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THE IMPACT OF INVESTOR SENTIMENT ON HOUSING PRICES AND THE PROPERTY STOCK INDEX VOLATILITY IN SOUTH AFRICA

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ABSTRACT

While prior studies have examined the predictive effect of macroeconomic and country risk components on property stock index dynamics, limited explanations exist in the literature regarding the time-varying effect of investor sentiment on housing prices. Accordingly, this study assesses the impact of investor sentiment on housing properties' returns and the effect of investor sentiment on the conditional volatility of housing price indices under different market conditions, using GARCH, GJR-GARCH, E-GARCH and Markov-switching VAR models. We found investor sentiment to significantly impact the risk premium of the property returns, where property returns increased with positive changes in investor sentiment, and conditional volatility of property returns decreased with the same changes in investor sentiment. Investor sentiment exerts positive predictive influences on the prices of small and medium houses, in both bullish and bearish market conditions but does not affect the large housing market segment. This makes the implementation of risk-related diversification across small and medium real estate portfolios more effective than large real estate portfolios. Our findings show that investor sentiment is a plausible driver of mass investor redemption actions under conditions of uncertainty.

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1. Introduction

Over the past two decades, investor sentiment, as a component of behavioral finance, has gained increasing attention from investors and scholars alike. Its popularity may be linked to the raging debate regarding the impact of rational and irrational investor behavior on financial asset pricing (Baker & Wurgler, 2007). The continued reporting of asset pricing anomalies seems to point to the conclusion that market participants do not always behave rationally. Instead, they are subject to certain behavioral biases. Investor sentiment represents an amalgam of most of these behavioral biases (Rupande et al., 2019). Further, the ubiquity of investor sentiment in subsections of the stock market such as industrials (Chen et al., 2013), food, financials and real estate (Hei-Ling Lam & Chi-Man Hui, 2018) may help explain its surge in popularity (Horta & Lobão, 2018).

Such ubiquitous effects of sentiment are not surprising, given that market-wide investor sentiment influences the movement of funds through purchases and liquidation of financial market securities (Muguto et al., 2019). However, there is evidence to suggest that, while investor sentiment effects reach virtually all subsections of financial markets, the same effects vary according to the prevailing market regimes (Goh et al., 2018; Xu et al., 2019). That is, sentiment effects depend on whether the market is bullish or bearish, in

a crisis or post-crisis period or whether it is in a bubble or a bubble burst period. Das et al. (2015) attributed the asymmetric impact of investor sentiment to investors' constant change in investment behavior – a switch between style investing and flight to liquidity – in response to the changing regimes.

Drawing from this assertion, this study sought to examine the impact of investor sentiment on the returns and volatility of the South African property index using GARCH models and Markov regime-switching models to determine the effect of investor sentiment on housing prices. Herein, the supposition that investors may switch their investments between real houses and the property index owing to the differences in liquidity is upheld. The application of the Markov switching framework helps to measure the risk level in a given investment with two or more possible regimes or states of nature. With the knowledge of the probability of being in a particular state of the market cycle, investors are able to optimize their stock selection choices (De la Torre-Torres et al., 2019). This study thus, conducts an empirical evaluation to determine the asymmetric impact of sentiment owing to varying liquidity properties of distinct types of financial assets.

2. Literature review

The decision-making process of acquiring property investments is expected to be based on a rational decision-making process. However, evidence point to a sentiment-driven process, especially where information limitations are perceived (Gallimore & Gray, 2002). Various existing studies (Clayton et al., 2009; Hui & Wang, 2014) suggest that the rational decision-making process is incompatible with the use of market-wide investor sentiment to make investment decisions. However, style investing theory can explain the link between investor sentiment and the property market. This theory is of the view that investors use sentiment to group risky assets into broad categories and treat those assets homogenously instead of considering each asset.

The flight to liquidity theory is premised on the noise trader theory. According to Lee et al. (1991), when sentiment-induced noise traders participate in the market, the systematic risk of assets increases. This, in turn, exposes rational investors to subsequent risks, which cannot be eliminated through rational arbitrage. Thus, in the presence of high sentiment-based trading, owing to the increased volatility because of noise trading, investors substitute high volatile assets for low volatility assets that will rarely be affected by sentiment. Thus, housing market sentiment affects property index returns. Subsequently, it may eventually affect housing prices if investors consider the highly volatile property index of the stock market as a substitute for the low volatile real housing market.

