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Determinants of South African Asset Market Co-Movement: Evidence from Investor Sentiment and Changing Market Conditions

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Abstract: The co-movement of multi-asset markets in emerging markets has become an important determinant for investors seeking diversified portfolios and enhanced portfolio returns. Despite this, studies have failed to examine the determinants of the co-movement of multi-asset markets such as investor sentiment and changing market conditions. Accordingly, this study investigates the effect of investor sentiment on the co-movement of South African multi-asset markets by introducing alternating market conditions. The Markov regime-switching autoregressive (MS-AR) model and Markov regime-switching vector autoregressive (MS-VAR) model impulse response function are used from 2007 March to January 2024. The findings indicate that investor sentiment has a time-varying and regime-specific effect on the co-movement of South African multi-asset markets. In a bull market condition, investor sentiment positively affects the equity–bond and equity–gold co-movement. In the bear market condition, investor sentiment has a negative and significant effect on the equity–bond, equity–property, bond–gold, and bond–property co-movement. Similarly, in a bull regime, the co-movement of South African multi-asset markets positively responds to sentiment shocks, although this is only observed in the short term. However, in the bear market regime, the co-movement of South African multi-asset markets responds positively and negatively to sentiment shocks, despite this being observed in the long run. These observations provide interesting insights to policymakers, investors, and fund managers for portfolio diversification and risk management strategies. That being, the current policies are not robust enough to reduce asset market integration and reduce sentiment-induced markets. Consequently, policymakers must re-examine and amend current policies according to the findings of the study. In addition, portfolio rebalancing in line with the findings of this study is essential for portfolio diversification.

Keywords: MS-AR; MS-VAR; investor sentiment; co-movement; asset markets; South Africa

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1. Introduction

In recent years, there has been an influx of investors in emerging markets due to the diverse asset markets and securities available to investors. The increase in investor participation has contributed significantly to economic growth in South Africa. However, it has also enhanced uncertainty through alternating market conditions, known as bull and bear periods (Moodley et al. 2022). This uncertainty has given rise to a phenomenon known as asset market integration, which in turn contributes significantly to investors' strategies and decision-making process (Ugurlu-Yildirim et al. 2021). Investor perception on the outlook of the market is an important determinant for asset market co-movement, where unexpected shocks and panic influence investor behaviour leading to asset markets moving together (Fang et al. 2018). This phenomenon was tested in South Africa, and it was found that excess co-movement of South African asset markets is indeed driven by investor sentiment in the form of noise traders (Ocran and Mlambo 2009). This implies that the behaviour of investors plays a role in the volatility of the South African market, which can cause asset markets to co-move.

A clear example of the noise-trading phenomenon was seen during the 2007/2008 Global Financial Crises (GFCs), as excess granting of credit by the United States (US) banks caused a credit crisis as many defaulted on loan repayments (Arner 2009). In an attempt to control the excess leverage, authorities undertook monetary policy adjustments in the form of inflation targeting and interest rate manipulation (Carmassi et al. 2009). This did not help mitigate the GFC as many investors switched from the banking sector to other sectors to reduce losses. However, the switching among banking sectors and, later on, asset markets intensified as many investors tried to mimic the actions of fellow investors, which saw heightened sentiment levels in the market (Chiu et al. 2018). The switching among asset markets was not only isolated to the US, but global investors also withdrew their investments from the US and went to other financial markets to reduce losses such as South Africa. However, the financial market uncertainty and elevated sentiment levels caused asset markets globally to move together (Nian et al. 2021). The co-movement of asset markets enhanced portfolio volatility, which reduced portfolio diversification and increased portfolio losses. This ultimately led to the crash of the global financial market with many investors losing all investments.

In an attempt to examine the cause of asset market co-movement during the GFC, academics examined the effect of macroeconomic variables on asset market co-movement during bull and bear market conditions. This was carried out as it was found that macroeconomic variables such as inflation and interest rates caused multi-asset markets to move together during the GFC (Poshakwale and Mandal 2016). Moreover, inflation targeting and interest rate manipulation during the GFC caused excessive asset market co-movement (Skintzi 2019). However, new evidence suggests that an additional determinant of asset market co-movement is investor sentiment (see, Zhou and Huang 2020; Su and Wang 2021; Gong and Fang 2023). However, such evidence is isolated to developed markets, with no evidence in emerging markets, which are more prone to heightened sentiment levels and market uncertainty. Consequently, if left unstudied, especially in emerging markets like South Africa, it will have a detrimental effect on investors because there will be reduced portfolio diversification and enhanced losses as investors' sentiment and changing market conditions may cause asset markets to move together over time.

Therefore, the aim of this article is to examine the effect of investor sentiment on the co-movement of South African multi-asset markets under bull and bear market conditions. In achieving the objective of this study, three research questions are considered. These include: (1) what effect does investor sentiment have on South African asset market co-movement in a bull regime? (2) What effect does investor sentiment have on South African asset market co-movement in a bear regime? (3) How does the South African asset market co-movement respond to shocks by investor sentiment in a bull or bear regime? The achievement of the research question requires a quantitative research methodology where empirical models such as the Markov regime-switching autoregressive (MS-AR) model and Markov regime-switching vector autoregressive (MS-VAR) model impulse response function are used.

Accordingly, this study contributes to the existing literature in several ways. First, this study consider multi-asset markets in South Africa as compared to previous studies which only consider selected asset market co-movement, such as equity–bond and cross-market co-movement. Therefore, this study makes pronunciations on a variety of asset markets in which investors actively invest, thereby assisting investors in reducing portfolio losses. Second, this study provides specific evidence on the driving effects of investor sentiment on the co-movement of South African multi-asset markets, based on a constructed market-wide investor sentiment index. Accordingly, these findings can be used to improve investment strategies which in turn improves portfolio performances as portfolio optimisation and risk management are alluded to in this study. Third, unlike other emerging market studies, we consider the volatility of emerging markets by considering switching market conditions. Therefore, this study provides insight into how investor sentiment influences multi-asset market co-movement in light of bull and bear periods. Therefore, investors can use the findings to optimise their portfolio during market stability and uncertainty, which further assists in portfolio diversification and portfolio return. Lastly, the findings of the study can be used by policymakers to better manage the South African financial market by introducing new robust policies to reduce asset markets moving together. This is fundamental to the economy of South Africa as asset markets moving together reduces portfolio diversification, which limits investor participation (Athari and Hung 2022).

The remainder of the research paper is ordered as follows: Section 2 presents the literature review, Section 3 formulates the research hypothesis and gap. Section 4 comprises the methodology, which is aggregated according to the data and empirical model specification. Section 5 provides the empirical results that are considered in terms of the preliminary results and empirical model results. Section 6 presents the discussion of results and Section 7 provides the conclusion and implications.

2. Literature Review

The theoretical framework underpinning multi-asset market co-movement is isolated to the fundamental-based theory and category-based theory. The former was developed by Barberis et al. (2005) and postulates that asset market co-movement is directly related to co-movement in news about fundamental values such as the state of the financial market. This framework is based on the premise that correlated deviations in rationally expected cashflows cause correlations in asset returns which enhances correlations in discount rates when the news associated with risk aversion/interest rate influence discount rates simultaneously. On the other hand, the category-based theory on co-movement suggests that the fundamental-based theory is not the only determinant of asset market co-movement, rather the co-movement can be caused by investors' trading patterns due to sentiment in the market. Barberis et al. (2005) argue that investors tend to first group assets into categories in relation to some characteristics when developing their portfolios and thereafter they allocate funds in relation to the level of categories as opposed to the level of individual securities. These characteristics are isolated to investors' perception of the market, which influences their decision making and ultimately the co-movement of the asset market pairs in their portfolio. The reason for such a process is that it makes the allocation of funds to a portfolio less rigorous and allows for ease of evaluating the performance of the portfolio.

Despite the above theories postulating market conditions and investor sentiment as a determinant for asset market co-movement, empirical literature is still centred around macroeconomic variables as a determinant of selected asset market co-movement. For example, Piljak (2013) examined the effect of macroeconomic variables on the co-movement of bond markets of emerging countries. The study used the multivariate generalised autoregressive conditional heteroscedastic–dynamic conditional correlation (MGARCH-DCC) model to generate the monthly co-movement parameters for emerging market country pairs for the period 2000 to 2011. Thereafter, it was used as a dependent variable in an ordinary least squared (OLS) model regression. The findings of the OLS model indicated that interest rates, inflation, and industrial production have a significant effect on bond market co-movement. More specifically, the South African and Brazil bond market co-movement was positively affected by inflation and interest rates, suggesting that macroeconomy increases co-movement and decreases diversification benefits. Similarly, Dimic et al. (2016) used the wavelet model to examine the effect of macroeconomic variables on stock–bond co-movement of emerging markets. The findings also illustrate that inflation influences the stock–bond co-movement in the short run and long run.

Behmiri et al. (2019) used a combination of the MGARCH-DCC model and the autoregressive distribution lagged (ARDL) model to examine the effect of macroeconomic variables on energy commodity futures co-movement. The MGARCH-DCC model was first estimated to examine the time-varying correlation and, thereafter, the dynamic correlation was used in the ARDL model. The findings demonstrate that policy uncertainty had a positive effect on the monthly commodity co-movement from 1989 to 2014. Accordingly, investors incorporating commodity futures in their portfolio must consider macroeconomic uncertainty and policy adjustments as they will reduce portfolio diversification. In a more recent study, Aggarwal and Saradhi (2024) examined the effect of macroeconomic factors on stock market co-movement of India and Asia-Pacific countries. The sample period consisted of monthly data for the period 1991–2021 and was used to estimate the MGARCH-DCC model and the OLS model. The MGARCH-DCC model was used to examine the time-varying correlations of the stock market co-movement and revealed that there are weak levels of stock market co-movement between India and Asia-Pacific countries. Thereafter, the dynamic correlations were used in the OLS model, and it was found that gross domestic product (GDP), inflation, and interest rates have a positive effect on stock market co-movement. This implies that India and Asia-Pacific countries' equity markets are integrated and influenced by macroeconomic uncertainty.

While the majority of empirical studies have limited their analysis to macroeconomic variables, some studies have considered the state of asset markets by introducing changing market conditions. For example, Poshakwale and Mandal (2016) examined the effect of macroeconomic factors on multi-asset market co-movement during market conditions. The Markov regime-switching model demonstrated that for the period 1987 to 2012, interest rates had a significant positive effect on stock–bond, stock–oil, and stock–housing co-movement in bear market conditions such as the 2007/2008 GFC. These findings demonstrate that the co-movement of a multi-asset market alternates with market conditions and the state of the asset market drives diversification benefits. The findings are corroborated by Skintzi (2019). The Bayesian model was used to examine the effect of macroeconomic variables on the stock–bond co-movement of Eurozone countries during financial market uncertainty. The findings revealed that for the period 1999 to 2016 the quarterly stock–bond co-movement is time-varying and is influenced by domestic factors such as volatility, macroeconomy, and changing market conditions. More specifically, it was found that inflation and interest rates have a positive effect on the stock–bond co-movement during a bear market (financial market distress) condition. This implies that unstable market conditions coupled with macroeconomic fluctuations cause stock–bond co-movement among the Eurozone countries to increase, thereby limiting diversification properties.

