such as Margani and Husodo (2022), Cai et al. (2023), and Shafiq et al. (2023) among others. Besides allowing correlations to vary, which aligns perfectly to the paper's objectives, the DCC model is superior to other models such as the CCC and the BEKK model for a number of reasons. Firstly, the DCC model results in less parameters than the BEKK and the CCC model making it relatively more parsimonious. Secondly, it is relatively less complicated than the BEKK model in that it involves two step parameter estimation procedures relative to numerous steps in the BEKK model.

Engaging more comprehensively with the empirical literature relating to this investigation, regardless of the discussed importance of carrying out this investigation, a strand of papers examining dynamic correlations in Europe and the United States, such as Chiang et al. (2015) focus mostly on the commonly researched stock-bond equity-equity correlation dynamics leaving a gap in the understanding of stock-FX, and bond-FX correlations. These studies also mostly concentrate on cross-country correlation dynamics, which offer implications for cross-country asset allocation and diversification, leaving a gap in the understanding of within-country dynamics, which are essential for guiding domestic asset allocation and diversification within local markets. Concerning these studies, Perego and Vermeulen (2013) examined the macroeconomic determinants of dynamic correlations of stocks and bonds in the Eurozone. Using the DCC model to derive the dynamic conditional correlations and OLS to ascertain the impact of macroeconomic factors, they find that relative market uncertainty and balance of payments are significant in explaining dynamic correlations across the Eurozone. Chiang et al. (2015) use the ADCC and the Logistic Smooth Transition models to delve into the stock-bond dynamic correlations and their determinants across the US, Germany, the UK, France, Italy, and Canada. They find overwhelming evidence pointing to the time-varying nature of stock-bond correlations across selected countries. They also find that the VIX index (used in this study as a proxy for global risk aversion), default risk, and the treasury bill rate have a significant impact on stock-bond correlations. The findings of this study, particularly on the dynamic nature of correlations and the impact of global risk aversion, coincide with studies by Connolly et al. (2005) who found similar results for the US.

Macmillan (2019) Investigated the time-varying asset correlations and their economic implications using the US and global stocks as a case study. Using the DCC model to estimate the time-varying correlations and the OLS to ascertain the impact of macroeconomic factors, he finds that the term structure of interest rates and consumer sentiments are the major factors driving the time-varying asset correlations across the US and the global markets. Kanda et al. (2018) ascertained the time-varying correlations and causality of equity and FX returns in the United Kingdom (UK). Using evidence from the DCC and Granger causality techniques, they found overwhelming evidence of time-varying correlations and causality between equity and FX markets. Despite uncovering equity-FX market correlation dynamics, this study, unfortunately, does not uncover the determinants of such correlations, leaving an evident research gap. Abuzayed et al. (2020) explored the dynamic correlations of Real Estate Investment Trusts (REITs) with stock market returns using evidence from France, the United Kingdom, and Germany. Using the DCC model, they found that REITs-stock correlations are dynamically correlated across selected countries. Analysing correlations during the 2007-2009 GFC and the European Sovereign Debt Crisis, they document that the REITs-stock correlations do not decouple in crisis periods. Hence, the REITs offer a limited opportunity for international diversification during crisis periods.

More recent studies focusing on Europe and the US have evidently not addressed the discussed research gaps. The emphasis of these studies lies in uncovering the Stock-bond, crude oil-bond, stocks-stocks correlations. Regarding these studies, Nie (2020) applies the K nearest neighbour (KNN) methodology to detect critical events in the correlation structure of financial markets in the US. They conclude that their method is able to detect anomalies in the financial market correlations. Particularly, their methodology is able to pick critical events such as the 2007/2009 GFC and the 2020 Covid 19 pandemic. However, though their study is plausible, it does not attempt to investigate the drivers of asset correlations leaving the identified gaps evident. Chiang (2020) ponders the impact of risk and policy uncertainty on the widely studied US stock-bond return correlations using the DCC GARCH model. He finds that stock-bond correlations are dynamic over time. His further analysis shows that the dynamic stock-bond correlations are negatively correlated with stock and bond market volatility measured by conditional variances of the respective markets while positively correlated with economic policy uncertainty. Although this paper gives a clue regarding relationships between these selected factors and dynamic correlations, they don't carry out impact analysis leaving clear research gap. Further studies such as Tsiaras (2020) investigated the time varying correlations between crude oil futures and US bond markets using the DCC GARCH model. They find that crude oil and bond markets correlations are significantly dynamic over time. Their further analysis shows that the correlations increases between the period 2012 and 2020 implying less diversification benefits during the period. Barigozzi et al. (2021) ponders the financial market connectedness of the US stocks. They find that the comovement between US stocks accelerates during periods of financial crisis. Karanasos and Yfanti (2021) investigates the determinants of dynamic correlations for stocks, real estate, and commodities for global markets. Using the Glosten-Jagannathan-Runkle (GJR)-GARCH model they find that economic policy uncertainty, financial uncertainty, credit conditions, business confidence and geopolitical risk are significant in explaining dynamic correlations.

Studies involving correlation dynamics of SA financial markets offer variegated insights. Although all studies have consensus on the dynamic nature of asset correlations in SA, some studies look into the determinants of these dynamic correlations, while some concentrate solely on the spillover implications of the dynamic correlations. Overall, though these studies are plausible in uncovering cross-country and within-country dynamics, they do not offer insights into the correlation dynamics between stock, bond, and FX markets. As discussed, such investigation is critical for the adoption of appropriate asset allocation and diversification strategies in SA. To unpack these studies, Katzke (2013) tests whether the SA sectoral equity index returns are dynamically correlated. Using the DCC and the ADCC models, he finds that the sectoral equity index returns are significantly dynamic over time. Using the OLS regression model, he finds that VIX (used in this study as a proxy for global risk aversion), exchange rate volatility, domestic asset market condition, and macroeconomic stability are all significant in explaining equity sectoral correlations. The rest of the SA studies concentrate on the spillover implications of dynamic correlations.

Ncube, Ndou, and Gumata (2016) examined time-varying equity market correlations between emerging markets using evidence from SA, Brazil, and India. Using rolling window correlations, they find evidence of comovement between equity correlations of the selected countries. Additionally, their analysis shows evidence of a high correlation between time-varying correlations and future real economic activity across countries. Sikhosana and Aye (2018) investigated the volatility spillovers between the real exchange rate and the stock returns in SA using the MV exponential GARCH model. They find evidence of bi-directional volatility spillovers between the markets. They conclude that while information about one market can be used to predict the other, these assets should not be included in the same portfolio due to higher dynamic correlations. Morema and Bonga-Bonga (2020) investigated the determinants of SA equity sectoral volatility, focusing on the impact of oil and gold price fluctuations using the Vector Auto-Regressive (VAR)-ADCC models. They find strong evidence suggesting that stock-gold and stock-oil correlations are dynamic over time, which they argue are signs of market spillovers between the markets. Interestingly, they find lower correlations between equity sectoral index returns and gold, suggesting greater diversification benefits between gold and equities, particularly during crisis periods.