Notably, most of the investigations on the impact of sentiment on the housing market center on the findings of inefficient pricing in particular periods that involve an increased incidence of sentiment-driven investors in financial markets (Clayton et al., 2009). This was confirmed by Jin et al. (2014), who found that investor sentiment is an essential exogenous determinant of the US real estate pricing. Moreover, the housing market was found to be sensitive to investor sentiment so much so that even the smallest negative perception by market participants caused a significantly negative outlook in the housing market. According to Hui and Wang (2014), sentiment effects remain significant even though the housing market contains many investors who have individual perceptions regarding housing prices and lack systematic information disclosure mechanisms.

Accordingly, Ling et al. (2010) found a positive relationship between investor sentiment and real estate returns in the short horizon. This is in line with the findings of Hengelbrock et al. (2013). However, a negative relationship between investor sentiment and real estate returns existed in the long horizon. This could indicate mean-reversion in sentiment effects. Choka (2014) investigated the effect of investor sentiment on real estate investment decisions in Kenya and showed that a majority of real estate investors use past performance as an indicator of future performance when investing in property. In contrast, other investors use news events and sentiment from peers when investing in the real estate market in Kenya. Lang and Schaefers (2015) evaluated the performance of European real estate equities, based on their degree of sentiment sensitivity and showed that while high-sensitivity real estate equities yielded significantly higher raw returns than those with low-sensitivity, sentiment-driven return behavior was, in fact, compensation for taking higher fundamental risks

Using the flight to liquidity and style investing theories, Das et al. (2015) examined the effect of commercial real estate investor sentiment on asset prices in the real estate investment trust (REIT) market and found that, in the pre-crisis period, investors

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switched capital back and forth in the REIT market based on their sentiment. In the post-crisis period, investors switched capital from the illiquid private markets to the liquid REIT market based on the prevailing sentiment. These findings suggest that investor sentiment and the property market are subject to changes in market conditions. This was also confirmed by Hao et al. (2016) who found that investor sentiment was a more suitable predictor variable in explaining REIT returns when the change in momentum is considered.

Focusing on changing conditions, Lin and Ning (2017) used a Markov regime-switching vector autoregressive model to investigate the relationship between investor sentiment and housing returns in China. They found that investor sentiment increases with housing returns in a bullish period, but there is no link in bearish periods. These findings show that sentiment effects and housing market efficiency vary according to the market regime, which points to the adaptive market hypothesis. The adaptive behavior between investor sentiment and the property market was also documented by Saydometov et al. (2020) and Soo (2018) in the USA, Hei-Ling Lam & Chi-Man Hui (2018) in the Hong Kong property market, Martens (2019) in the Australia market, Hong and Li (2020), and Cepni et al. (2020) in the Chinese housing market.

The empirical evidence of the sentiment effect on house prices in the international market provides context for the examination of the same relationship in the South African market. This is motivated by the realization that, while a lot of studies have been conducted to examine influencing factors such as macroeconomic factors (Salihu & Yusof, 2017; Sunde & Muzindutsi, 2017) and country risk components (Muzindutsi et al., 2021), not much has been done on the sentiment effects on housing prices. Yet, given the role that real estate markets play in the economic growth of emerging markets (Cepni et al., 2020), it is an investigation that is vital to ensure that optimum functioning and pricing are maintained. The development of timely measures for controlling the property market in different sentiment periods to avoid significant distortions in the future may be enhanced by such analyses (Hei-Ling Lam & Chi-Man Hui, 2018).

3. Data and empirical framework

This study employs daily data on the South African Listed Property Index (J253) over the period June 2004 to December 2020 and monthly data on the Amalgamated Banks of South Africa (ABSA) housing price indices (HPI) over the period January 1995 to December 2020. These two data sources represent the major indices for real estate/housing investments in South Africa. The HPIs are categorized into small (80 m2 -140 m2), medium (141 m2 –220 m2) and large (221m2 – 400m2) categories, respectively (McGregor BFA, 2021). The data was obtained from the McGregor BFA database, but the ABSA housing price index was only available up to December 2016. Thus, Standard Bank and First National Bank housing prices were used to generate housing segment data from 2017 to 2020. The property index series was converted into returns (Rt) based on the closing price on day t (Pt), the previous day's closing price (Pt-1) and the dividend yield (DYt) as specified in Equation 1 for use in the GARCH models. The smoothed housing price indices were converted into real terms (RHPIt) using the consumer price index (CPI) as specified in Equation 2 before the estimation of Markov regime-switching models:

$$R_t = \ln\{[P_t + ((DY_t * P_t)/100)]/P_{t-1}\} * 100 \quad (1)$$

$$RHPI_{i,t} = \ln(HPI_{i,t}/CPI_t) \quad (2)$$

3.1 Measurement of investor sentiment

For investor sentiment, two indices - a daily index of Rupande et al. (2019) and a monthly index of Muguto et al. (2019) are employed, both updated to fit the study period herein this study. These indices were generated from a set of selected proxies, with the principal component analysis (PCA) technique employed as the method of construction. Through this approach, an integrated sentiment index is modelled to minimize the differences in the set of data employed, to allow for ease of interpretation while maintaining the deterministic power of information regarding the effect of sentiment on returns and volatility in South Africa. Given the subjective nature of the fitted proxies, a common component – the sentiment component – is identified using orthogonal transformation. To maximize the variance of the loadings in a rotation, the Varimax rotation mechanism was used to rotate the PCA matrix. Scholars explain that some sentiment proxies evolve within a longer period while others become evident within a short time (Baker & Wurgler, 2006). To capture these dynamics, an index with the first principal components of the current values and the one-period lagged values were modelled, after which the correlation between the first stage index and the current and lagged values of each of the proxies were

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evaluated. Subsequently, a composite index for sentiment which reflects the first underlying feature of the correlation matrix of the factors, where each corresponding proxy's current or lagged values, whichever reports a greater correlation with the first-stage index, was generated.

The daily index was built using the Rand-Dollar exchange rate, the prime rate, the Treasury bill rate, the repo rate, trading volume, the volume-weighted average price changes, and the SAVI index (Equation 3). The monthly index was built using share turnover, the equity issue ratio, the Advance/Decline ratio, the Rand-Dollar bid-ask spread, the Rand-Euro bid-ask spread, the Rand-Pound bid-ask spread and the term structure of interest rates (Equation 4). These were updated to fit the sample period in this study:

$$\mathrm{InvSent_t} = \theta_1 \mathrm{Exch_{i,t}} + \theta_2 \mathrm{Prime_{i,t}} + \theta_3 \mathrm{Treasury_{i,t}} + \theta_4 \mathrm{Repo_{i,t}} + \theta_5 \mathrm{Volume_{i,t}} + \theta_6 \mathrm{Vwap_{i,t}} + \theta_7 \mathrm{Savi_{i,t}} \quad (3)$$

$$\mathrm{InvSent_t} = \theta_1 \mathrm{Turn_{i,t}} + \theta_2 \mathrm{Equity_{i,t}} + \theta_3 \mathrm{AdvDec_t} + \theta_4 \mathrm{BidAskD_{i,t}} + \theta_5 \mathrm{BidAskP_{i,t}} + \theta_6 \mathrm{BidAskE_{i,t}} + \theta_7 \mathrm{TSIR_{i,t}} \quad (4)$$

The order of integration in the data was examined using the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The Ljung-Box and the ARCH-LM tests were also conducted before estimations to ensure correct specification and to check for suitability of the GARCH models, and after the estimation as model adequacy checks.

3.2. Generalized autoregressive conditional heteroskedasticity models

To assess the impact of investor sentiment on the conditional volatility of the property returns, the GARCH (Bollerslev, 1986), the GJR-GARCH (Glosten et al., 1993) and the E-GARCH (Nelson, 1991) models were employed. The lag order of 1.1 was used as the empirical work in South Africa has shown that it captures the ARCH effects and the autocorrelation in the variance (Mandimika & Chinzara, 2012). The estimation of the GJR-GARCH and the E-GARCH models, in addition to the simple GARCH, was warranted by the failure of the latter to account for asymmetry in volatility. In these GARCH models, InvSent was introduced into both the mean and variance equations to capture the role of investor sentiment in property returns and volatility.

The estimated GARCH models have the same mean equation with the conditional variance nested in to capture the risk premium on the property returns. This allowed for any direct feedback between the mean and conditional variance to be observed. It was specified as:

$$\mathrm{Y_t} = \mu + \theta \mathrm{Y_{t-1}} + \nu \varepsilon_{t-1} + \delta \mathrm{h_{t-1}} + \varphi \mathrm{InvSent_t} + \varepsilon_t \quad (5)$$