Tronzano (2020) also examined the effect of macroeconomic variables on asset market co-movement under changing market conditions. However, the focus was on the commodity and foreign exchange market co-movement for the period 1999 to 2018. The monthly asset market pair correlations were extracted from the MGARCH-ADCC model and used in the OLS model as a dependent variable. The study demonstrated that, during a bear market regime, policy uncertainty, interest rates, and inflation caused the co-movement between gold, oil, and exchange rates (Swiss franc/US dollar) to increase. Consequently, bear market conditions coupled with macroeconomy have a detrimental effect on investors' portfolio diversification, therefore portfolio rebalancing was advocated for. Similarly, Yunus (2023) found that during bear market conditions the co-movement of multi-asset markets, such as stock, bond, oil, and housing markets, was influenced by macroeconomic uncertainty. These findings suggest that macroeconomic variables have a positive influence on asset market co-movement, irrespective of the specific asset market under observation.

Although monetary policy influences asset market co-movement, the recent evidence of emerging markets containing heightened sentiment levels with changing market conditions has raised many concerns. One of which is the impact of sentiment-induced markets and different market conditions on multi-asset market co-movement. Consequently, scholars have since shifted their analysis to investor sentiment and market conditions. However, the shift in recent years has made empirical literature very scarce in this regard. For example, Aloui et al. (2016) used the wavelet model to examine the effect of investor sentiment on the US–Islamic equity market co-movement from 1990 to 2010. The findings reveal that the US–Islamic equity market co-movement is time-varying and dynamic. More specifically, investor sentiment tends to co-move with US and Islamic equity markets, such that investor sentiment has a negative effect on equity market returns during financial market uncertainty. The findings are supported by Chelley-Steeley et al. (2019) who used the order flow imbalance methodology to determine the effect of investor sentiment on the co-movement of portfolio and market returns. The findings demonstrate that portfolio market return co-movement responds negatively to shocks to market-wide investor sentiment and institutional investor sentiment. Thus, investors' sentiment is most likely to increase portfolio returns when investors incorporate individual asset securities and benchmark indices in a portfolio.

Fang et al. (2018) used the DCC- Mixed-Data Sampling (MIDAS) approach to examine the effect of investor sentiment on the US equity–bond market co-movement under changing market conditions. The sample period comprised of daily data for the period 1986 to 2015. The findings revealed that investor sentiment has a positive effect on the long-term equity–bond co-movement and that in a period of bear market conditions the effect decreases but not in great amounts. Niţoi and Pochea (2020) examined the effect of investor sentiment on 24 European countries' equity market co-movement. The sample period comprised monthly data for the period 2004 to 2016, which were used in the DCC-MIDAS model. The findings suggest that during bear market conditions, as attributed to financial market uncertainty, investor sentiment had a positive effect on equity market co-movement. This implies that investor sentiment and bear market conditions reduce portfolio diversification. On the contrary, Nian et al. (2021) also examined the effect of investor sentiment on the stock market co-movement in a bear market condition, but the focus point was on the US and China stock market co-movement. The findings reveal that the investor sentiment indices of both the US and China have a positive and negative effect on stock market co-movement of both countries during a bear market condition. This suggests that investor sentiment increases diversification benefits, which provides evidence that the effect is time-varying and dictated by market conditions.

3. Research Hypothesis and Gap

The theoretical framework of the fundamental-based theory postulates that asset market co-movement is directly aligned with fundamental values such as market conditions.

This implies that asset market co-movement is influenced by the state of the financial market, i.e., bull and bear market conditions. Furthermore, the category-based theory introduces investors' perception of the market when making calculated investment decisions which in turn influences asset market co-movement. Thus, based on theoretical understanding, changing market conditions coupled with investor sentiment affect asset-market co-movement. This is supported by empirical literature such as studies by Aloui et al. (2016), Chelley-Steeley et al. (2019), Fang et al. (2018), Niţoi and Pochea (2020), and Nian et al. (2021) that found in developed markets that investor sentiment has either a positive or negative effect on asset market co-movement in a bull or bear market condition. On this basis the following hypothesis are formulated:

H_0: *Investor sentiment has a significant effect on the South African multi-asset market co-movement in a bull and bear market condition.*

H_1: *The South African multi-asset market co-movement responds positively/negatively to shocks in investor sentiment in the short run/long run when the market is in a bullish state or bearish state.*

Despite theoretical and empirical evidence, it is observed that the majority of the literature that examines the determinants of asset market co-movement focuses on macroeconomy as opposed to factors like investor sentiment. Moreover, where studies have examined the influence of macroeconomy on asset market co-movement, it is isolated to stock–bond co-movement and market integration, with little to no emphasis on multi-asset markets. Further to this, the introduction of changing market conditions such as bull and bear periods is limited to bear market conditions caused by financial market uncertainty with no consideration of bull periods, whereby markets are stable and reflect positive outcomes. Moreso, the recent incorporation of investor sentiment and market conditions as a determinant of asset market co-movement is very limited and tends to be centred around stock–bond co-movement and not multi-asset markets of emerging markets. In South Africa, the literature on sentiment and changing market conditions as a driving force for multi-asset market co-movement is nonexistent, which raises serious implications for investor decision making in terms of asset selection and portfolio diversification. It is, therefore, essential that this study be carried out as Ocran and Mlambo (2009) argues that investor behaviour as captured by investor sentiment is an important determinant of South African asset market co-movement. Therefore, if left unstudied it could expose investors to losses as portfolio diversification may not be optimal in risk mitigation. Accordingly, this study not only contributes to empirical literature in emerging markets but also to the fundamental principles of risk and return and portfolio return.

4. Data and Methodology

4.1. Sample Selection

In answering the desired objective of this study, the authors proposed a sample period consisting of monthly data from the period March 2007 to January 2024 to account for historical financial market events such as the 2007/2008 GFC and the COVID-19 pandemic. The selection of the data frequency and sample period was dictated by the availability of data, specifically the independent variable, the investor sentiment index. That being, the South African volatility index (SAVI), which is a proxy used in constructing the market-wide investor sentiment index, was only available from February 2007. The choice of the sample period and data frequency followed that of Nhlapho (2023), Muguto et al. (2022), and Muzindutsi et al. (2023). The dependent variable and independent variable of the study comprised asset market correlations and a market-wide investor sentiment index, respectively. The data were obtained from the Bloomberg database and EViews was the preferred econometric program to run the analysis.

4.2. Presentation of Variables

4.2.1. Asset Market Correlations

It is noted from the literature that Piljak (2013), Behmiri et al. (2019), Tronzano (2020), Banerjee (2022), and Aggarwal and Saradhi (2024) used the MGARCH-A/DCC model to generate the desired correlations of asset markets when analysing the determinants of asset market co-movement. On this basis this study applies the same procedure, such that the generated output of the MGARCH-ADCC model of the authors' previous study is used in this study, refer to Moodley et al. (2024b). The generated correlations were derived from proxies associated with each South African asset market. That being, the equity market was proxied by the JSE-All share index, bond market by the JSE-All bond index, property market by the First National Bank (FNB) house price index, and commodity market by future gold as traded on the commodity exchange (COMEX) (GC1). The asset market pairs consist of equity–bond, equity–property, bond–property, and bond–gold correlations. However, for the equity–gold and the property–gold correlations, this study uses the MGARCH-DCC output as the asset market pairs did not express significant asymmetrical terms as seen in Moodley et al. (2024b). Refer to Appendix A, Table A1 for the detailed output.

4.2.2. Investor Sentiment Index

As with the asset market correlations, the market-wide investor sentiment index as presented in the authors' previous study (refer to Moodley et al. 2024a) is used in this study as the independent variable. It is important to note the investor sentiment index of Muguto et al. (2019) is updated and augmented. Consequently, the constructed investor sentiment index includes proxies such as the equity issue ratio, share turnover ratio, and advance/decline ratio of Baker and Wurgler (2006). However additional proxies such as the rand/dollar bid–ask spread, South African volatility index (SAVI), CNN fear and greed index, and the South African consumer confidence index (CCI) are considered. This is carried out as studies such as Muguto et al. (2019), Rupande et al. (2019), Muguto et al. (2022), and Muzindutsi et al. (2023), found these proxies to be a more reliable measure of sentiment in the South African financial market. Accordingly, these proxies were considered in addition to that of Baker and Wurgler (2006) to ensure a robust measure of sentiment in the South African financial market. The detailed explanation of each proxy is presented in Appendix B, Table A2.

The construction of the investor sentiment index followed the process of Baker and Wurgler (2006), such that a principal component analysis (PCA) was used to formulate the composite market-wide investor sentiment index. In Appendix C, Table A3, the first principal component accounts for 51.04% of total variance as compared to Baker and Wurgler (2006, 2007) of 49%, Reis and Pinho (2020) of 47%, and Muguto et al. (2022) of 43.71%. This indicates that the proxies used in the formulation of the investor sentiment index are able to capture a significant portion of investor sentiment in the South African market, which provides robustness for the inclusion of the proxies. The variables that correlated the most with the first principal component are the rand/dollar bid–ask spread (0.5125), SAVI (0.5128), and CCI (0.4915). However, the share turnover ratio (-0.2423), equity issue ratio (-0.2874), and the CNN fear and greed index (-0.2993) also have some significant correlation with the first principal component. The first principal component is positively correlated with three variables and negatively correlated with four variables. Therefore, increasing values of the rand/dollar bid–ask spread, SAVI, and CCI increases the value of the first principal component. Conversely, the increasing values of the share turnover ratio, equity issue ratio, advance/decline ratio, and the CNN fear and greed index decrease the value of the first principal component.

The signs assigned to each proxy depict that the constructed investor sentiment index captures both positive and negative sentiment in the market. During bearish periods, market participants have a negative outlook of the market, therefore they attempt to exit the market as they sell off shares (Febrianto and Ekawati 2015). This raises liquidity issues in the market which drives down share prices. The reduced share prices cause negative sentiment in the market as evident by the negative sign of the share turnover ratio. Similarly, market participants monitor the share issues of companies, such that when the market is in a bearish state, companies do not issue shares. This causes market participants to have a negative outlook on the financial stability of the market as seen by the negative sign of the equity issue ratio. During a bearish period, the number of shares declining is greater than the number of shares advancing, and this causes a negative outlook on the market as seen by the negative sign of the advance/decline ratio. Moreover, when the market is bearish the demand for domestic securities decreases, and this causes the bid–ask spread to increase as foreign investors omit rand-denominated securities as seen by the positive sign of the rand/dollar bid–ask spread (Brown and Cliff 2004). Similarly, the positive sign of the SAVI suggests that sentiment in the market is bearish as increased volatility exposes investors to losses which limit market participation (Ph and Rishad 2020). Conversely, the positive sign of the CCI is only associated with bullish periods as consumers are willing to invest in the financial market. Lastly, the negative sign of the CNN fear and greed index suggests that foreign market participants have a negative outlook on the South African financial market which limits foreign direct investments, suggesting the market is in a bearish state (Verma and Soydemir 2006).

Table 1 below provides the summary of the variables used in the study as discussed in Sections 4.2.1 and 4.2.2.

Table 1. Summary of dependent and independent variables.