Similar studies have been replicated in other emerging markets across Europe and Asia with no improvement in the highlighted research gaps. These studies also show close to unanimous utilisation of the DCC model for ascertaining the dynamic nature of correlations and OLS for impact assessment. However, a small fraction of these studies use other methodologies, such as rolling window correlations and Auto Regressive-Distributed Lag (ARDL) models, among others. Ananchotikul and Zhang (2014) find equity, bond, and FX market correlations significantly dynamic across European, Asian, and Latin American Emerging Markets (EMs). Although their investigation is plausible, it did not carry out an impact study on the dynamic correlations, leaving the impact of global risk aversion and domestic macroeconomic factors unknown to these EMs. Rehman (2016) Pondered on the financial contagion in Emerging Frontier Asian (EFA) markets. He concludes that the stock correlations between the EFA countries are significantly dynamic. He also highlights evidence of elevated correlations between EFA countries during crisis periods, which suggests diminishing diversification benefits between EFA countries during periods of crisis. Eraslan (2017) reveals that sovereign credit rating announcements have a significant impact on dynamic FX correlations across 11 EM countries. This investigation, though it uncovers cross-country FX correlation dynamics, does not address the research gaps at hand. Demirer et al. (2018) document that global risk aversion has a consistently positive significant impact on equity correlations of EM countries. Alomari et al. (2018) discover strong evidence of the dynamic nature of the equity sectoral correlations of the Amman stock exchange. They further conclude that dynamic correlations are significantly explained by inflation, interest rates, financial crises, and news.

Moving further with papers concentrating on other emerging markets, recent studies continue to shade light on the dynamic nature of asset correlations and their drivers. However, as we show in this discussion, no studies have studied the combined impact of global risk aversion and domestic macroeconomic factors on dynamic correlations between stock, bond, and FX markets. Going ahead with these studies, Gungor and Taştan (2021) investigates the macroeconomic determinates of stock market dynamic correlations of G7 and BRICS countries. Their analysis shows that dynamic correlations are significantly determined by GDP growth, economic policy uncertainty, and credit default spreads. Hashmi et al. (2021) demonstrate that correlations between global economic policy uncertainty and Indonesian stock market returns are significantly dynamic over time. They further find that inflation, crude oil prices, GDP, and world crude oil production have a significant impact on these dynamic correlations. Chen et al. (2022) ponders the drivers of stock-bond volatility and correlations for China. They find that macroeconomic fundamentals including industrial production growth is significant in explaining volatility in stock and bond markets. However, their findings further show that the stock bond-correlations are weakly dynamic over time.

Margani and Husodo (2022) ascertain that stock-bond correlations across Malaysia, Singapore, India, and Thailand are significantly dynamic. Interestingly, they find that crisis periods are associated with decoupling correlations for Thailand and Malaysia, which contradicts Katzke (2013), who found that crisis periods are associated with elevated intersectoral equity correlations in SA. Shafiq et al. (2023) confirm the dynamic nature of commodities, bonds, forex, and equity market correlations using evidence from Bangladesh, Pakistan, Indonesia, Philippines, Vietnam, and Turkey. This study leaves out an impact assessment, which is important for dynamic correlations forecasting and prediction required for improving market timing. Cai et al. (2023) investigated the impact of COVID-19 on the time varying stock-bond correlations across 21 financial markets. Using the DCC model, they find that the impact is variegated across regions. For North America and Asia-Pacific countries, their results show that the stock bond correlations decoupled at the initial phases of the pandemic leading to increased diversification benefits which soon faded as the correlations started to increase. However, they note that this phenomenon is not prevalent for European stocks.

This paper contributes to the academic literature by examining the impact of global risk aversion and domestic macroeconomic factors on dynamic conditional correlations from an emerging market (SA) perspective. Further, it provides additional insights not covered in the current body of literature by examining not only the equity-bond correlations but also the equity-FX and the bond-FX market correlations relevant for advising investors about the diversification strategies available outside the SA equity-bond market bounds. Expanding asset allocation and diversification beyond the traditional stock-bond mix has been the central theme in academic literature following the tendency of stock-bond correlations to surge during periods of crisis reducing diversification effectiveness (Rehman, 2016).

3. Methodology

3.1 Data and variables

To explore the impact of global risk aversion and domestic macroeconomic factors on dynamic conditional correlations, this study uses monthly time series data covering 14 years from January 2008 to December 2021. This research period is chosen firstly because it captures events such as the 2007-2009 GFC, the European Debt Crisis of 2010, the taper tantrum of 2013, the commodity price slump in 2015, and the COVID-19 pandemic-induced market volatility in 2020. Hence, the research period provides sufficient runway and crisis episodes for comprehensively ascertaining the impact of global risk aversion and domestic macroeconomic factors post-global financial crisis and for the generation of insights that will guide policy formulation in similar episodes in the future. Further, the research period is sufficient for our analysis, with a total of 168 observations per variable. Lastly, the research period is in line with the objectives of the paper, which is to uncover the insights up to the end of the COVID-19 crisis. For the analysis, this study uses the returns of the JSE All Share Index (RJSEALSH), which is used as a proxy for equity market returns, JSE All bond Index returns (RJSEALB) used as a proxy for bond market returns, and US dollar to Rand exchange rate returns (RFX) used as a proxy for foreign exchange market returns. The returns were derived using the following logarithmic formula:

$$Rt = ln\frac{Pt}{Pt-1}$$

where Rt are returns at time t, Pt are prices at time t, and $Pt{-}1$ are prices at time $t{-}1$

In line with the empirical literature discussed in the second section, this study uses the log of the Chicago Board of Options (CBO) volatility index (LVIX) as a proxy for global risky aversion. By calculation, VIX is derived by averaging the weighted prices of out-of-the-money calls and puts for a variety of US option maturities with the aim of deriving market consensus on the expected 30-day volatility. Hence, VIX represents the global market fear and uncertainty (risk aversion) consensus. Higher VIX values indicate increased global risk aversion, while lower values signal less global risk aversion (Chiang et al., 2015). This paper follows Katzke (2013), Chiang et al. (2015) and Hashmi et al. (2021) in adopting the VIX as a proxy for global risk aversion, LINF, which denotes the log of the rate of inflation, LM3 which stands for the log of broad money supply, CABALANCE which is the current account balance, DMU standing for the domestic market uncertainty which is measured by the ratio of conditional variances of market return series following Perego and Vermeulen (2016) and Chiang (2020). LTB which is the log of treasury bill yield, and LGDS representing the log of savings as a percentage of GDP as explanatory variables. Data on inflation was obtained from the SARB data portal, while the rest of the data was obtained from Bloomberg. This study utilised the data from these sources due to their uncompromising quality, accuracy, and reliability (Péer et al., 2021).