Where: $\mathrm{Y_t}$ are the property returns, δ is the risk premium, θ captures the effect of the past returns, ν captures the effect of past shocks, and φ captures the sentiment effect. The conditional variance for the GARCH, GJR-GARCH and the E-GARCH were modelled respectively as:

$$\mathrm{h_t} = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i \mathrm{h_{t-i}} + \varphi \mathrm{InvSent_t} \quad (6)$$

$$\mathrm{h_t} = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i \mathrm{h_{t-i}} + \gamma \varepsilon_{t-1}^2 \mathrm{d_{t-1}} + \varphi \mathrm{InvSent_t} \quad (7)$$

$$\ln(\mathrm{h_t}) = \omega + \sum_{j=1}^{q} \alpha_j \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{\mathrm{h_{t-j}}}} - \mathrm{E}\left(\frac{\varepsilon_{t-j}}{\sqrt{\mathrm{h_{t-j}}}}\right) \right| \right] + \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{\mathrm{h_{t-k}}}} + \sum_{i=1}^{p} \beta_i \ln \mathrm{h_{t-i}} + \varphi \mathrm{InvSent_t} \quad (8)$$

where: $\mathrm{h_t}$ is the conditional variance in all models. A positive γ denotes the leverage effect in Equation 7.

However, since the non-negativity constraints may still be violated under the GJR-GARCH model, the condition for non-negativity where ω > 0, α > 0, β ≥ 0, and α + γ ≥ 0 must be satisfied. The model is still permissible, even if γ < 0, provided that α + γ ≥ 0. With the E-GARCH in Equation 8, there is no need to artificially impose the non-negativity constraints as it models conditional variance in logs. The log of conditional variance makes the leverage effect exponential instead of quadratic, and therefore, the estimates of the conditional variance are guaranteed to be non-negative. However, the following conditions still need to be met where ω0 > 0, αj + βi < 1. The leverage effect under the E-GARCH is shown when γ < 0. Equations 6, 7 and 8 were estimated and compared under all three error distribution assumptions – normal, Student's t and generalized. The best model was selected based on the model that minimized Schwarz's Bayesian Information Criterion (SBIC).

3.3. Markov regime-switching VAR model

The Markov-switching approach was used to analyze the interaction between house prices and investor sentiment. Initially developed as switching regressions by Goldfield and Quandt (1973), important extensions and refinements followed, with Hamilton (1989) and Krolzig (1998) combining the switching models with vector autoregression to create the MS-VAR. This model is particularly appealing because of its applicability in characterizing macroeconomic

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fluctuations in the presence of structural breaks or shifts and asymmetries. It also allows for the examination of impulse response functions to track the dynamics of the variables of concern following shocks to the system (Simo-Kengne et al., 2013). In this study, the MS-VAR framework was applied in modelling bullish and bearish periods as switching regimes of the stochastic process that generates the growth rate of the housing prices while examining the impact of investor sentiment in each of the two regimes.

Employing a special case of the MS-VAR framework, the MSIAH(m)-VAR(p) model, all parameters of the autoregression, including the intercept term and the variance, were allowed to switch between regimes. Let Yt be a bivariate VAR in investor sentiment (InvSent) and real house price growth (ΔRHPI) of either the three housing segments – large, medium and small – employed individually. The use of real house prices growth and InvSent in levels was based on the standard unit roots and stationarity tests. As in Simo-Kengne et al. (2013), the joint dynamics of InvSent and ΔRHPI were given by the following MSIAH-VAR specification:

$$Y_t = \begin{cases} \alpha_1 + \beta_{11}Y_{t-1} + \cdots + \beta_{p1}Y_{t-p} + A_{p1}\varepsilon_t, & \text{if} \quad S_t = 1 \\ \alpha_2 + \beta_{12}Y_{t-1} + \cdots + \beta_{p2}Y_{t-p} + A_{p2}\varepsilon_t, & \text{if} \quad S_t = 2 \end{cases} \quad (9)$$

The housing prices and investor sentiment shocks were identified using a Cholesky identification scheme, with the variables ordered as InvSent and ΔRHPI, which follows Simo-Kengne et al. (2013). The latent variable St indicated bull markets - a high mean growth rate of house prices and a stable state – and bear markets - a low mean growth rate of house prices and a volatile state. The fundamental residuals εt were assumed to be uncorrected at all leads and lags, and their variance was set to unity to ensure the identity variance-covariance matrix. However, as each fundamental residual is pre-multiplied by a switching matrix Ai, the variance-covariance matrix Σi of the structural disturbances Aiεt is regime-dependent as:

$$\Sigma_i = E(A_i\mu_t\mu'_tA'_i) = A_iE(\mu_t\mu'_t)A'_i = A_iI_2A'_1 = A_iA'_i \quad (10)$$

Notably, the Markov chain is unobservable. Thus, the expectation-maximization algorithm, which is designed for a general class of models where the observed time series depends on some hidden stochastic variables, was used. To determine the cyclical variation in the responses of variables to a particular shock, regime-dependent impulse response functions were employed as specified in Equation 11. The impulse response functions trace the expected path of the endogenous variables at time t+h following a one standard deviation shock to the initial disturbance at time t, conditional on regime i (Ehrmann et al., 2003).