Variable	Proxy	Type of Variable	Abbreviation
Panel A: South African Asset Markets			
JSE All-Share index	South Africa equity market	Dependent	EQUITY
JSE All-Bond index	South Africa bond market	Dependent	BOND
First National Bank house price index	South African property market	Dependent	PROPERTY
Future gold	South African commodity market	Dependent	GOLD
Panel B: Investor Sentiment Proxies			
Share turnover ratio	-	Independent	Share_Turn
Equity issue ratio	-	Independent	EQ_ISSUE
Advance/decline ratio index	-	Independent	ADV_DEC
Rand/dollar bid–ask spread	-	Independent	R/$BID_ASK
South African volatility index (SAVI)	-	Independent	SAVI
CNN fear and greed index	-	Independent	CNN
South African consumer confidence index	-	Independent	CCI

Notes: 1. Source: Authors' own compilation (2024).

4.3. Methodology

The objective of this study is to examine the effect of investor sentiment on the co-movement of South African multi-asset markets under bull and bear market conditions. In achieving the objective of this study, we consider the three research questions mentioned previously. Poshakwale and Mandal (2016) and Mathlouthi and Bahloul (2022) argued that when a study's objective is to examine the determinants of multi-asset market co-movement under changing market conditions, the most appropriate model to use is the Markov regime-switching model as it outperforms conventional nonlinear models. On the basis that this study considers multi-asset market co-movement and changing market conditions, this study proceeds to use the switching framework of Hamilton (1989). More specifically, research questions 1 and 2 will be answered by implementing an MS-AR model and research question 3 will be answered using the impulse response function generated from the MS-VAR model. Thus, the succeeding sections describe each model.

4.3.1. MS-AR Model

This study uses the MS-AR model to capture the effect of investor sentiment on the co-movement of asset markets under changing market conditions. The MS-AR model is selected as it differs from other nonlinear models such that it allows for constant changes with varying time periods, whereas other nonlinear models only consider exogenous changes with constant time periods. The MS-AR model does not require inputs of the periods of bull and bear market conditions, as it automatically captures the period in the sample period. These fundamental advantages have made the model the most used empirical model in the literature when considering market conditions and it is deemed sufficient for the analysis of this study (see Moodley et al. 2022; Moodley 2024; Lawrence et al. 2024). Therefore, the MS-AR model of conditional mean with constant transition probabilities as presented by Moodley et al. (2024a) is:

$$\Delta I_t = \mu_{ct} + \alpha_{0ict}\Delta SENT_t \ + \alpha_{1ict}\Delta DEP_{t-1} + \varepsilon_{c_{t,}} \tag{1}$$

where $\varepsilon_{c_{t,}}$ i.i.d $\left(0, \sigma^2_{c_{t,}}\right)$, ΔI_t is the MGARCH-A/DCC correlations of the South African asset market pairs as found in Moodley et al. (2024b), the state-dependent mean and variance are given by μ_{ct} and $\sigma^2_{c_{t,}}$. The model captures two regimes (C_t), namely bull (1) and bear (2) regimes. $\Delta SENT_t$ is the change in the investor sentiment index of Moodley et al. (2024a). ΔDEP_{t-1} is the lagged dependent variable introduced to cater for serial correlation in the MS-AR model, as the dependent variable provides correlated parameters between asset market pairs. ε_{c_t} is the state-dependent error term.

The bull and bear regimes follow a first-order Markov process, which is given by the transition probability matrix. Consequently, the probability of being in a bull or bear regime is dependent on the most recent regime, given by:

$$Prob(C_t = j | C_{t-1} = i) = Prob_{ij}(t) \tag{2}$$

where ij is the probability of switching from a bull regime (i) in a period $t-1$ to a bear regime (j) in a specific period (t). The probability is constant over both periods such that $Prob(t) = Prob_{ij}$. Hence, the matrix for a bull and bear regime model is given by:

$$Prob[C_t = 1 | C_{t-1} = 1] = Prob_{11} \tag{3}$$

$$Prob[C_t = 2 | C_{t-1} = 1] = 1 - Prob_{11} \tag{4}$$

$$Prob[C_t = 2 | C_{t-1} = 2] = Prob_{22} \tag{5}$$

$$Prob[C_t = 1 | C_{t-1} = 2] = 1 - Prob_{22} \tag{6}$$

The above equations are simplified into a single equation:

$$Prob = \begin{bmatrix} Prob(C_t = 1/C_{t-1} = 1) & Prob(C_t = 2/C_{t-1} = 1) \\ Prob(C_t = 2/C_{t-1} = 2) & Prob(C_t = 1/C_{t-1} = 2) \end{bmatrix} = \begin{bmatrix} Prob_{11} & Prob_{21} \\ Prob_{22} & Prob_{12} \end{bmatrix} \quad (7)$$

where $Prob_{11}$ is the probability that the multi-asset market co-movement is in a bullish state and will not move, $Prob_{21}$ is the probability that the co-movement are in a bullish state and will move to a bearish state. $Prob_{22}$ is the probability that the co-movement are in a bearish state and will not move, $Prob_{12}$ is the probability that the co-movement are in a bearish state and will move to a bullish state (Brooks 2019).

4.3.2. MS-VAR Model

In achieving the desired research objective of this study, research question 3 must be answered and, in doing so, it requires an empirical model that presents the impulse response functions that cater for alternating market conditions. Consequently, this study selects the MS-VAR model. The advantage of using such a model lies in the determination of the regime-dependent impulse response function, which provides an indication of the state-dependent response of variables to shocks in the economic system (market conditions). Using the MS-VAR model will therefore add to the analysis as it will assist in understanding how asset market co-movement responds to shocks in investor sentiment (research question 3). Moreover, nonlinear impulse response functions are generated from the MS-VAR model. This study considers different forms of the MS-VAR model to adequately specify the impulse response functions. The MS-VAR model is an extension of the MS-AR model presented above, and there are two forms of the MS-VAR model, one being the MS-VAR with intercept (MSI-VAR) and the other the MS-VAR with conditional mean (MSM-VAR). The model specification for the MSI(m)-VAR(p) model is as follows:

$$I_t = \mu_{ct} + \sum_{j=1}^{P} \alpha_j I_{t-j} + \varepsilon_t \quad (8)$$

μ_{ct} is the regime-switching intercept term with X_{ct} matrices, P is the number of lags of the autoregressive parameter (α_j), *and* ε_t is the variance. The residuals are normally distributed, contingent on the regime, where $\varepsilon_t \text{i.i.}d\ (0, \sum_{ct})$. $I_t = (I_{1t}, \ldots\ldots, I_{Nt})$ and the Markov dimensional time series vector is given by T = 1. . .. N. The variance–co-variance matrix of the Gaussian zero-mean error process is $\sum ct$. Equation (8) fixes the autoregressive parameter and variance–co-variance matrix between regimes. However, the intercept term depends on an unobservable regime variable, CT, which is a random variable that allows I_t to change between regimes.

MSM(m)-VAR(p) allows for regime dependency in the mean and is given by:

$$\Delta I_t - \varepsilon_{ct} = \sum_{j=1}^{R} \alpha_j (y_{t-j} - \varepsilon_{ct}) + \varepsilon_{ct} \sim \varepsilon_t \text{i.i.}d\ (0, \sum_{ct}) \quad (9)$$

MSI-VAR and MSM-VAR can be extended to include regime-dependent autoregressive and error co-variance coefficients. The study will also consider the Markov regime-switching model with regime-dependent intercepts and heteroscedasticity (MSIH-VAR) and it is given by:

$$I_t = X_{ct} + \sum_{j=1}^{R} \alpha_j (y_{t-j} - \varepsilon_{ct}) + \varepsilon_{ct} \quad (10)$$

The constant transition probabilities for the MSI(m)-VAR(p), MSM(m)-VAR(p), and MSIH(m)-VAR(p) are given by Equations (2)–(7). This study firstly estimated the optimal lag for the MS-VAR model by considering the lag length criteria and, thereafter, the various MS-VAR models were estimated with optimal lag, and the best-fitting model was considered by examining the information criteria for each model.

4.3.3. MS-VAR Impulse Response

Once the optimal specification of the MS-VAR model was analysed, the estimation of the MS-VAR model presented the desired impulse response function, which assisted in answering research question 3 of this study. The general form of the impulse response function containing shocks to the system, ε_t^0, is given by:

$$G_s = \left[\left(X_{T+N}\middle|\varepsilon_t = \varepsilon_t^0,\ \mu_{t-1}^0 - E(C_t + \mu_{t-1}^0\right)\right] \quad (11)$$

μ_{t-1}^0 captures the known history of the process up to t − 1. The impulse response function is estimated assuming that:

$$\varepsilon_t \sim N(0, \textstyle\sum) \quad (12)$$

The one-period shock is given by $E(\varepsilon_t|\varepsilon_{\varkappa t} = \delta_\varkappa) = (\sigma_{1\varkappa}, \sigma_{2\varkappa}, \ldots, \sigma_{\varkappa N})' \sigma_{\varkappa\varkappa}^{-1} \delta_\varkappa$, where $\delta_\varkappa = \left(\sigma_{\varkappa\varkappa}\right)^{-\frac{1}{2}}$. When considering the nonlinear situation, the effect will depend on the shocks that take place between T and T+N and on past shocks, j_{t-1}. Hence, using the approach by Ehrmann et al. (2003), the regime-dependent generalised impulse response function (GIRF) is given by:

$$GIRF = (N,\ \delta_\varkappa,\ j_{t-1}) = E(I_{it+N}|\varepsilon_{\varkappa t} = \delta_\varkappa, \varkappa_{t-1}) - E(I_{it+N}|\varkappa_{t-1}) \quad (13)$$

One of the observed advantages of the GIRF is that the ordering of the variables in the system does not affect the generalised responses as compared to other orthogonality approaches. Hence, the GIRF permits the interpretation of the response of variables to shocks to the economic system (market conditions).

It is important to note that the MS-VAR model is not suitable for answering research questions 1 and 2. That being, the MS-VAR model presents all variables and their lags as explanatory variables. However, the objective of the study is limited to the effect of investor sentiment in its current form on asset market co-movement. Consequently, having more than one explanatory variable, other than investor sentiment, and its lag values does not assist in answering research questions 1 and 2, which limits the achievement of the study's research objective. On this basis, the study does not consider the MS-VAR model output but rather uses the MS-VAR model to generate the impulse response functions, thereby assisting in answering research question 3 and the desired research objective.

5. Analysis and Interpretation of Results

5.1. Graphical Representation

As mentioned previously, this study uses the MGARCH-A/DCC correlations of South African asset markets as presented in the authors' previous study (refer to Moodley et al. 2024b). Consequently, Figure 1 below provides the graphical representation of the MGARCH-A/DCC correlations of South African asset markets. It can be seen for the South African asset market co-movement that there exist many peaks and troughs, suggesting that asset market correlation is time-varying and dynamic in nature. More importantly, all asset market pair correlations, except for the bond–gold asset market pair correlation, have positive and negative correlations, suggesting that the range of dispersion from the mean correlation level is between positive and negative values. Moreover, it is evident from the figures that key historical financial market events have an impact on asset market pair correlations. For example, before the 2007/2008 GFC the correlations for all asset market pairs were positive but, during the GFC, the equity–bond (equity–property), equity–gold, bond–gold, and property–gold asset market pair correlations decreased (increased). Similarly, pre-COVID-19 pandemic the correlations are relatively stable but during the COVID-19 pandemic the correlations tend to fluctuate at heightened levels. These findings indicate that historical market events influence South African asset market pair correlations, which justify the necessity of this study considering alternating market conditions in the analysis.