3.2 Model specification

The methodology of this study is twofold. Firstly, the study uses the DCC-GARCH model to ascertain whether the market correlations are dynamic and to derive the dynamic conditional correlations Secondly, it then uses the OLS regression model to ascertain the impact of global risk aversion and domestic macroeconomic factors on dynamic conditional correlations following most of the papers discussed in the literature review section. As highlighted, the DCC model is preferred because it is more parsimonious than other models, as it results in fewer parameters. Secondly, the DCC is estimated using 2 step procedure, making it relatively less ambiguous than other models, such as the BEKK model. Hence, this paper employs the DCC following leading papers such as Morgani and Husodo (2022), Cai et al. (2023), and Shafiq et al. (2023), among others. Further, this study adopted the OLS for its simplicity and best, linear, unbiased estimator properties.

3.2.1 Specification of the DCC-GARCH model

According to Engle (2002), the DCC model is given by the following:

$$H_t = D_t R_t D_t \tag{1}$$

Where: D_t : is a k × k diagonal matrix of conditional volatilities of the market returns

Rt: denotes the k × k conditional correlation matrix of the market returns.

Engle (2002) further specifies that the DCC GARCH model computes the conditional volatilities and correlations in 2 stages. First, the conditional volatilities of the market returns are computed from the mean equations using the standard GARCH (1) models. Hence, Dt can be expressed as follows.

$$D_t = \left(h_{iii}^{\frac{1}{2}}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots h_{kkt}^{\frac{1}{2}}\right) \tag{2}$$

Where h_{iii} through to h_{kkt} are the conditional variances of each market return series and follow the GARCH (1) process detailed in equation (3)

$$h_{i,t+1} = \omega_i + \sum_{p=1}^{pi} \lambda_{i,p}\epsilon_{i,t-p}^2 + \sum_{q=1}^{qi} \gamma_{i,q} h_{i,t-q} \tag{3}$$

Where: λ and γ must be greater than 0 and their sum be less than 1; these conditions need to be met for the univariate GARCH models to be stationary. Hence, in short, $\lambda_{i,p}>0$; $\gamma_{i,q}>0$ and $\sum_{p=1}^{p\ i} \lambda_{,p}\epsilon_{i,t-p}^2 + \sum_{q=1}^{qi} \gamma_{i,q} h_{i,t-q}<1$ conditions must be met (Katzke, 2013).

In the second stage, the zero mean returns innovations are then standardised by the conditional variances computed in stage 1 such that the DCC model is given by the following equation:

$$\phi_t = (1 - \alpha\text{-}\beta)\overline{\phi} + \alpha\mu_{t-1}\mu_{r-1}{}' + \beta\phi_{t-1} \tag{4}$$

Where: ϕ_t is the n × n matrix of the unconditional variance between the return pairs and $\overline{\phi}$ is the n × n Matrix of the unconditional covariance. Equation (4) follows the GARCH (p,q) framework such that the dynamic conditional correlations can be generated by equation (5).

Parameter α captures the persistence of correlation whilst β captures the impact of past shocks on contemporaneous conditional correlations (Katzke, 2013). Engle (2002) asserts that for the Stability of the DCC model, it is required that $\alpha + \beta < 1$.

The dynamic correlations between 2 markets will now be computed as follows:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\overline{q}_{12,} + \mu_{1,t-1}\mu_{2,t-1+\beta q_{22,t-1}}}{\sqrt{[(1-\alpha-\beta)\overline{q}_{11,} + \alpha\mu_{1,t-1}^2 + \beta q_{11,t-1})}\sqrt{[((1-\alpha-\beta)\overline{q}_{22} + \alpha\mu_{2,t-1}^2 + \beta q_{22,t-1})]}} \tag{5}$$

Where: $\rho_{12,t}$ is the dynamic conditional correlation coefficient between markets 1 and 2 at time t and $\overline{q} = \frac{1}{T}\sum_{t-1}^{T} \mu_1\mu_1'$.

Following Engle (2002) the DCC GARCH model in equation (4) is computed by using the maximum likelihood function. This study uses the Fiszeder et al. (2019) approach, which allows for the computation of the DCC GARCH model in 2 steps simultaneously. Following the procedures outlined above and in line with studies by Fiszeder et al. (2019) and Katzke (2013) this study uses the GARCH (1) specification for the variance equations in step 1.

3.2.2 Specification of the OLS model

As discussed earlier, to ascertain the impact of global risk aversion and macroeconomic factors on the time-varying correlations, we followed many studies, such as that of Katzke (2013), using the OLS model. The following OLS model was specified:

$$Y = \beta_0 + \beta_1 LVIX_t + \beta_2 LINF_t + \beta_3 LM3_t + \beta_4 CABALANCE_t + \beta_5 DMU_t + \beta_6 LTB_t + \beta_7 LGDS_t + \varepsilon$$

Where:

Y- represents the dynamic conditional correlations of the equity, bond, and foreign exchange market pairs derived from the DCC-GARCH models.

To ensure the accuracy of results, this study uses various diagnostic tests such as the Augmented Dickey-Fuller (ADF) test for testing for stationarity, the ARCH LM test and the Breusch-Pagan-Godfrey test for testing for heteroscedasticity, and the correlogram Q statistics and the Breausch- Godfrey LM test for autocorrelation (Gujarati, 2012).

4. Empirical results

4.1 Descriptive statistics

Table 1 details key descriptive statistics.