$$\theta_{ki,h} = \partial E_t Y_{t+h}/\partial U_{k,t} \,|_{\,s_t=\ldots=s_{t+h}=i} \quad for\ h \geq 0 \quad (11)$$

As the expectation-maximization algorithm only provides estimates of the variance-covariance matrix Σi and not the matrices Ai, structural inferences from the data can only be made if the structural disturbances (Ai) are identified. Thus, sufficient restrictions were imposed on the parameter estimates to derive a separate structural form for each regime, from which regime-dependent impulse response functions were computed. As in the standard VAR, the housing price indices were ordered last with the assumption that the housing market reacts directly to changes in investor sentiment. Through the standard bootstrapping technique, the Ai were combined with the parameter estimates of the Markov-switching unrestricted VAR to derive the response vectors.

4. Results and discussions

4.1. Descriptive and preliminary analysis

Table 1 displays the stationarity results from the ADF unit roots test and the KPSS stationarity test. From Table 1, only the listed property index returns series was stationary based on both tests.

Table 1

Stationarity and unit roots tests

Variable	ADF		KPSS		Order of integration
	I(0)	I(1)	I(0)	I(1)	
lnPrp	-23.6236***	-	0.088566	-	I(0)
HPL	-2.208649	-5.620420***	1.999465***	0.277647	I(1)
HPM	-2.583436	-6.343953***	2.009353***	0.344674	I(1)
HPS	-2.739364	-4.994334***	1.991947***	0.137705	I(1)
InvSentd	-0.591456	-61.90950***	0.899007***	0.098292	I(1)
InvSentm	0.151669	-20.61918***	2.013420***	0.053251	I(1)

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.
Source: Authors' estimations (2022).

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The other variables – large, medium and small house prices and the two sentiment indices were all integrated of order 1 - that is, they were stationary in first differences Accordingly, they were differenced once before being used in the estimations. From Table 2, the mean return on the property index was very low over the sample period. However, the index returns had a very high maximum return and a very low minimum return, all possibly attributable to the coronavirus pandemic currently ravaging the world. In terms of distribution, the series was negatively-skewed and the kurtosis was significantly above 3. The null hypothesis of normal distribution was also rejected based on the Jarque-Bera test. As can be observed from Table 2 below, both sentiment indices had mean values nearly equal to 0.00, suggestive of mean reversion in sentiment over the sample period.

Table 2

Descriptive statistics

	lnPrp	HPS	HPM	HPL	InvSentd	InvSentm
Mean	0.0001	571540.6	780305.7	1176755.0	0.0000	0.0000
Median	0.0002	652764.1	916184.9	1359957.0	-0.1948	0.2907
Maximum	0.1101	1112145.0	1549853.0	2362498.0	4.0340	6.7253
Minimum	-0.1808	129377.4	170219.6	255336.0	-4.4777	-5.4903
Std. Dev.	0.0111	318157.5	451964.1	694961.6	2.3103	3.6424
Skewness	-2.2471	-0.0286	-0.0062	0.0338	-0.0390	0.0988
Kurtosis	53.9250	1.6264	1.6069	1.6008	1.7499	1.7681
Jarque-Bera	465104***	24.33***	24.98***	25.26***	279.18***	20.04***

Notes: ***, ** and * *denote significance at the 1%, 5% and 10% levels, respectively.*

Source: Authors' estimations (2022).

In terms of their maximums and minimums, the monthly index showed a greater range than the daily index. In addition, the monthly index exhibited higher variability, as shown by a standard deviation value relative to the daily value. The former was also positively skewed while the latter was negatively skewed). However, both indices had few outliers in the data as evidenced by kurtosis values of less than 3 of normal distribution. The small, medium and large house prices series means, maximums and minimums were reflective of the relative sizes of the houses in each series. The large-sized house prices exhibited higher variability, as shown by a higher standard deviation relative to the small and medium-sized housing prices ones. In terms of their distribution, the small- and medium-sized house prices were negatively skewed, while the large-sized house prices series was positively skewed. However, all three statistics were very close to 0. All three series had a kurtosis value of less than 3 of normal distribution and the null hypothesis of normal distribution was also rejected in all three series. Figures 1 and 2 below confirm the findings from the stationarity tests and the descriptive statistics above.