Figure 1. MGARCH-A/DCC Asset Market Correlations. Notes: 1. Source: Authors' own estimation (2024).

5.2. Descriptive Statistics, BDS Tests, Unit Root, and Stationarity Test Results

Table 2 presents the preliminary results associated with the objective of this study. More importantly, the descriptive statistics of the associated variables are considered in Panel A of Table 1. The average correlations for the equity–bond, equity–property, equity–gold, and bond–gold asset market pairs are positive and range between 0.1 and 0.3. However, for the bond–property and property–gold asset market pairs the average correlations are negative and range between −0.02 and −0.04. These findings suggest that in the absence of a sentiment-induced market and changing market conditions, investors will generate added diversification benefits by constructing a portfolio that contains securities from South African multi-asset markets. These findings are supported by Nhlapho (2023) who also found that South African multi-asset markets provide added diversification properties.

Table 2. Preliminary results.

Variables	EQUITY–BOND	EQUITY–PROPERTY	EQUITY–GOLD	BOND–GOLD	BOND–PROPERTY	PROPERTY–GOLD	ΔSENT
Panel A: Descriptive Statistics							
Mean	0.2569	0.1267	0.2002	0.2991	−0.0220	−0.0412	3.76×10^{-2}
Median	0.2622	0.1170	0.2055	0.3006	−0.0087	−0.0387	−0.1180
Maximum	0.5666	0.3765	0.6555	0.4512	0.1975	0.3342	4.6239
Minimum	−0.1940	−0.1004	−0.2747	0.1354	−0.9999	−0.6524	−3.4905
Std. Dev.	0.1351	0.0901	0.1106	0.0553	0.0977	0.1115	1.8943
Skewness	−0.2359	0.2982	−0.3220	−0.0393	−5.3323	−0.4000	0.2031
Kurtosis	3.6838	3.5421	7.4743	2.9145	51.5776	8.0326	1.9804
Jarque–Bera	5.8393	5.4954	172.8442	0.1140	209.2191	219.6420	11.8442
Probability	0.053950	0.0640	0.0000	0.9445	0.0000	0.0000	0.0000
Observations	203	203	203	203	203	203	203
Panel B: Nonlinearity Test							
BDS	0.1374 ***	0.1212 ***	0.0668 ***	0.1111 ***	0.1478 ***	0.0658 ***	0.1440 ***
Panel C: Stationarity and Unit root Tests In levels							
ADF	−3.2958 **	3.8129 ***	−28.4150 ***	−4.0848 ***	−8.2269 ***	−6.5749 ***	−14.5517 ***
PP	−3.3213 **	−3.8343 ***	−30.8530 ***	−3.9281 ***	−8.2520 ***	−6.5749 ***	−27.9346 ***
KPS	0.5059	1.0874	0.0404	0.1394	0.3843	0.4154	0.4013
ADF-Break	−4.4608 **	−5.4799 ***	−32.0800 ***	−4.5590 **	−10.7745 ***	−8.1557 ***	−20.7143 ***
Order	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)	I (0)

Notes: 1. Where BDS is the Brock, Dechert, and Scheinkman test, ADF is the Augmented Dicky–Fuller test, PP is the Phillips–Perron test, KPSS is the Kwiatkowski–Phillips–Schmidt–Shin test, and ADF-Break is the Augmented Dicky–Fuller breakpoint test. 2. ***, and **, indicate a statistical significance level of 1% and 5%, respectively. 3. The KPSS critical values at 1%, 5%, and 10% statistical significance levels are 0.7390, 0.4630, and 0.3470, respectively. 4. BDS has two dimensions. 5. Source: Authors' own estimation (2024).

The maximum values associated with all asset market pairs are positive, but the equity–gold asset market pair attains the highest correlation value of 0.6555 followed by the equity–bond asset market pair of 0.5666 and bond–gold asset market pair of 0.4512. These findings indicate that although these asset market pairs' average correlations are relatively low as seen by the mean values, the maximum correlation values indicate high correlations, which limit diversification benefits. Accordingly, investors must time their entry and exit for these asset markets as the correlations behave differently over time. These findings are supported by Moodley et al. (2024b) who found that investment periods are important determinants for portfolio diversification as the correlations are dynamic and time-varying. The minimum values associated with all asset market pairs, except the bond–gold asset market pair, are negative. The property–gold asset market pair attains the highest minimum value of −0.6524, followed by that of the equity–gold asset market pair of −0.2747 and that of the equity–bond asset market pair of −0.1940. Conversely, the bond–gold asset market pair attains a positive minimum value, implying that the correlations does not go below zero and the diversification benefits may be limited at face value.

Despite the presence of both positive and negative correlation values among asset market pairs, the associated volatility of the asset market pair correlations is positive and close to 1. This implies that the asset market pair correlations are not volatile as the dispersions from the mean correlation values are not extreme. Similarly, the equity–property asset market pair correlation is positively skewed, whereas the remaining asset market pair correlations are negatively skewed. The former suggests that the mean is larger than the median and the values lie to the right of the mean, whereas the latter suggests that the mean is less than the median and the values lie to the left of the mean. This implies that the asset market pair correlations do not follow a normal bell-shaped curve, which suggests that the asset market pairs are not normally distributed. These findings are confirmed by the Jarque–Bera test of normality, as the null hypothesis that the asset market pair correlations are normally distributed is rejected in favour of the alternative hypothesis that the asset market pair correlations are not normally distributed. Moreover, it is evident that all asset market pairs correlations, except for the bond–gold asset market pair correlations, present a kurtosis of greater than three. This indicates that the distribution of the asset market pair correlations has peaked means and fatter tails compared to a normal distribution.

The investor sentiment index has a positive maximum value and a negative minimum value, which suggests that the constructed investor sentiment index captures positive and negative sentiment in the market. Furthermore, the mean value is negative which implies that there is more negative sentiment in the market as opposed to positive sentiment. These findings align with the literature as the sample period considers various historical financial events like the contagion effect of the US dot-com bubble, the US housing bubble in the early 2000s, the 2007/2008 GFC, European debt crises, and the COVID-19 pandemic. The standard deviation is positive, but it is close to two, which indicates that the investor sentiment index does not have a heightened level of dispersion from the mean, but there are adequate variations in sentiment as supported by the maximum and minimum values. The positive skewness of the investor sentiment index indicates that the mean sentiment level is greater than the median sentiment levels, whereas the kurtosis of less than three suggests that the investor sentiment index is not normally distributed as supported by the Jarque–Bera test of normality.

The BDS test for nonlinearity is presented in Table 2, Panel B. The BDS test statistic is greater than the associated critical values at a 5 percent level of significance. Consequently, this study rejects the null hypothesis that the asset market pair correlations and investor sentiment index are independently and identically distributed. This study concludes that the asset market pair correlations and investor sentiment index portray nonlinear dependency and as such a nonlinear model is required.

Table 2, Panel C provides the stationarity and unit root tests for each variable. It is seen that the ADF test statistics are more negative than the associated critical values at a 5 percent level of significance. Accordingly, this study rejects the null hypothesis that the asset market pair correlations and investor sentiment index contain a unit root and accepts the alternative hypothesis that the time series is stationery in levels. These findings are supported by the PP test as the null hypothesis of the variables containing a unit root is rejected at a 5 percent level of significance, suggesting that the time series are stationery in levels. Similarly, the KPSS test statistic is less than the associated critical values for the investor sentiment index and all asset market pair correlations, except for the equity-property asset market pair correlation. Consequently, the study fails to reject the null hypothesis of the time series being stationery at a 5 percent level of significance. The findings for the equity-property asset market pair correlation do not raise any concerns as both the ADF and PP test confirms the variable is stationery in levels. Moreover, the ADF break point test confirms that the variables are stationery in the presence of structural breaks as the ADF break point test statistic is more negative than the critical values at a 5 percent level of significance. Therefore, the study confirms that the asset market pair correlations and investor sentiment index is stationery in levels and integrated of order I(0).

It is evident from the above findings that the properties required for the estimation of the MS models are met, such that there exists nonlinear dependency among the selected variables, advocating for a nonlinear model and the variables is stationery in levels and in the presence of structural breaks. Accordingly, the study proceeds to estimate the MS-AR model and the MS-VAR impulse response function.

5.3. MS-AR Model

This section presents the MS-AR model results, which includes firstly accounting for the possibility of autocorrelation and heterosckedasticity among the time series data as this study uses correlations of South African asset market pairs as the dependent variable. Secondly, the MS-AR model is provided and thirdly the constant transition probabilities with the expected duration are considered.

5.3.1. Autocorrelation and Heterosckedasticity Detection

As mentioned previously, the dependent variable of this study is the MGARCH-A/DCC correlations as generated in Moodley et al. (2024b). This implies there is a heightened possibility that there will be autocorrelation among the residuals of the MS-AR model. Accordingly, Table 3 accounts for this assumption by providing the results of the Breusch–Godfrey serial correlation LM test and the Durbin–Watson (DW) test. It is evident that, when the MS-AR model is regressed and autocorrelation is tested, the DW-statistic is close to zero for the equity–bond, equity–property, bond–gold, bond–property, and property–gold model. However, for the equity–gold model it is close to three, and this suggests that there is positive and negative autocorrelation in the residuals of the MS-AR model. These findings are further supported by the Breusch–Godfrey test, as the LM statistic is significant at a 5 percent level of significance, suggesting that this study rejects the null hypothesis that there is no autocorrelation in the residuals of the model in favour of the alternative hypothesis that there exists autocorrelation in the residuals in the model. Refer to Appendix D, Table A4, Panels A and B for the detailed output. Moreover, this study further examines the robustness of the estimated MS-AR model by testing the presence of heterosckedasticity. In Table 3, the F-statistic associated with the White heterosckedasticity test is presented. It is evident that the F-statistic is insignificant for the equity–bond, equity–property, equity-gold, bond–gold, and property–gold model. This suggests that this study should not reject the null hypothesis of homoscedasticity, which implies there is no probable sign of heterosckedasticity. Refer to Appendix D, Table A4, Panel C for the detailed output.

Table 3. Autocorrelation and heterosckedasticity tests.