One can note that RJSEALSH and RJSEALB recorded positive mean returns over the sample period, while RFX recorded a negative mean return. LTB, LM3, LGDS, LINF, and LVIX recorded positive mean values except for CABALANCE, which recorded a negative mean value. The mean values of returns imply that over the sample period, the equity and the bond markets performed relatively better than the foreign exchange market, at least on a mean return basis. The means also evidently suggest that LTB, LM3, LGDS, LINF, and LVIX were as expected, generally on the positive segment throughout the sample period. However, the negative mean value of CABALANCE suggests that SA recorded negative current account balances in most of the sample period, which is also confirmed by the CABALANCE graph in Figure 1. Looking into the maximums, among the returns, RJSEALSH recorded the highest maximum return of 12.3%, followed by RFX with 10.8%, and lastly, RJSEALB recorded a maximum of 8.2% return. It's quite surprising that regardless of the maximum returns, the RJSEALB outperformed all the markets, recording a mean return of 0.69%, which is above that of RJSEALSH and RFX. In terms of minimum values, it can be noted that the RFX had the biggest slide during the sample period, recording a return of -16.6%, followed by RJSEALSH, recording a return of -15%, and RJSEALB, recording -10.3%. On the other hand, standard deviation numbers, which carry information about the riskiness of the returns, show that RFX is the riskiest, followed by JSEALSH and RJSEALB, respectively. Investors are thus advised to consider the risk-return profiles of these markets when making investment decisions to align their choices with their risk tolerance and investment objectives. The Jarque-Bera p-value, which tests the hypothesis of normality, is also reported on the table. Since the p values are less than 5% for all the variables except for LTB, we can reject the null hypothesis that the variables are normally distributed and conclude that the variables are not normally distributed except for LTB. This paper accounted for this variable nonnormality in subsequent modelling.

4.2 Cross correlations

Table 2 shows the cross-correlations between the variables. Weak positive correlations can be noted among the returns except for the correlation between RFX and RJSEALB, which shows a moderate positive correlation coefficient of 0.54. The correlation between returns and the included explanatory

Table 1. Measures of central tendency and data distribution.

	Mean	Median	Maximum	Minimum	Std. Dev	Jarque-Bera P value
RJSEALSH	0.55	0.78	12.35	−15.03	4.48	0.00
RJSEALB	0.69	0.71	8.16	−10.26	2.28	0.00
RFX	−0.43	−0.19	10.84	−16.56	4.59	0.01
LTB	1.84	1.84	2.48	1.25	0.26	0.70
LM3	14.82	14.81	15.27	14.35	0.27	0.00
LGDS	2.70	2.67	2.89	2.56	0.10	0.00
LINF	1.72	1.76	2.84	−0.36	0.62	0.00
LVIX	2.93	2.88	4.09	2.25	0.38	0.00
CABALANCE	−2.90	−2.83	4.43	−5.50	2.17	0.00

Source: Author's own computation.

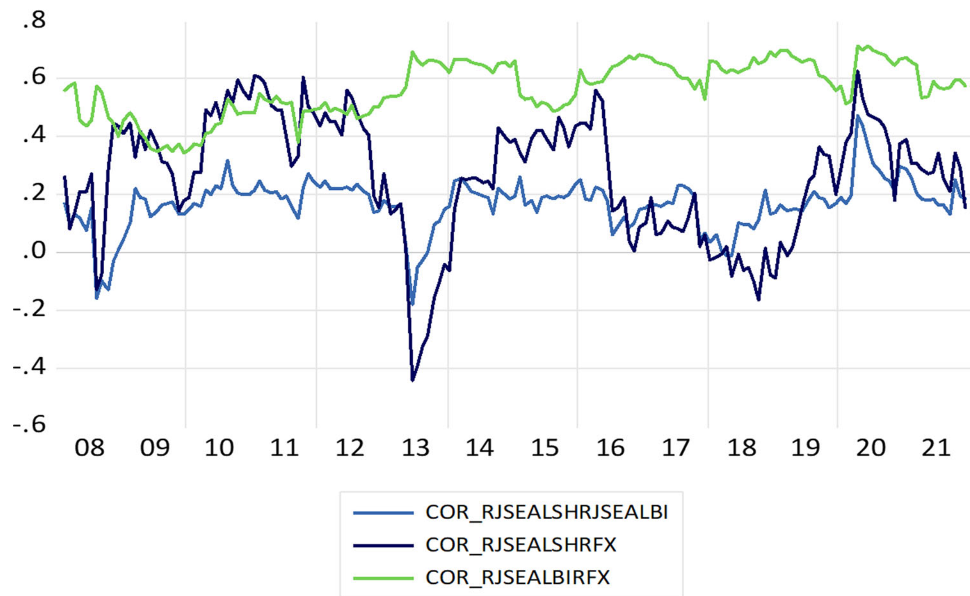

Figure 1. Dynamic conditional correlation graphs.
Source: Author's own computation.

Table 2. Cross correlations.

	RJSEALSH	RJSEALB	RFX	CABALANCE	LTB	LM3	LGDS	LVIX	LINF
RJSEALSH	1								
RJSEALB	0.17	1							
RFX	0.30	0.54	1						
CABALANCE	0.07	0.02	0.08	1					
LTB	−0.20	0.01	−0.04	−0.59	1				
LM3	−0.001	−0.02	0.01	0.50	−0.43	1			
LGDS	−0.05	0.01	0.09	0.44	−0.05	−0.38	1		
LVIX	−0.21	−0.06	−0.19	0.08	0.06	−0.31	0.40	1	
LINF	−0.12	0.04	0.02	−0.33	0.48	−0.37	0.24	0.23	1

Source: Author's own computation.

Table 3. Unit root results.

Variable	Level	1st Difference	Integration order
RJSEALSH	−13.66***		I (0)
RJSEALB	−14.35***		I (0)
RFX	−13.02***		I (0)
LTBILL	−1.40	−9.68***	I (1)
LM3	−0.83	−3.65***	I (1)
LGDS	−2.33	−12.79***	I (1)
LINF	−3.30**		I (0)
LVIX	−4.35***		I (0)
CABALANCE	−0.56	−3.69***	I (1)

The reported test statistics are from the ADF unit root test. *: Test statistic is significant at 10%, **: Test statistic is significant at 5%, ***: Test statistic is significant at 1%.
Source: Author's own computation.

variables and the correlations between explanatory variables is evidently weak. This suggests that we won't encounter any challenges of multicollinearity in the models as the correlation coefficients between the explanatory variables are less than 0.8 (Gujarati, 2012).

4.3 Unit root tests

Table 3 below posts the test statistics and the p-values from the ADF test.

Stationarity is required to avoid spurious regressions (Gujarati, 2012). As can be seen on the table, RJSEALSH, RJSEALB, RFX, LINF, LVIX, and CABALANCE are stationary at level hence integrated of the order 0 while LTB, LM3, and LGDS are first difference stationary, meaning they are integrated of order I.