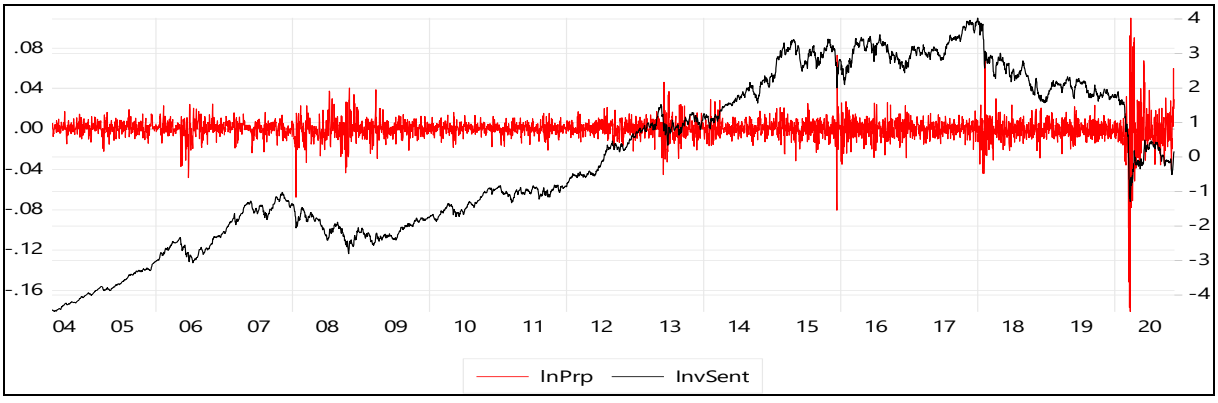


Fig. 1. Investor sentiment and the property index. *Source*: Authors' estimations (2022).

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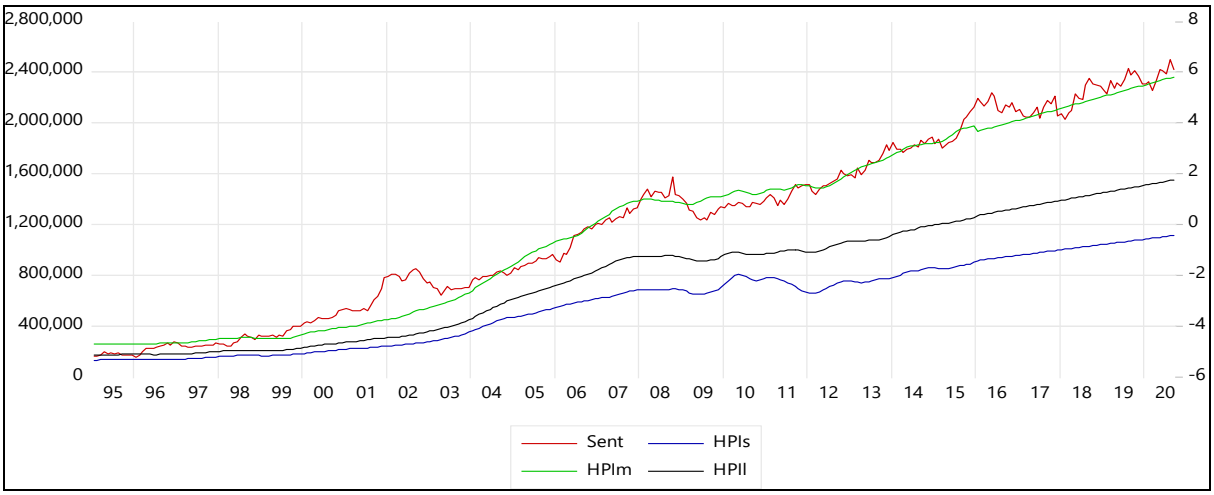


Fig. 2. Investor sentiment and housing price indices. *Source*: Authors' estimations (2022).

For instance, the property index in Figure 1 exhibited a constant mean, indicative of a stationary series, while all the variables were trending upwards, establishing higher lows and higher highs. The property index returns exhibited some volatility clustering, especially towards the end of the sample period, a period that coincides with the beginning of the coronavirus pandemic. The clustering corresponds with various volatile sentiment periods, suggestive of a relationship between the two series. A similar pattern also appears in Figure 2, although not as clear as in Figure 1. The smoother movements in the series in Figure 2 relative to Figure 1 are a result of using monthly data. Overall, in both figures, there is some indication of significant sentiment effects on property returns and house prices.

4.2. GARCH analysis of property return and investor sentiment

In addition to the descriptive statistics, serial correlation tests and ARCH effects tests were conducted on the property returns and the results are shown in Table 3 below.