Tests	Original Model	Model with Lagged Dependent Variable
	EQUITY–BOND	
DW-STAT	0.2288	2.1083
LM-STAT	159.8008 ***	3.3262
F-STAT	0.2552	-
	EQUITY–PROPERTY	
DW-STAT	0.2890	2.0249
LM-STAT	151.2408 ***	1.3603
F-STAT	0.5841	-
	EQUITY–GOLD	
DW-STAT	3.0664	2.0937
LM-STAT	68.4657 ***	1.8880
F-STAT	0.9431	-
	BOND–GOLD	
DW-STAT	0.7392	2.0110
LM-STAT	141.2298 ***	0.4747
F-STAT	0.4799	-

Table 3. *Cont.*

Tests	Original Model	Model with Lagged Dependent Variable
	BOND–PROPERTY	
DW-STAT	1.2265	2.1627
LM-STAT	51.1290 ***	2.2936
F-STAT	0.2777	-
	PROPERTY–GOLD	
DW-STAT	0.7449	2.1016
LM-STAT	83.9290 ***	0.0514
F-STAT	0.1505	-

Notes: 1. Where DW-STAT is the Durbin–Watson test statistic, LM-STAT is the LM test statistic associated with the Breusch–Godfrey test and the F-STAT is the F-statistic associated with the White heterosckedasticity test. 2. *** indicate a 1% level of significance, respectively. 3. Source: Authors' own estimation (2024).

Having found the presence of autocorrelation in the residuals of the MS-AR model, this study introduces the one-period lagged dependent variable as one of the explanatory variables to remove the presence of autocorrelation. Consequently, the study retests for autocorrelation in the MS-AR model and this is presented in Table 3. It is evident that for all MS-AR models that the DW-statistic is 2, which indicates there is no presence of autocorrelation in the residuals of the model. Moreover, the Breusch–Godfrey test confirms these findings as the DW-statistic is insignificant, indicating that this study should not reject the null hypothesis and confirms there is no autocorrelation in the residuals of the MS-AR models. Therefore, this study proceeds by estimating the MS-AR model with a one-period lag of the dependent variable as the independent variable.

5.3.2. MS-AR Model Results

In Table 4, the results of the MS-AR model are presented. The average correlations as provided by the intercept (C) in the bull market condition are positive and significant for the equity–gold and bond–gold asset market pairs. However, in the bear market condition, the average correlations for the equity–bond, equity–property, equity–gold, and bond–gold (bond–property and property–gold) asset pairs are positive (negative) and significant. This implies that on average the co-movement of asset market pairs is positive and increasing in bull and bear market conditions, which suggest limited added diversification benefits during stable and uncertain financial market events. On the contrary, the co-movement of bond–property and property–gold is decreasing during volatile market conditions, which suggest that securities from the bond market, property market, and commodity market can be used to enhance portfolio diversification during financial market uncertainty. These findings do not come as a surprise as they are supported by Moodley et al. (2024b), who also found that the safe haven proposition of gold, bond, and property securities is still prevalent in the South African financial market.

The error variance (σ) of all asset market pairs is negative and significant in bull and bear market conditions. However, the error variance is more negative in a bear market condition than in a bull market condition. This implies that the bear market condition is the volatile regime and that the correlations of all asset market pairs fluctuate constantly. These findings are supported by Moodley et al. (2022), Moodley (2024), Lawrence et al. (2024), and Moodley et al. (2024a) who also found that the bear market condition is the most volatile. Moreover, Moodley et al. (2024b) also found that during financial market uncertainty the co-movement of asset pairs is found to increase due to excess volatility in the market.

Table 4. MS-AR results for asset market pairs.

Variables	Bull Regime	Bear Regime
	EQUITY–BOND	
C	0.0300	0.0280 ***
ΔSENT	0.0025 *	−0.0007
σ	−2.4483 ***	−4.2133 ***
EQUITY–BOND$_{t-1}$	0.8990 ***	0.8835 ***
	EQUITY–PROPERTY	
C	0.0164	0.0193 ***
ΔSENT	−0.0005 *	−0.0008 *
σ	−2.6605 ***	−3.7843 ***
EQUITY–PROPERTY$_{t-1}$	0.8809 ***	0.8470 ***
	EQUITY–GOLD	
C	0.2905 ***	0.3429 ***
ΔSENT	0.0071 ***	−0.0004
σ	−2.1268 ***	−3.5339 ***
EQUITY–GOLD$_{t-1}$	−0.6961 ***	−0.5652 ***
	BOND–GOLD	
C	0.0566 **	0.0358 ***
ΔSENT	−0.0013 **	−0.0002 ***
σ	−3.1873 ***	−4.9128 ***
BOND–GOLD$_{t-1}$	0.8278 ***	0.8657 ***
	BOND–PROPERTY	
C	−0.0022	−0.1593 *
ΔSENT	0.0003	−0.1458 *
σ	−3.3833	−1.4342 ***
BOND–PROPERTY$_{t-1}$	0.6155	0.2508
	PROPERTY–GOLD	
C	−0.0014	−0.0219 ***
ΔSENT	−0.0001 *	−0.0006
σ	−1.9835 ***	−3.2722 ***
PROPERTY–GOLD$_{t-1}$	1.1091 ***	0.4817 ***

Notes: 1. C is the intercept, ΔSENT is the investor sentiment index, σ is the error variance, and $t-1$ is the one-period lagged dependent variable. 2. ***, **, and * indicate a 1%, 5%, and 10% level of significance, respectively. 3. Source: Authors' own estimation (2024).

In the bull market condition, investor sentiment (ΔSENT) has a positive significant effect on the equity–bond and equity–gold correlations. However, in the same market condition, equity–property, bond–gold, and property–gold correlations are negatively significantly affected by investor sentiment. In the bear market condition investor sentiment has a negative significant effect on the equity–bond, equity–property, bond–gold, and bond–property correlations. It is also worth noting that, in a bull market condition, investor sentiment coefficients are much larger than the bear market condition coefficients. This implies that, in a bull market condition, the effect is much more pronounced as appose to the bear market condition. Although investor sentiment causes the co-movement of asset pairs to decrease in a bear market condition, such a decrease is not substantial enough to increase portfolio diversification if asset market securities are contained in a portfolio. However, in the bull market condition the effect is much more pronounced due to the larger coefficients, which have significant effects on a portfolio diversification if such asset market security pairs are contained in a portfolio.

The lagged dependent variables are significant for all asset market pairs, and this indicates that the previous month's asset market correlation influences current period asset market correlation, where the coefficients present positive and negative effects. These findings are supported by Moodley et al. (2024b) who show that South African asset market co-movement is dynamic and time-varying. The robustness of the model is confirmed by the diagnostic tests presented in Section 5.3.1.

5.3.3. Transition Probabilities and Expected Duration

In Table 5, the transition probabilities and expected durations are presented for all asset market pairs. It is seen that the transition probabilities in a bull market condition for the equity–bond, equity–gold, and bond–gold correlations are 0.4329, 0.4758, and 0.5063, respectively. However, in the bear market conditions, they are higher at 0.4344, 0.6544, and 0.5191, respectively. This implies that the equity–bond, equity–gold, and bond–gold correlations have more periods of bear conditions than of bull conditions. This is further supported by the expected duration of these asset market pair correlations as it is longer in a bear market condition than a bull market condition. Although the correlations are decreasing more than they are increasing, these increases and decreases are not persistent for prolonged periods as the transition probabilities are closer to 0 than 1. This suggests that the co-movement of the equity–bond, equity–gold, and bond–gold asset pairs is constantly changing and varying over time. Moreover, the findings demonstrate that the bear market condition is more persistent among the equity–bond, equity–gold, and bond–gold asset market pairs. This suggests that the safe haven properties of gold and bond securities are still prevalent because when they are combined with bonds and equities it causes the co-movement to decrease. These findings are supported by Moodley et al. (2024b) who found that when gold and bond securities are combined in a portfolio with equity and property securities, it decreases the co-movement and increases portfolio diversification.

Table 5. Transition probabilities and expected duration.

	EQUITY–BOND	
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.4329	0.5670
Bear Regime (P2)	0.5655	0.4344
Expected Duration (T)	1.7636	1.7681
	EQUITY–PROPERTY	
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.8248	0.1751
Bear Regime (P2)	0.0984	0.9015
Expected Duration (T)	5.7080	10.1596
	EQUITY–GOLD	
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.4758	0.5241
Bear Regime (P2)	0.3455	0.6544
Expected Duration (T)	1.9077	2.8937
	BOND–GOLD	
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.5063	0.4936
Bear Regime (P2)	0.4808	0.5191
Expected Duration (T)	2.0256	2.0797

Table 5. *Cont.*

BOND–PROPERTY		
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.9549	0.0450
Bear Regime (P2)	0.6020	0.3979
Expected Duration (T)	22.2218	1.6608
PROPERTY–GOLD		
Transition Probabilities	Bull Regime (P1)	Bear Regime (P2)
Bull Regime (P1)	0.3556	0.6443
Bear Regime (P2)	0.2497	0.7502
Expected Duration (T)	1.5518	4.0042

Notes: 1. Source: Authors' own estimation (2024).

The constant transition probabilities for the equity–property and property–gold correlation (bond–property correlation) in the bull market condition are 0.8248 and 0.3556 (0.9549), respectively. However, in a bear market condition they are 0.9015 and 0.7502 (0.3979), respectively. This indicates that the bear market condition is more persistent in the equity–property and property–gold correlations, but the bull market condition is more persistent in the bond–property correlations. This is supported by the expected duration values as the equity–property and property–gold correlations stayed longer in a bear market condition whereas the bond–property correlation stayed longer in a bull market condition. The former suggests the co-movement is decreasing over the sample period, but the latter suggests that the co-movement is increasing over the sample period, which increase and decrease diversification benefits, respectively.

5.4. MS-VAR Model

In answering research question 3 (how does South African asset market co-movement respond to shocks by investor sentiment in bull and bear regimes?), this study implements the impulse response function. However, to generate the impulse response function, one needs to estimate the MS-VAR model, although the MS-VAR model output is not required. In doing so, the correct procedure must be followed to generate the impulse response functions. Accordingly, a two-step procedure is considered, by first determining the optimal lag length of the MS-VAR model and secondly estimating the correct MS-VAR model. This procedure is presented in the succeeding section.

5.4.1. Lag Length Criteria

Following the above explanation, this study first estimates the lag length for the MS-VAR model, which is presented in Table 6 (refer to Appendix E, Table A5 for the complete output). It is evident from the information criteria that the optimal lag is one, as presented by all the information criteria. Accordingly, this study proceeds to estimate the MS-VAR model using one lag. The identification of one lag is in line with a study by Nhlapho (2023) who also found that the optimal lag was one for South African asset markets.

Table 6. VAR lag length criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	640.0322	NA	3.57×10^{-12}	−6.49263	−6.3751	−6.4450
1	1205.924	**1085.352 ***	$\mathbf{1.78 \times 10^{-14}}$ *****	**−11.7940 ***	**−10.8541 ***	**−11.4135 ***

Table 6. *Cont.*

Lag	LogL	LR	FPE	AIC	SC	HQ
2	1240.999	64.7530	2.06×10^{-14}	−11.6512	−9.8888	−10.9377
3	1274.750	59.8873	2.42×10^{-14}	−11.4948	−8.9100	−10.4483

Notes: 1. LogL forms part of the Bayes information criteria, LR is the likelihood ratio, FPE is the final predictor error, AIC is the Akaike information criteria, SC is the Schwarz information criteria, and HQ is the Hannan–Quinn criteria. 2. The bold figures (*) represent the optimal lag model for each information criterion. 3. Source: Authors' own estimation (2024).