Following these results, RJSEALSH, RJSEALB, RFX, LINF, LVIX, and CABALANCE are used in levels, while LTBILL, LM3, and LGDS are used in their first difference in subsequent modelling.

4.4 Arch effects

Table 4 reports the results of the ARCH and Durbin Watson tests conducted on mean equations. These tests were conducted to confirm the presence of heteroskedasticity in the return series, as is necessary under GARCH models. Results show that the p-values of the ARCH F- statistic are all less than 5% for all the models. Hence, the null hypothesis of homoscedasticity was rejected, allowing us to confirm the presence of heteroscedasticity (Arch effects) in the data. Additionally, the d values for the Durbin-Watson test all round up to 2 for all the models, suggesting no first-order serial correlation.

4.5 DCC GARCH results

This section discusses the DCC GARCH results following the methodology detailed in section 3.

4.5.1 DCC GARCH step one results

Table 5 details the DCC-GARCH (1) results obtained from the DCC GARCH first step.

The above results indicate that the constant terms ω's, the ARCH terms λ's, and the GARCH terms γ's are significant except for the GARCH terms of RJSEALB and RFX. This implies that the conditional variance of RJSEALSH is significantly determined by its constant, past innovations, and past variance, whilst RJSEALB and RFX are significantly determined by their constants and past innovations only. Furthermore, the coefficients of the ARCH and GARCH terms are positive for all models, hence satisfying the GARCH condition with no negative coefficients (Engle, 2001). This finding validates the appropriateness of the model specifications. Additionally, the sum of the ARCH and the GARCH terms are less than 1 for all the models, hence allowing us to conclude that the GARCH models are stationary (Engle, 2001). On the same note, the sum of the ARCH and the GARCH terms for RJSEALSH amount to 0.9, which is closer to 1. This indicates that the RJSEALSH is characterised by high volatility persistency. Such persistency implies that the past volatility of RJEALSH remains entrenched for extended periods. Hence, investors must update their risk management strategies to account for the longer-lasting effects of volatility shocks on RJEALSH. Comparatively, RJSEALB and RFX have low volatility persistency, with the sum of their ARCH and GARCH terms amounting to less than 0.5. This shows that the SA equity, bond, and foreign exchange markets have different levels of volatility persistency, which investors can exploit during periods of turmoil. For example, investors can capitalise on the volatility persistency differential between markets by adopting long-term momentum strategies for the equity market and short-term momentum strategies for the bond and foreign exchange markets. Results also show that RJSEALSH's GARCH term is greater than the ARCH term, which indicates that its current volatility is more sensitive to its past volatility than its past innovations. This is not the case for RJSEALB and RFX. The finding reinforces the need for short-term risk management and trading strategies for bond and foreign exchange markets and longer term for the equity market in SA.

4.5.2 DCC-GARCH step two results

Table 6 presents the results from the DCC-GARCH step 2, which posts the DCC parameters.

The above results indicate that the DCC parameter alpha (α) which measures the impact of past standardised shocks on contemporaneous conditional correlations, is significant for the RJSEALSH _FX

Table 4. Arch effects.

Dependent Variable	Durbin Watson	ARCH F statistic	ARCH P-Value
RJSEALSH	2.05	12.79	(0.00)***
RJSEALB	1.86	10.25	(0.00)***
RFX	2.21	10.80	(0.00)***

The table reports the Durbin Watson d values and the test statistics and p values for Arch test. P values are posted in parenthesis with: *: Test statistic is significant at 10%, **: Test statistic is significant at 5%, ***: Test statistic is significant at 1%.
Source: Author's own computation.

Table 5. DCC-GARCH step 1 extracts: univariate GARCH output.

	Variable Coefficients		
Parameters	**RJSEALSH**	**RJSEALB**	**RFX**
ω	2.59	3.47	14.02
	(0.07)*	(0.00)***	(0.06)**
λ	0.26	0.24	0.25
	(0.03)**	(0.09)*	(0.08)*
γ	0.60	0.11	0.10
	(0.00)***	(0.64)	(0.77)

The table reports DCC GARCH (1) components. Reported in the table are coefficients and their p values in parenthesis. *: Coefficient is significant at 10%, **: Coefficient is significant at 5%, ***: Coefficient is significant at 1%.
Source: Author's own computation.

Table 6. DCC GARCH step 2 Extracts: Dynamic conditional correlations output.

	Correlation Models		
Parameters	RJSEALSH_RJSEALB	RJSEALSH _FX	RJSEALB _FX
α	0.06	0.11	0.06
	(0.33)	(0.02)**	(0.10)*
β	0.72	0.79	0.89
	(0.01)***	(0.00)***	(0.00)***
Mean Rho	$\mu rt = 0.17$	$\mu rt = 0.26$	$\mu rt = 0.57$
Standard deviation of Rho	$\delta rt = 0.09$	$\delta rt = 0.22$	$\delta rt = 0.10$

$\alpha + \beta < 1$ condition is met for all the models. The p values of the coefficients are written in parenthesis while the coefficients are above the p values. *Significant at 10%, **Significant at 5%, ***Significant at 1%.
Source: Author's own computation.

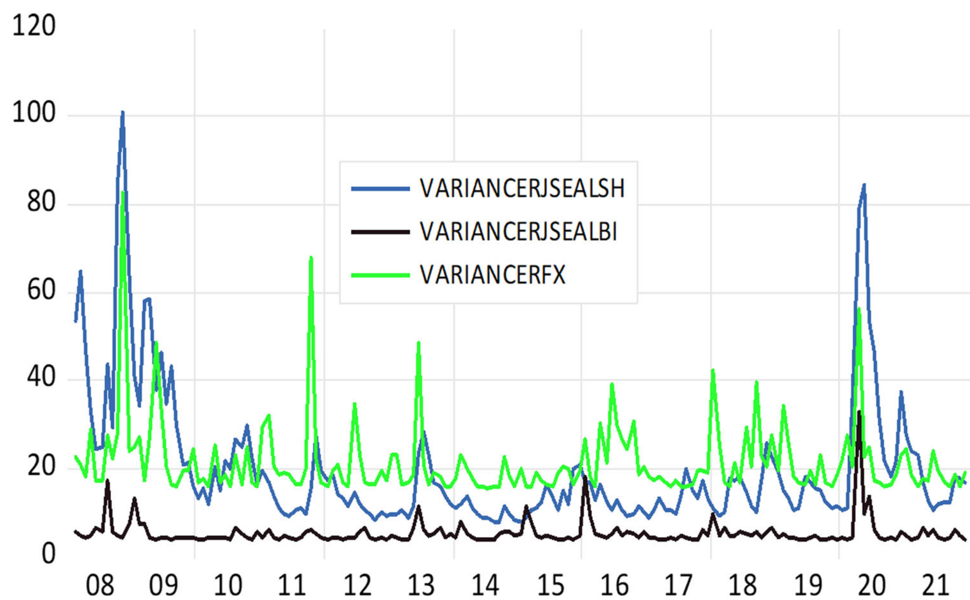

Figure 2. Conditional Variance graphs.
Source: Author's own computation.