Table 3

Serial Correlation tests and heteroscedasticity

	LNPRP
LB statistic	317.73***
Breusch-Godfrey LM statistic	302.59***
LB^2 statistic	4690.80***
Engle ARCH LM statistic	2040.67***

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Source: Authors' estimation (2022).

The LB statistic was significant for all series suggesting the presence of serial correlation and this was confirmed by the Breusch-Godfrey serial correlation LM test results. The serial correlation in the property returns series contrasts the assertion of informational efficiency in the EMH as proposed by Fama (1970). This is because past property returns may be used to predict future property returns. Evidence of serial correlation was also documented by Chan (2011) on the South African property market, who evidenced significant autocorrelation in commercial property returns over the period 1995 – 2007. This suggests autocorrelation in property return has not changed given the vast difference in the study periods of this study and Chan's (2011).

The LB squared statistic was also statistically significant for the property returns suggesting serial correlation in the squared returns. This reveals that the series' second moments are time-varying, meaning that there is heteroscedasticity. Engle's (1982) ARCH LM test for heteroscedasticity was also conducted on the property returns. Consistent with the LB squared test results, the results confirmed the presence of ARCH effects, as the LM test statistic was significant. Thus, GARCH modelling of the conditional volatility was appropriate given the evidence of ARCH effects as they capture time-varying conditional volatility.

Table 4 shows the selected models for the property returns under the sentiment augmented models and the models without sentiment. The study employed both symmetric and asymmetric GARCH models and sentiment augmented GARCH models and GARCH models without sentiment under the normal, student's t and generalized error distribution assumptions. The best model was chosen based on the SBIC. It can be noted that, generally, all the sentiment augmented models outperformed the respective models without

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sentiment, as all the SBICs for all the error distribution assumptions minimized the SBIC. This suggests that investor sentiment is an important factor in explaining property returns.

The symmetric GARCH-M (1.1) specification under the student's t error distribution assumption was chosen as the best model under the sentiment augmented models whereas the asymmetric GJR-GARCH-M (1.1) under the GED error distribution assumption was selected under the models without sentiment. The difference in model selection in the presence of investor sentiment and in the absence of it shows that accounting for investor sentiment in modelling the conditional volatility of the property returns may explain the asymmetries found in models without sentiment. Consistent with the Jaque-Bera test, none of the GARCH specifications selected were based on the normal error distribution assumption but the student's - t and the GED. More so, the student's - t and the GED have thick tails to capture the leptokurtic pattern evidenced in the descriptive statistics section better (Brooks 2019). As such, the standard error estimates from one of these two distributions should be more reliable than based on a normal distribution. Also, parameter estimates are not overly influenced by extreme observations that occur with a low probability, such as market crashes if these distributions are used, considering that the sample spans over the 2007-2008 financial crisis, the 2015 Chinese stock market crash and the 2020 US stock market crash and the COVID-19 pandemic.

Table 4

Model selection based on the SBIC

Model	Distribution	With sentiment	Without sentiment
GARCH-M (1.1)	Normal	-7.8558	-6.8337
	Student's -t	**-7.9229**	-6.9083
	GED	-7.9205	-6.9091
GJR-GARCH (1.1)	Normal	-7.8562	-6.8416
	Student's -t	-7.9215	-6.9093
	GED	-7.9195	**-6.9107**
E-GARCH (1.1)	Normal	-7.8463	-6.8327
	Student's -t	-7.9164	-6.9044
	GED	-7.9139	-6.9059

Notes: *SBICs in bold font denote the selected models.*

Source: Authors' estimation (2021).

Table 5 reports the outputs for the selected model. From the table, the risk premium parameter δ, in the mean equation, was negative and statistically significant for the model without sentiment.

This shows that mean daily property returns decreased as risk, measured by conditional variance, increased, implying a negative risk-return relationship. This finding of a negative risk premium was also evidenced by Mandimika and Chinzara (2012) on the JSE sectors, who attributed it to thin trading and illiquidity. However, when sentiment was added to the GARCH model, there was no evidence of a risk premium as shown by the insignificant parameter. This suggests that sentiment might explain the non-synchronous trading in the property market.

Table 5

Selected model outputs

Country	**With sentiment**	**Without sentiment**
Selected model	GARCH-M (1.1) Student's-t	GJR-GARCH-M (1.1) GED
μ	0.0005**	0.0011**
δ	-0.0880	-0.0991***
θ	0.3470***	0.4550***
ν	-0.2477*	-0.3452***
φ	0.1242***	-
ω	0.0000***	0.0000***
α	0.0811***	0.0936***
β	0.8903***	0.8403***
γ	-	0.0830***
φ	-0.0000***	-
α + β	0.9714	0.9339
HL	23.8876	27.8287

Notes: ****, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

Source: Authors' estimation (2022).