5.4.2. Model Selection

Having identified the optimal lag, the second step entails correctly specifying the MS-VAR model as it is evident that there are many variants of the model. Accordingly, this study follows the doctoral thesis of Nhlapho (2023) by estimating all variants of the MS-VAR model and selecting the information criteria that express the highest values. The model selection results are provided in Table 7, and it is evident that the likelihood ratio and AIC associated with the MSIAH (2)-VAR (1) model attain the highest values. Consequently, the most appropriate model is MSIAH (2)-VAR (1), which contains two regimes and the switching regressors are the intercept, lagged variables, and variance. Nhlapho (2023) argues that the likelihood ratio of Garcia and Perron (1996) is only estimated when there are discrepancies in the information criteria, thus the study does not consider the likelihood ratio as both LR and AIC confirm the most suitable model is MSIAH (2)-VAR (1). Accordingly, the MSIAH (2)-VAR (1) model is estimated in order to generate the impulse response function.

Table 7. Model specification.

Model	LR	AIC	SIC	No. of Coeff
Linear VAR (1)	1181.638	−11.0610	−9.9106	70
MSM (2)-VAR (1)	1346.405	−12.4099	−10.8868	93
MSMH (2)-VAR (1)	-	-	-	-
MSIH (2)-VAR (1)	1726.182	−15.7028	**−13.9112**	121
MSA (2)-VAR (1)	1324.452	−11.7767	−9.5657	135
MSIA (2)-VAR (1)	1430.889	−12.7612	−10.4356	142
MSIAH (2)-VAR (1)	**1758.157**	**−15.7243**	−12.9401	170
MSIAH (3)-VAR (1)	1602.160	−13.3481	−9.1882	254

Notes: 1. The bold figures represent the best-fitting model for each information criterion. 2. Source: Authors' own estimation (2024).

5.4.3. MSIAH (2)-VAR (1) Impulse Response Function

The complete impulse response function generated from the MSIAH (2)-VAR (1) model is presented in Appendix F, Figure A1 and Appendix G, Figure A2. On the basis of answering research question 3, the study only considers the impulse response functions of investor sentiment as presented in Figures 2 and 3 below.

In Figure 2, the response of asset market co-movement to innovations in sentiment in a bull regime is presented. It can be seen in a bull market condition that the equity–bond co-movement increased during months one and two from a one standard deviation shock by investor sentiment. However, the co-movement between the two asset market pairs decreased between months two and five, before it returned to an equilibrium value in the subsequent months. The equity–property correlations in the bull regime also responded positively to a one standard deviation shock by investor sentiment, but they increased from months one to three and, thereafter, decreased back to an equilibrium level. Similarly, a one standard deviation shock in investor sentiment has a positive impact on the equity–gold and bond–property co-movement in a bull regime, However, the equity–gold co-movement only increased from months one to two and, thereafter, it decreased and returned to equilibrium. However, the bond–property co-movement in a bull regime peaked at month three and fell back to an equilibrium value in month four. On the other hand, the bond–gold co-movement responded positively to shocks by investor sentiment in a bull regime, such that it peaked at month four, whereas the property–gold co-movement peaked at month three before it decreased and then peaked again at month five.

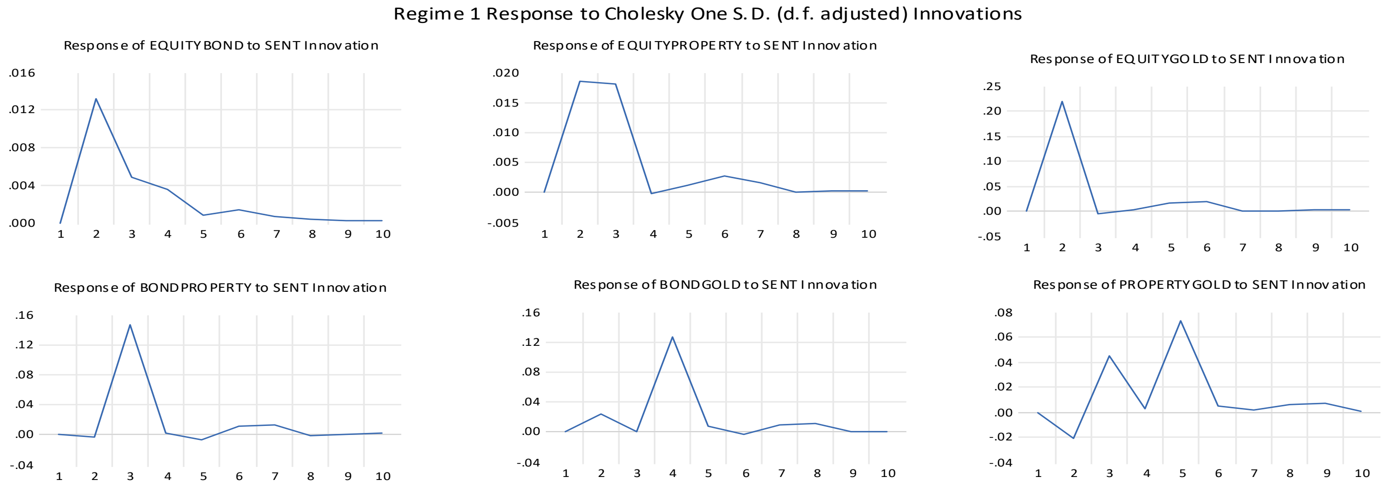

Figure 2. Bull regime impulse response function. Notes: 1. Source: Authors' own estimation (2024).

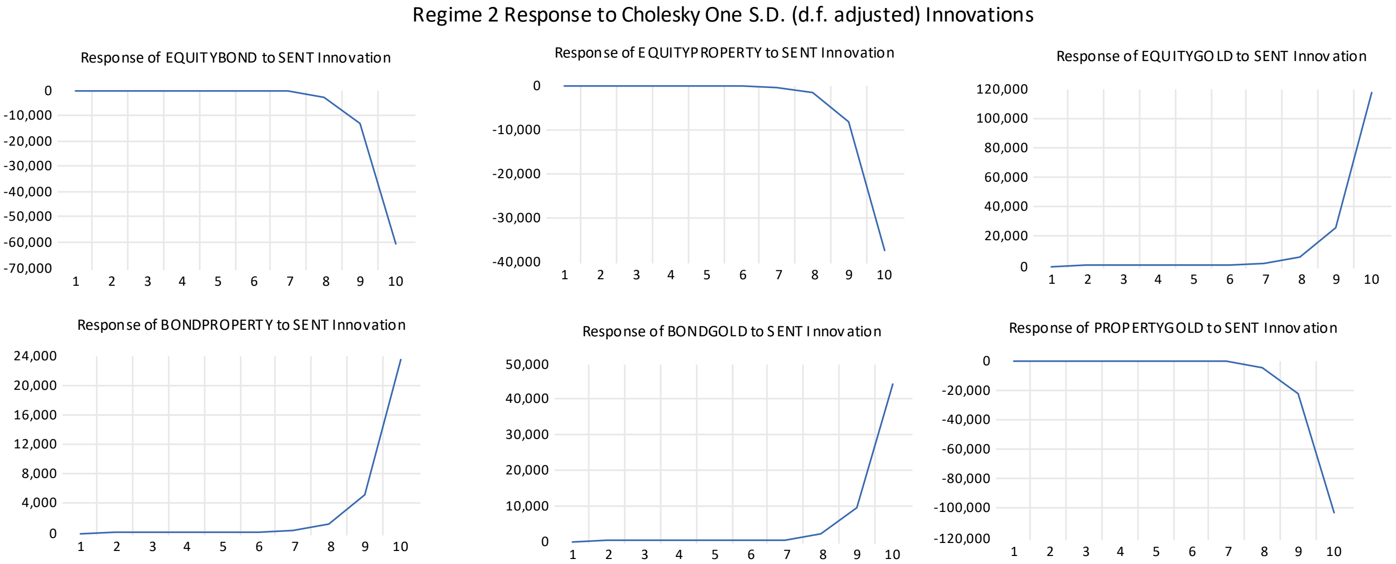

Figure 3. Bear regime impulse response function. Notes: 1. Source: Authors' own estimation (2024).

Similarly, Figure 3 provides the response of South African asset market co-movement to shocks in investor sentiment in a bear regime. It is evident that the equity–bond, equity–property, and property–gold asset market co-movement responds negatively to a one standard deviation shock by investor sentiment. However, such a response is only evident from months seven to ten and, from months one to seven, the co-movement remains at an equilibrium level. On the other hand, equity–gold, bond–property, and bond–gold respond positively to a one standard deviation shock by investor sentiment from months seven to ten. These findings demonstrate that asset market co-movement in a bull regime was more responsive to shocks in investor sentiment in the short term. However, in a bear regime the asset-market co-movement was responsive to shocks in investor sentiment in the long term. Moreover, although shocks by investor sentiment increase and decrease asset market co-movement in bull and bear regimes, they are not persistent as they immediately diminish over time.

6. Discussion of Findings

The following section presents the discussion of the findings presented in Section 5. These findings are considered in terms of the MS-AR model, MS-VAR model impulse response function, and the theoretical discussion. It is important to note at the outset of this section that empirical literature is very limited surrounding the effect of investor sentiment on multi-asset market co-movement under changing market conditions. This implies that comparing the findings to other studies will be limited but the authors have endeavoured to provide a detailed analysis.

6.1. MS-AR Model

It is evident from the findings that investor sentiment has a positive effect on the equity–bond and equity–gold co-movement in a bull market condition, which affirms hypothesis H_0. These findings suggest that when the South African market is in a bullish state, investor sentiment will enhance the co-movement of both asset market pairs. This implies that there will be no added diversification properties for investors if such asset market pairs are included in a portfolio when the asset markets are stable and sentiments are at heightened levels. Consequently, investors should conduct portfolio rebalancing such that these asset market pairs should not be included in their portfolios in a sentiment-induced market with stable market conditions as it will enhance portfolio risk and reduce portfolio diversification. Similarly, in the same market condition investor sentiment has a negative effect on the equity–property, bond–gold, and property–gold co-movement. Accordingly, the co-movement between these asset markets in a stable market condition will decrease because of heightened levels of sentiment in the market. This suggests that there will be added diversification benefits for investors by incorporating these asset market pairs in their portfolio as it will enhance portfolio return. These findings do not come as a shock as the literature demonstrates the safe haven properties of gold if incorporated in a portfolio. That being, when there is enhanced risk caused by investor sentiment in the market, incorporating safe haven assets such as gold in a portfolio will reduce the co-movement of asset market pairs and enhance portfolio return. Therefore, the commodity market provides safe haven properties to South African multi-asset market investors and as such the safe haven proposition is still prevalent in South Africa as found by Nhlapho (2023) and Moodley et al. (2024b).

In the bear market condition, investor sentiment has a significant negative effect on the equity–bond, equity–property, bond–gold, and bond–property co-movement, which affirms hypothesis H_0. However, investor sentiment has no significant effect on the equity–gold and property–gold co-movement in the same market condition. The study's findings are not uncommon as it is known that bond, gold, and property securities carry safe haven properties, such that, when there is market uncertainty as seen in bear market conditions, investors can incorporate securities from these asset markets into their portfolio to limit risk and enhance portfolio diversification. The findings are supported by Aloui et al. (2016) and Nian et al. (2021) who also found that investor sentiment has a negative effect on asset market co-movement in a bear market condition. However, Fang et al. (2018) and Niţoi and Pochea (2020) found that investor sentiment has a positive effect on equity–bond co-movement. This contradiction in the findings is because the studies by Fang et al. (2018) and Niţoi and Pochea (2020) focused on developing markets whereas this study is limited to emerging markets. That being, emerging markets differ from developed markets in terms of market sizes and structures and, as such, one will find contradicting findings (Marozva 2020).