(stock and foreign exchange market correlations) and the RJSEALB _FX (bond and foreign exchange market correlations) and insignificant for the RJSEALSH_RJSEALB (stock and bond market correlations). This implies that RJSEALSH_FX and RJSEALB_FX are significantly explained by their past standardised shocks, whilst RJSEALSH_RJSEALB is not. Results also indicate that the DCC parameter Beta (β) which measures the impact of lagged conditional correlations on contemporaneous conditional correlations, which are strongly significant for all models, implying that all correlation pairs are significantly explained by their lagged conditional correlations. The model stability condition of $\alpha + \beta < 1$ is met for all the models, hence confirming that the models correctly fit and are valid. Additionally, the sum of Alpha and Beta is closer to 1 for all models, confirming the appropriateness of the fitted DCC models in modelling dynamic correlations. Figure 1 visualises the dynamic correlations, while Figure 2 visualises the conditional variances drawn from the DCC-GARCH computations.

Unsurprisingly, the dynamic correlations plots confirm the DCC results by revealing the ever-changing nature of asset correlations in SA. As highlighted, the dynamic nature of asset correlations means that diversification benefits across SA financial markets vary from time to time, as the effectiveness of diversification is indirectly related to the level and direction of asset correlations. Looking into the visualisations, one can realise that asset correlations are mostly oscillating within the positive segment throughout the sample period implying lower diversification benefits or effectiveness in general. However, there is a noticeable short-lived decoupling of stock-bond (COR_RJSEALSHRJSEALBI) and stock-foreign exchange (COR_RJSEALSHRJSEFX) correlations into the negative segment in 2008, 2013, and 2018, suggesting high diversification benefits between these markets over the highlighted periods. However, the plots show that while the stock-bond and stock-FX correlations remain generally positive, they tend to have moments of decrease during crisis periods (2007-2009 GFC and the 2019/20 Covid-19 crisis), which signals the short-lived improvement in diversification benefits between these markets during episodes of turmoil. These findings coincide with findings by Cai et al. (2023) who similarly observed shot lived decoupling of stock-bond correlations at the initial stages of COVID and then increased there after.

This study, therefore, resonates with Katzke (2013), who argues, from the perspective of SA's JSE equity subsector index correlations, that diversification opportunities are very thin when most needed in SA due to dominating positive correlations. On the other hand, the bond-FX correlations are generally high throughout the sample period, implying low diversification benefits between these markets over the sample period. On asset volatility, Figure 2 exhibits that asset volatility is quite high during crisis periods. This is evident as all the markets recorded their highest volatilities in 2007-2009 GFC and the 2019/2020 Covid-19-induced crisis. The graph also shows that during crisis periods, the VARIANCERJSEALSH (stock market) is highly volatile, followed by the VARIANCERFX (foreign exchange market) and VARIANCERJSEALBI (bond market) with the least volatility. In general, however, excluding the crisis periods, the foreign exchange market is highly volatile throughout the sample period, more than any other market in discussion, whilst the bond market is the least volatile and only records its highest levels in 2020. As a result, these insights suggest that investors should be very cautious during periods of crisis as the riskiness of assets evidently tends to go up, increasing the chances of losses. However, the graph shows that by holding everything constant, investors can find refuge in the bond market, which has lower relative volatility in the same periods.

4.5.2.1 Discussion on dynamic conditional correlations and their implications for SA. The DCC results and the corresponding dynamic correlation graphs confirm the significantly dynamic nature of stock-bond, stock-FX, and bond-FX correlations in SA. These findings align with studies by Katzke (2013), Margani and Husodo (2022), Shafiq et al. (2023), among others who found similar results. However, this study stretches beyond the stock-bond correlations, which are covered in most of the literature, by providing evidence of the dynamic nature of stock-FX and bond-FX market correlations. These findings undoubtedly underline the ineffectiveness of static correlation models, especially as they apply to asset allocation and diversification over time. This is because static models assume that correlations are constant over time, resulting in infrequent portfolio rebalancing, which negates the effectiveness of diversification as asset correlations evolve. Investors should be aware that any changes in asset correlations necessitate the reconstruction of optimal portfolio weights, asset allocation, and diversification strategies for portfolios to remain fully diversified. Hence, considering the dynamic nature of correlations, this study advises investors and investment managers to adopt dynamic asset allocation and diversification strategies that will necessitate investors to respond timely and accordingly to changes in asset correlations in SA. This can be done by implementing dynamic correlation models such as the DCC model for the derivation of the latest dynamic correlations, then reviewing and adjusting asset allocations and diversification based on the latest correlation data on a continuous periodic basis (Shafiq et al., 2023).

4.6 Diagnostics for the DCC GARCH (1,1)

Table 7 contains the correlogram Q statistics and the ARCH test results.

Table 7. Diagnostics of the DCC GARCH (1,1).

Test conducted	RJSEALSH	RJSEALB	RFX
Correlogram Q for serial correlation: 15th Lag	6.76	17.08	9.45
	(0.96)	(0.31)	(0.85)
ARCH test for Heteroscedasticity	2.08	0.30	0.23
	(0.13)	(0.74)	(0.79)

The p values of the coefficients are written in parenthesis while the test statistics are above the p values. *: Test statistic is significant at 10%, **: Test statistic is significant at 5%, ***: Test statistic is significant at 1%.
Source: Author's own computation.

Table 8. OLS regression equation outputs.

Variable	Equity and Bond correlation	Equity and FX correlation	Bond and FX correlation
CONSTANT	0.05	−0.11	0.10***
CORRELATION (-1)	0.78***	0.86***	0.89***
LVIX	−0.01	0.05**	−0.02***
D(CABALANCE)	0.03**	0.03	0.01
DMU	0.00	−0.014	0.06**
D(LTB)	−0.37***	−0.30	−0.06
D(LGDS)	−0.22*	−0.39**	0.01
	R-squared: 0.67 Prob(F-statistic):0.00 Durbin-Watson stat: 2.02 *: Coefficient is significant at 10%, **: Coefficient is significant at 5%, ***: Coefficient is significant at 1%	R-squared: 0.81 Prob(F-statistic):0.00 Durbin-Watson stat: 2.01 *: Coefficient is significant at 10% **: Coefficient is significant at 5% ***: Coefficient is significant at 1%	R-squared: 0.90 Prob(F-statistic):0.00 Durbin-Watson stat: 2.04 *: Coefficient is significant at 10% **: Coefficient is significant at 5% ***: Coefficient is significant at 1%

Source: Author's own computation.

The p-values from the correlogram Q statistic and ARCH test are greater than 5% across models. Hence, the models are free from autocorrelation and heteroscedasticity, respectively.

4.7 OLS regression equation outputs

Table 8 shows the regression results from the parsimonious models as proposed by Gujarati (2012). Gujarati (2012) contends that parsimonious models result in high explanatory power and more significant coefficients. Hence, in the spirit of parsimony, LM3 and LINF were dropped from the models as their inclusion did not make the models better. Additionally, lagged dependent variables were included as a panacea for serial correlation. The EVIEWS 12 indicator saturation functionality was also used for the detection and removal of outliers.

For results discussion, this study specifies 2 themes. The first theme deals with the impact of global risk aversion, while the 2nd theme deals with the impact of domestic macroeconomic factors.

4.7.1 Impact of global risk aversion on dynamic conditional correlations

Results from the OLS models indicate that global risk aversion proxied by the Logarithm of the CBO Volatility index (LVIX) has a negative insignificant impact on equity-bond market correlations. These findings align with the findings by Panchenko and Wu (2009), who similarly found global risk aversion insignificant in their study involving emerging market countries. This study, however, deviates from the conclusions drawn by Connolly et al. (2005) and Chiang et al. (2015), who found global risk aversion to be negative and significant for the US, Canada, France, Italy, and Germany. As argued by Tachibana (2020), the expectation is that elevated global risk aversion, which occurs in periods of turmoil, should lead to the decoupling of stock-bond correlations necessitated by the phenomenon of flight to quality where investors shift their portfolio positions from risky assets such as stocks to safer assets such as bonds. Subsequently, and as highlighted earlier, the resultant decoupling of stock-bond correlations should thus lead to the increase in diversification benefits between these markets. However, against these priori expectations, and sadly for SA investors, this study's findings suggest that elevated global risk aversion does not translate into significant decoupling of stock-bond correlations in SA and hence does not significantly increase diversification benefits between these markets. Thus, these findings mean that the traditional diversification strategy, which involves the mixing of equities and bonds, does not provide the anticipated level of risk mitigation during periods of elevated global risk aversion in SA. As a result, SA investors may need to explore an alternative mix of asset classes to better safeguard their investments during such periods. Such strategies include mixing equities and gold, as proven to work in periods of crisis by Chkili (2016), equities and energy commodities, as recommended by Kumar et al. (2019), and equities and real estate investment trusts (REITs) as recommended by Anderson et al. (2021). The lack of diversification opportunities between equity and bond markets in times of elevated global risk aversion may exacerbate capital losses. Hence, policymakers are encouraged to enact measures targeting reducing the vulnerability of SA financial markets to heightened global risk aversion. These measures could include setting up an investment insurance fund that deals with investment losses for retail and institutional investors. Similar efforts have been realised through the creation of the Export Credit Insurance Corporation of SA (ECIC) which covers foreign investment losses for SA entities (ECIC, 2024). This study proposes the deepening and widening of the scope of such corporations to include covering losses for SA institutional and retail investors invested domestically and internationally. These interventions may provide cover for investors during crisis periods.

Evidence from the equity-FX correlation model shows that global risk aversion has a positive and significant impact on equity-FX market correlations. These findings show that increases in global risk aversion significantly increase the correlation between the equity and FX markets, consequently reducing the diversification benefits between these markets. This is so because increases in global risk aversion trigger flight to quality from stocks and the Rand to low-risk assets such as gold and safe haven currencies such as the US dollar (Tronzano, 2023). This leads to a decline in both equity and Rand prices, consequently heightening the correlation between these markets. Given these findings, it follows that holding a mix of SA equities and the Rand in the FX market may not provide effective portfolio risk protection in periods of high global risk aversion. However, the inverse of these findings suggests that during periods of high global risk aversion, SA equities are negatively correlated with the US dollar as the US dollar tends to appreciate against the Rand while the SA equities fall. Hence, investors should consider opening foreign exchange accounts which enable them to hedge equity positions by allocating a portion of their capital into US dollars. This approach will not only mitigate equity market risk but will also capitalise on the safe haven property of the US dollar which may provide more returns as it appreciates during crisis periods.

Further, this study finds that global risk aversion has a negative and significant impact on bond-FX correlations. In line with priori expectations, increases in global risk aversion trigger flight to safety by investors (Fleming et al.,1995). As a result, investors take long positions on safe assets such as bonds and short positions on risky assets such as the Rand. This causes divergence in the bonds and Rand prices, which consequently leads to falling correlation levels between these assets. The findings on bond-FX correlations suggest that heightened global risk aversion increases the diversification opportunities between the bond and FX markets. Consequently, this study advises investors to hold a combination of bonds and the Rand in the FX market during episodes of high global risk aversion to mitigate idiosyncratic risks during such periods. Furthermore, the findings also suggest that in periods where global risk aversion is low, diversification benefits may fall between these markets necessitated by increasing correlations. Hence, we argue that investors must track global risk aversion as an indicator and implement dynamic asset allocation by ensuring periodic portfolio optimisation in line with ever changing level of asset correlation and global risk aversion.