6.2. MS-VAR Impulse Response Function

The findings of the MS-VAR impulse response function affirm hypothesis H_1 as they reveal that South African asset market co-movement responds positively to shocks in sentiment in a bull regime, but this is only evident in the short run. However, in a bear market regime, asset market co-movement responds both positively and negatively to shocks by investor sentiment, but this is only persistent in the long run. These findings imply that when the South African market is in a bull market condition, changes in sentiment in the market will cause asset market pairs to co-move in the short run. This implies that investors will not benefit from portfolio diversification if they incorporate multi-asset markets into their portfolio in the short run when there are high levels of sentiment and the market is stable. However, there will be added diversifications in the long run when the market is stable as the co-movement of multi-asset markets returns to equilibrium. Similarly, in the long run, shocks by investor sentiment decrease the co-movement of equity–bond, equity–property, and property–gold co-movement in a bear market condition. Therefore, to generate the highest diversification properties under market uncertainty and at heightened sentiment levels, investors must consider the equity–bond, equity–property, and property–gold asset pairs in their portfolio. However, investors must only consider the equity–gold, bond–property, and bond–gold asset pairs in the short run under sentiment-induced markets with heightened market uncertainty.

6.3. Theoretical Discussion

The findings of the MS-AR and MS-VAR models demonstrate that the effect investor sentiment has on South African multi-asset market co-movement is time-varying, regime-specific, and alternates with the state of the market. These results from a theoretical perspective demonstrate that the findings contradict the efficient market hypothesis (EMH) as the theory postulates that all investors are rational and investors base their decisions on rational conceptualisation of risk and return in the market (Fama 1965). This suggests that investor sentiment does not exist and as such will not influence asset market co-movement. However, these findings are supported by behavioural finance, as the theory suggests that investors seldomly always act rationally as they base their decisions on past experiences and use their cognitive emotions to make decisions (Tversky and Kahneman 1974). This implies that investor sentiment will influence asset market co-movement, which this study found. Moreover, the findings align with the adaptive market hypothesis (AMH) which postulates that market conditions are important determinants of asset market co-movement such that the effect investor sentiment will have on asset market co-movement will be nonlinear (Lo 2004). This implies that it will alternate with bull and bear market conditions, as found in this study. Accordingly, the equity, bond, property, and commodity markets are adaptive and not efficient as proposed by the EMH.

7. Conclusions and Implications

The objective of this study was to examine the effect of investor sentiment on South African multi-asset market co-movement. In achieving the desired objective, this study presented three research questions. The study used a constructed investor sentiment index as the independent variable and the MGARCH-DCC correlations as the dependent variable for the period March 2007 to January 2024. In answering research questions 1 and 2, this study implemented the MS-AR model, whereas the MS-VAR impulse response function was estimated to answer research question 3.

Research questions 1 and 2 demonstrate that, in a bull regime, investor sentiment has a significant positive (negative) effect on the equity–bond and equity–gold (equity–property, bond–gold, and property–gold) co-movement. In a bear regime, investor sentiment significantly negatively affects the equity–bond, equity–property, bond–gold, and bond–property co-movement. Moreover, it is evident that the co-movement of asset market pairs experiences bull and bear periods that are not persistent, implying that the co-movement is dynamic and time-varying. Accordingly, the effect investor sentiment has on South African multi-asset market co-movement is dependent on the prevailing market condition, such that it will alternate with bull and bear periods. It is worth noting that the findings of research question 3 demonstrates that South African multi-asset market co-movement is positively influenced by shocks in investor sentiment in the short run when the market is in a bullish state. Conversely, in a bearish state, South African multi-asset market co-movement responds both positively and negatively to shocks in investor sentiment in the long run.

The findings of this study are unique and are an important determinant for emerging market investors as they have adverse implications. A sentiment-induced market and changing market conditions pose a serious threat to investor returns when combining securities from different asset markets in South Africa into a portfolio. That being, if the securities from each asset market move together over the investor's investment period, it will cause the correlation of the investor's portfolio to increase and reduce the diversification benefits of a multi-asset market portfolio. The findings of the study demonstrate that investor sentiments coupled with bull and bear market conditions cause the co-movement to increase, which reduces portfolio diversification and enhances portfolio losses. Accordingly, it is advised that investors use the findings of the study to conduct portfolio rebalancing when the South African financial market experiences bull and bear market conditions and when sentiment in the market is at heightened levels. Accordingly, when the South African financial market is experiencing a bullish market condition and there are heightened sentiment levels, investors must not include a combination of equity–bond and equity–gold market securities in their portfolio. However, they should include a combination of equity–property, bond–gold, and property–gold securities in their portfolio as it will provide the highest level of diversification benefits. Similarly, when the South African financial market is in a bearish market condition, investors must only consider a combination of equity–bond, equity–property, bond–gold, and bond–property securities.

Moreover, short-run and long-run periods are pivotal to asset market co-movement in South Africa. If investors are seeking short-term investment horizons, they should note that heightened sentiment levels in a bearish market condition will enhance portfolio correlation if a combination of securities from the equity–gold and bond–property market is contained in a portfolio. Moreover, investors with long-term investment horizons in a bearish market with heightened sentiment levels must consider a combination of equity–bond, equity–property, and property–gold securities as it will reduce portfolio correlation, enhance diversification, and mitigate portfolio losses. The South African financial market authorities must develop more robust policies to limit asset markets moving together. That being, policymakers must control the entry of market participants into the South African market as high participation causes sentiment-induced markets and changing market conditions, which enhance the co-movement of asset markets. If such policies are not developed it will have a negative effect on South African economic growth as investors will not want to participate in a financial market that has limited diversification benefits.

While this study fills a gap in the existing literature by considering the effect of investor sentiment on South African asset market co-movement and demonstrates that sentiment and changing market conditions are important determinants for asset market co-movement and in turn portfolio diversification, the results must be evaluated in the context of certain limitations. This study considers four asset markets, namely, equity, bond, property, and commodity markets, as these are the most invested asset markets. Future research can extend the analysis by considering the foreign exchange market and cryptocurrency market. Moreover, the sample period of the study is 2007 to 2024, in light of the research objective of this study, but it is recommended that future research extend the sample period and include a comparative analysis for periods before, during, and after historical market events like the GFC and COVID-19 pandemic. It is further recommended that academics also extend the study to other emerging markets and compare findings to comment on the level of diversification benefits offered to emerging market investors. Moreover, South African financial market authorities must develop an investor sentiment measure for the South African market, like the CNN fear and greed index. This will permit investors to constantly monitor the sentiment levels in the market and make calculated decisions to enhance portfolio diversification and mitigate portfolio risk.

Author Contributions: It is important to note that the research article was written in its entirety by F.M., a Doctor of Philosophy candidate in Risk Management at Northwest University. The additional authors, S.F.-S. and K.M., are the doctoral candidate's supervisors who assumed advisory roles and provided comments to improve the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. A/DCC-EGARCH (1.1) model results.

	θ_1	θ_2	θ_3	ρi,j (min)	ρi,j (max)	ρi,j (σ)
			MGARCH-DCC			
Equity–Gold	−0.0284 ***	1.0037 ***	-	0.0771	0.4201	0.04891
Property–Gold	−0.0702 ***	0.8648 ***	-	−0.7224	0.3907	0.1296
			MGARCH-ADCC			
Equity–Bond	0.0640	0.8216 ***	0.0163 **	−0.1941	0.5666	0.1352
Equity–Property	0.0369 ***	0.9114 ***	0.0081 **	−0.1004	0.3766	0.0902
Equity–Gold	0.0577 *	0.5898 *	0.1847	−0.2747	0.6556	0.1107
Bond–Property	0.0354 ***	0.7363 ***	0.0286 ***	−0.9999	0.1975	0.0978
Bond–Gold	0.0289 *	0.8463 ***	0.0211 ***	−0.1355	0.4512	0.0553
Property–Gold	0.0674 ***	0.7733 ***	0.0080	−0.6524	0.3342	0.1115

Notes: 1. ***, **, and * indicate a statistical significance level of 1%, 5%, and 10%, respectively. 2. θ_1 and θ_2 capture past shocks and dynamic conditional correlations based on current dynamic condition correlations, whereas θ_3 is the asymmetrical term. 3. Source: MGARCH-DCC output is the authors' own estimations (2024), whereas the MGARCH-ADCC is sourced from Moodley et al. (2024b).

Appendix B

Table A2. Investment proxies.

Investor Sentiment Proxy	Explanation
Share turnover ratio	The share turnover proxy is contained in this study's investor sentiment index, as found in the index of Muguto et al. (2019). The proxy is calculated by taking the total volume of shares traded and dividing it by the number of average shares listed in the South African stock market. The variable selection follows that of Baker and Stein (2004), who argue that numbers of noise traders are high when there are short-sale characteristics in the market because the arbitrate of rational investors does not drive noise traders out of the market. This causes stock prices to be overvalued. Studies such as Rupande et al. (2019), Muguto et al. (2022), and Muzindutsi et al. (2023) used the proxy for investor sentiment.
Equity issue ratio	The equity issue ratio is contained in this study's investor sentiment index, as found in the index of Muguto et al. (2019). The calculation of the proxy entails taking the number of issued shares of total equity and dividing it by the total issue of debt in South Africa. Baker and Wurgler (2006, 2007) argue that elevated share issues predict low market returns. That being said, companies wanting to expand will issue shares when sentiment in the market is high, making equity overvalued. Thus, overvaluation is associated with high-sentiment periods because sentiment-induced investors underestimate risk and overestimate returns (Baker and Wurgler 2006). Studies by Muguto et al. (2019) and Muzindutsi et al. (2023) use the proxy to measure market sentiment.
Advance/decline ratio index	The advance/decline ratio index is contained in this study's investor sentiment index, as found in the index of Muguto et al. (2019). It is measured by the number of advancing and declining shares, adjusted for their volume (Brown and Cliff 2004). Positive sentiment is indicated by positive market breadth, whereas negative sentiment is indicated by negative market breadth. Consequently, many studies have used it as a measure of market sentiment; these include Muguto et al. (2019), Reis and Pinho (2020), and Gong et al. (2022).
Rand/dollar bid–ask spread	The bid–ask spread is within this study's investor sentiment index, as found in the index of Muguto et al. (2019). It is determined by the demand for domestic securities, where negative sentiment attributed to poor economic performance shows a decline in capital inflows. This causes the bid–ask spread to increase as foreign investors omit rand-denominated securities (Hengelbrock et al. 2011). Studies by Muguto et al. (2019), Rupande et al. (2019), and Muguto et al. (2022) used it as a proxy for market sentiment.
South African volatility index (SAVI)	The South African volatility index (SAVI) will replace the rand/pound bid–ask spread in the Muguto et al. (2019) investor sentiment index. This is performed by including both the rand/dollar bid–ask spread and rand/pound bid–ask spread, as carried out by Muguto et al. (2019), which will enhance high correlation levels. Consequently, adding the SAVI proxy will remove the correlation bias, which contributes significantly to the robustness of the constructed market-wide sentiment index. The SAVI provides the 90-day future level of volatility associated with the entire financial market of South Africa. High levels of volatility indicate fear among investors in the market. Rupande et al. (2019) used the index as a proxy for market sentiment.
CNN fear and greed index	The CNN fear and greed index will replace the term structure of interest proxy proposed in the Muguto et al. (2019) index. This is performed to increase the robustness of the constructed investor sentiment index as investors participating in the South African financial market are not limited to domestic investors but also include foreign investors (Liu et al. 2020). According to the annual report by the JSE (2023), the countries with the highest foreign investments in South Africa consist of the United States (US), United Kingdom (UK), and China. Given that this study constructs an investor sentiment index for the South African financial market which is based on the JSE, it is essential to select the country with the biggest stock exchange as it will provide a better gauge for foreign sentiment. Therefore, in the absence of a direct proxy for foreign investor sentiment in South Africa, the CNN fear and greed index is used as a proxy in this study. The fear and greed index is a global index that comprises seven different proxies that CNN uses to formulate a market sentiment index for the US financial market. The proxy is unique to this study as previous South African studies (Muguto et al. 2019; Rupande et al. 2019; Muzindutsi et al. 2023) have not captured sentiment of foreign investors in the South African financial market. Moreover, Beirne and Renzhi (2024) argue that in any market-wide investor sentiment index, it is essential for foreign market participation to be captured as financial markets are not limited to domestic investors but also include foreign investors. Consequently, studies by Liutvinavicius et al. (2017), Halliday (2018), and Chen et al. (2021) used the index as a measure for market sentiment.

Table A2. *Cont.*

Investor Sentiment Proxy	Explanation
South African consumer confidence index	The consumer confidence index (CCI) is added to the study's constructed investor sentiment index. This is carried out because financial markets consist of investors with different financial statuses, high-end individuals and lower-end individuals (Junaeni 2020). Consequently, it is important that the market-wide investor sentiment captures both types of investors and is not limited to high-end individuals, which distorts the level of sentiment. The CCI provides household consumption and savings prospects based on their financial status (OECD 2022). Although stock prices do not affect consumers' opinions, the index is highly correlated with sentiment in the financial market (Rahman and Shamsuddin 2019). This is because market participants' financial status dictates their ability to participate in financial markets; if they do not have income, they will not participate, but the opposite holds if they do have income. Hence, high-value signs reflect increased consumer confidence in future economic conditions, allowing investors to participate in financial markets. Koy and Akkaya (2017) demonstrate that CCI has evolved as a critical measure for sentiment following financial crises. Hamurcu (2021) found that the index as a proxy for sentiment influences the Turkish stock market. Therefore, the proxy will contribute to the South African context as previous studies in South Africa (Muguto et al. 2019; Rupande et al. 2019; Muzindutsi et al. 2023) did not capture consumer sentiment in their sentiment index, which is a vital flaw given that these domestic consumers also participate in the South African financial market.

Notes: 1. Source: Moodley et al. (2024a).

Appendix C

Table A3. Principal Component Analysis.

Panel A: Eigenvalues: (Sum = 7, Average = 1)							
Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proposition		
1	3.5731	2.4690	0.5104	3.5731	0.5104	N/A	
2	1.1041	0.2217	0.1577	4.6772	0.6682		
3	0.8824	0.1559	0.1261	5.5596	0.7942		
4	0.7265	0.0742	0.1038	6.2861	0.8980		
5	0.6523	0.6143	0.0932	6.9384	0.9912		
6	0.0380	0.0144	0.0054	6.9763	0.9966		
7	0.0236	---	0.0034	7.0000	1.0000		
Panel B: Eigenvectors (Loadings)							
Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
Share Turn	−0.2423	0.2841	0.7379	−0.5421	0.1021	0.0762	0.0776
EQ_ISSUE	−0.2874	−0.1567	0.4806	0.7586	0.2929	0.0265	−0.0055
ADV_DEC	−0.0447	0.8601	−0.0419	0.3343	−0.3784	−0.0301	−0.0266
R/$BID_ASK	0.5125	0.0893	0.1225	0.0503	0.1473	0.7098	−0.4317
SAVI	0.5128	0.0985	0.0845	0.0967	0.1768	0.0593	0.8222
CNN	−0.2993	0.3433	−0.4130	−0.0842	0.7770	0.1031	0.0233
CCI	0.4915	0.1397	0.1736	0.0020	0.3223	−0.6890	−0.3609
Panel C: Wald Test							
F-Stat	2.3823	N/A					
p-Value	0.0298						

Notes: 1. Source: Moodley et al. (2024a).

Appendix D

Table A4. Autocorrelation results.

F-Statistic	Prob. F	Obs*R-Squared	Prob. Chi-Square
Panel A: Breusch–Godfrey Serial Correlation LM Test of Original Model			
Original Model			
Equity–Bond			
368.0665	0.0000	159.8008	0.0000
Equity–Property			
290.7400	0.0000	151.2408	0.0000
Equity–Gold			
50.6364	0.0000	68.4657	0.0000
Bond–Gold			
227.4945	0.0000	141.2298	0.0000
Bond–Property			
33.4977	0.0000	51.1290	0.0000
Property–Gold			
70.1341	0.0000	83.9290	0.0000
Panel B: Breusch–Godfrey Serial Correlation LM Test Model with Lagged Dependent Variable			
Equity–Bond			
1.6491	0.1949	3.3262	0.1895
Equity–Property			
0.6678	0.5140	1.3603	0.5065
Equity–Gold			
0.9293	0.3965	1.8880	0.3891
Bond–Gold			
0.2320	0.7931	0.4747	0.7887
Bond–Property			
1.1312	0.3247	2.2936	0.3176
Property–Gold			
0.0250	0.9752	0.0514	0.9746
Panel C: White Heterosckedasticity Test			
Equity–Bond			
0.2552	0.7750	0.5167	0.7723
Equity–Property			
0.5841	0.5585	1.1790	0.5546
Equity–Gold			
0.9431	0.3911	1.8966	0.3874
Bond–Gold			
0.4799	0.6195	0.9696	0.6158
Bond–Property			
0.2777	0.7578	0.5623	0.7549
Property–Gold			
0.1505	0.8604	0.3050	0.8585

Notes: 1. Source: Authors' own estimation (2024).

Appendix E

Table A5. Lag length Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	640.0322	NA	3.57×10^{-12}	−6.4926	−6.3751	−6.4450
1	1205.924	1085.352 *	1.78×10^{-14} *	−11.7940 *	−10.8541 *	−11.4135 *
2	1240.999	64.7530	2.06×10^{-14}	−11.6512	−9.8888	−10.9377
3	1274.750	59.8873	2.42×10^{-14}	−11.4948	−8.9100	−10.4483
4	1303.297	48.6030	3.01×10^{-14}	−11.2851	−7.8778	−9.9055
5	1325.550	36.2897	4.02×10^{-14}	−11.0107	−6.7810	−9.2982
6	1355.399	46.5324	4.99×10^{-14}	−10.8143	−5.7621	−8.7687
7	1373.067	26.2767	7.10×10^{-14}	−10.4930	−4.6183	−8.1144
8	1417.312	62.6230	7.77×10^{-14}	−10.4442	−3.7471	−7.7326

Notes: 1. * represent the optimal lag model for each information criterion. 2. Source: Authors' own estimation (2024).

Appendix F

Figure A1. Regime 1 Impulse response function. Source: Authors' own estimation (2024).

Appendix G

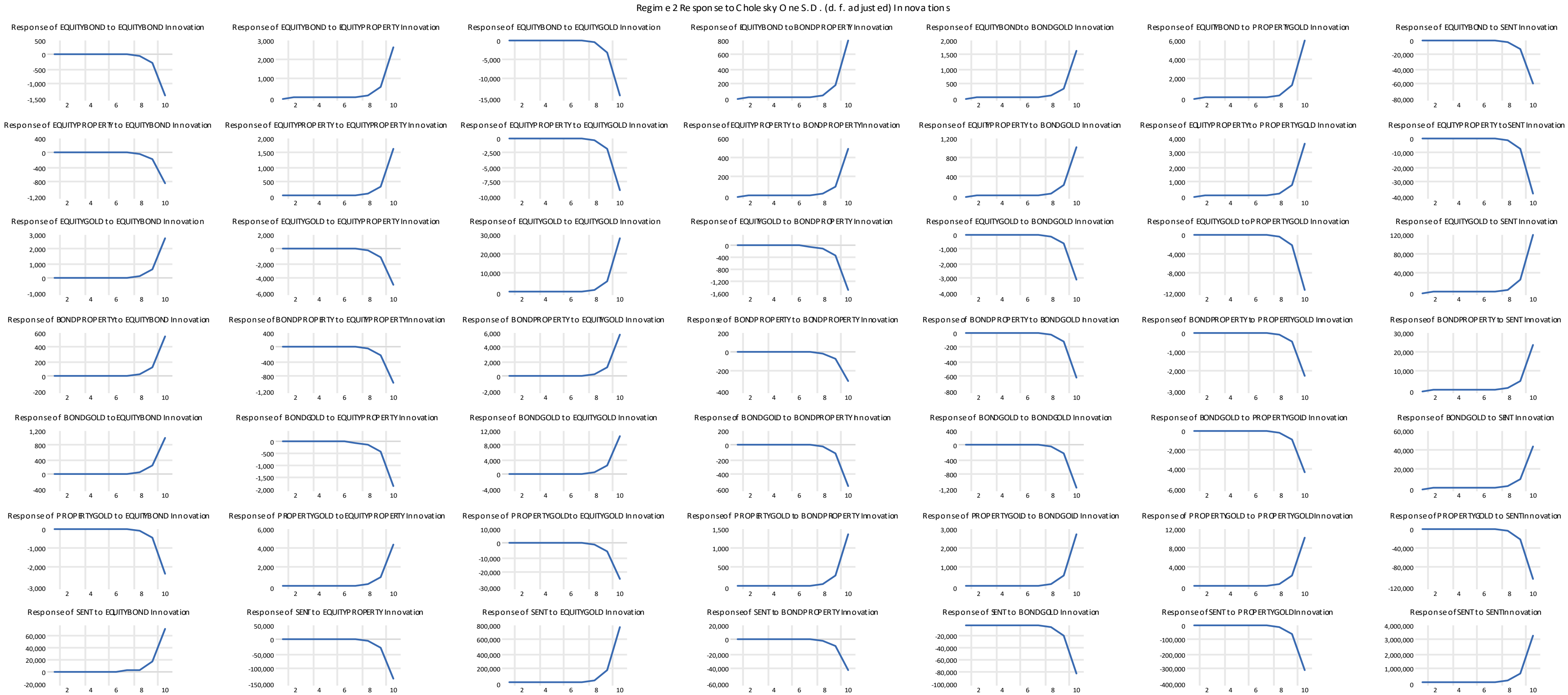

Figure A2. Regime 1 Impulse response function. Source: Authors' own estimation (2024).

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