4.7.2 Impact of domestic macroeconomic factors on dynamic conditional correlations

This study finds that current account balance has a positive impact on dynamic conditional correlations. In particular, its impact is significant for stock-bond pairs, which suggests that an increase in the current account balance increases the correlation between equity and bond markets, consequently reducing the diversification benefits between these markets. This finding coincides with the findings of Perego and Vermeulen (2013), who found similar results. Additionally, this study establishes that domestic market uncertainty has both negative and positive impacts on the dynamic conditional correlations. However, its p-values show that it is only significant in explaining bond-FX market correlations. Its positive coefficient suggests that increases in domestic market uncertainty reduce the diversification benefits between these markets. This study also ascertains that treasury bill rate has a negative impact on dynamic conditional correlations. However, its impact is only significant in explaining the stock-bond correlations coinciding with flight to liquidity assertions by Chiang et al. (2015), where investors move from risky assets to more liquid and less risky assets, causing the asset correlations to decouple. As such, these findings suggest that increases in treasury bill rates increase the diversification benefits between stock and bond markets in SA. Lastly, this study establishes that savings have a negative and significant impact on stock-bond and stock-FX correlations, thus suggesting that an increase in savings increases diversification benefits between these asset classes. Following these findings and implications, this study recommends the adoption of dynamic asset allocation and diversification strategies that respond to changes in dynamic correlations, global risk aversion, and domestic macroeconomic factors for portfolios to remain fully diversified at all times. On this note, investors can monitor the changes in global risk aversion and domestic macroeconomic factors and recalibrate asset allocation and diversification accordingly on a continuous periodic basis. In light of this, and as emphasised by Brownlees and Llorens-Terrazas (2020), this study advocates for the adoption of robust dynamic correlation modelling and forecasting that includes these factors. We posit that dynamic correlation forecasts can work as early warning signals for investors, thus helping them to foresee potential adverse and favourable market conditions and strategise for diversification beforehand. On the macroeconomic policy front, the highlighted results and implications paint a clear picture of the crucial role of global risk aversion and macroeconomic factors in determining the effectiveness of portfolio risk management in SA. Hence, this study appeals to policymakers to consider financial market implications when formulating macroeconomic policies. Specifically, we argue that policymakers should enact policies that bring certainty and confidence as well as stability in the macroeconomic environment, as this is crucial for creating an enabling environment for portfolio risk management in SA.

4.8 OLS residual diagnostics

Table 9 below posts the results from the LM test for serial correlation and BPG test for heteroscedasticity. The p-values for both the LM and BPG tests are greater than 5%. Hence, this study concludes that the models are free from serial correlation and heteroscedasticity.

5. Summary and conclusion

This study aimed to assess the impact of global risk aversion and domestic macroeconomic factors on the dynamic conditional correlations of asset returns using evidence from SA equity, bond, and FX markets. Two fundamental questions fueled this investigation. Firstly, whether correlations between SA equity, bond, and FX market pairs are dynamic, and secondly, whether global risk aversion and domestic macroeconomic factors have any significant impact on these dynamic correlations. Using the DCC-GARCH model, this study finds that the correlations between SA equity and bond market, equity and FX market, and bond and FX market are significantly dynamic over time. The fluctuating nature of asset correlations implies that diversification benefits are not always present. Hence, this study advises investors and investment managers to adopt dynamic asset allocation and diversification strategies to adjust portfolios in a timely manner that is appropriate to the everchanging level of asset correlations in SA. The study cautions against the use of static strategies in SA's evidently dynamic environment and further

Table 9. OLS residual diagnostics.

Test conducted	Equity Bond correlation	Equity FX correlation	Bond and FX correlation
LM test for serial correlation	1.62	0.40	0.55
	(0.44)	(0.82)	(0.76)
BPG test for Heteroscedasticity	5.83	5.51	4.88
	(0.44)	(0.48)	(0.90)

The p values of the coefficients are written in parenthesis while the test statistics are above the p values. *: Test statistic is significant at 10%, **: Test statistic is significant at 5%, ***: Test statistic is significant at 1%.
Source: Author's own computation.

contends that such may undermine portfolio risk management efforts and subject portfolios to high market risks.

Using evidence from the OLS regression models, this study finds that global risk aversion has a variegated impact on dynamic conditional correlations. Results indicate that its impact is negative and insignificant on stock-bond correlations, positive and significant on stock-FX correlations, and negative and significant on bond-FX correlations. These findings imply that periods of elevated risk aversion lead to no significant increase in diversification benefits between stock and bond markets, less diversification benefits between equity and FX markets, and increased diversification benefits between bond and FX markets. As a result, these findings underline the inadequacy of traditional diversification methods in periods of crisis. Thus, these findings mean that the traditional diversification strategy, which involves mixing equities and bonds, may not provide the anticipated level of risk mitigation during periods of elevated global risk aversion. As a result, SA investors may need to explore an alternative mix of asset classes to better safeguard their investments during such periods. Such mix may include bonds and currencies in the FX market, equities and the US dollar in the FX market, equities and REITs, and equities and gold. Chkili (2016), Kumar et al. (2019), and Anderson et al. (2021) provide supporting evidence. Additionally, OLS results also show that domestic macroeconomic factors such as current account balance, domestic market uncertainty, treasury bill rate, and savings have a heterogeneous impact on the dynamic conditional correlations. In light of these findings, this study advises investors to adopt active and dynamic asset allocation and diversification strategies. These are strategies that take into consideration the variegated nature of the level and direction of stock-bond, stock-FX, and bond-FX correlations and variegated impact-responses of these correlations to global risk aversion and domestic macroeconomic factors whilst responding to changes in dynamic correlations, global risk aversion, and domestic macroeconomic factors to keep portfolios fully diversified at all times. To implement these strategies, we advise investors to continuously monitor and recalibrate their asset allocation and diversification strategies in accordance with changing asset correlations, global risk aversion, and macroeconomic factors. Crucially, and based on the research findings, this study advocates for the inclusion of global risk aversion and domestic macroeconomic factors in robust dynamic correlation modeling and forecasting due to their significance in explaining dynamic correlations.

In conclusion, this paper contributes to the field of financial economics by enhancing the understanding of the impact of global risk aversion and domestic macroeconomic factors on dynamic conditional correlations from an emerging market (SA) perspective. Further, this paper provides additional insights not covered in the current body of literature by examining not only the equity-bond correlations but also the equity-FX and the bond-FX market correlations relevant for advising investors about the diversification strategies available outside the traditional stock-bond market bounds. Expanding asset allocation and diversification beyond the traditional stock-bond mix has been the central theme in academic literature, following the tendency of stock-bond correlations to surge during periods of crisis, reducing diversification effectiveness (Rehman, 2016). For future research, this paper recommends the expansion of the study period beyond 2021 to capture evolving dynamics beyond this study. Researchers can also expand on explanatory variables by exploring other sets of domestic macroeconomic factors such as unemployment, interest rates, and GDP. Researchers can also explore subsector dynamics, which will enable more granular analysis. Researchers can also consider other asset classes, such as commodities, gold, and real estate, to provide a solution to failing traditional asset classes such as stocks and bonds.

Author contribution statement

Kelleb Mloyi and Edson Vengesai were both involved in the conception and design, Kelleb Mloyi in the analysis and interpretation of the data, Kelleb Mloyi in the drafting of the paper, Edson Vengesai revising it critically for intellectual content, supervising the project and the final approval of the version to be published. All authors agree to be accountable for all aspects of the work.

Disclosure statement

The authors report there are no competing interests to declare.

Funding

This research received no external funding.

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Data availability

Data is available upon request.

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