As can be observed from Table 5 above, evidence of the predictability of returns suggests the presence of market frictions, such as non-synchronous trading in the property market. This is in line with the risk premium findings of a negative risk premium which suggested thin trading and illiquidity of the property market. The effect of past shocks on returns, ν, was negative and statistically significant for both models.

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This suggests that past negative shocks could be used to explain future property returns. This is a phenomenon consistent with inefficiency and suggests the prevalence of noise traders and rational traders' failure to counter noise trading.

The investor sentiment parameter, φ, was positive and statistically significant. This implies that property returns increase with positive changes in sentiment. These results are like the findings of Martens (2019) in Australia and Hong and Li (2020) in China, where a positive and statistically significant relationship between sentiment and property returns was reported. All these findings show the explanatory power of sentiment on property returns as echoed by Cepni et al. (2020) in China, another emerging market like South Africa.

In the conditional variance equation, the leverage effect parameter, γ, was positive and statistically significant suggesting the presence of the leverage effect as negative shocks increased volatility more than positive shocks of the same magnitude. This evidence of asymmetry affects the pricing of securities and portfolio selection. The effect of past shocks, α, was positive and significant for all the models. This indicates that past innovations could explain the current volatility in the property market. The investor sentiment parameter in the variance equation φ was negative and statistically significant, implying a negative relationship between changes in investor sentiment and the conditional volatility of property returns. These findings are like the findings by Rupande et al. (2019) on the South African market. This negative relationship suggests that sentiment is mean-reverting, thus resulting in low volatility on the market as noise traders exit the market, reducing their impact on the market.

The degree of volatility persistence, as measured by $\alpha + \beta$, was high for both models suggesting the presence of volatility clustering. This implies that current volatility shocks influence the expectation of volatility for many periods in the future (Engle & Patton 2001). However, volatility persistence was highest for the sentiment augmented model. This implies long memory in the conditional variance, and that shocks persist for many future periods. This shows that not adjusting for sentiment may result in the underestimation of volatility persistence in the property market. The stationarity condition was met for both models. The volatility half-life measure shows that it took 23.88 days under the model with sentiment and 27.82 days for the model without sentiment, for a shock on the conditional volatility to decline by half. The model without sentiment recorded the highest half-life measure despite having the lowest volatility persistence. Therefore, not accounting for sentiment may result in the overestimation of the half-life measure. The non-negativity conditions in the volatility equation ($\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $\alpha+\gamma \geq 0$) are all satisfied, which makes the models for the conditional variance permissible for all the markets.

4.3. Analysis of interaction between investor sentiment and housing prices

This section presents the analysis of the interaction between investor sentiment and housing prices based on Markov regime-switching VAR estimation results. The presentation comprises the choice of the MS-VAR model and lag selection, parameter analysis of the MS-VAR (2) results, smoothed regime probabilities, analysis of bullish and bearish conditions of the three housing segments, and the impulse-response functions based on different regimes.

4.3.1. Choice of MS-VAR model and lag selection

Table 6 presents the information criteria employed to select the optimum number of lags for different regime-switching VAR models. These estimated models include a two-regime model with constant variance, a two-regime model with regime-dependent variance, a three-regime model with constant variance and a three-regime model with regime-dependent variance. The selected best estimation is a two-regime model with regime-dependent variance. Table 6 summarizes the results of the lag order selection criteria for different two-regime models with regime-dependent variance. The Schwarz information criterion (SC) selects 1 lag order 1, while Akaike information criterion (AC) and Hannan-Quinn information criterion (HQ) select 2 lags. Two lags are selected as per AC and HQ. Thus, a two-lag Markov switching VAR (MS-VAR (2)) model was estimated with mean returns and variances varying under 2 different regimes.

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Table 6

VAR Lag Order Selection Criteria

Lag	SC	AC	HQ
0	14.81904	14.79470	14.80443
1	14.06927*	13.99626	14.02546
2	14.09532	13.97364*	14.02230*
3	14.16562	13.99526	14.06339

Notes: ****, ** and * denote significance at the 1%, 5% and 10% levels, respectively.*

Source: Authors' estimation (2022).

4.3.2. Parameter analysis of the MS-VAR (2) results

Table 7 presents the summary results of the MS-VAR model specified in Equation 9. The equation was estimated separately for InvSent and Small HPI, InvSent and Medium HPI, and InvSent and Large HPI.

Table 7

MS-VAR (2) results

Independent variables	Regime	Dependent variables	
		$InvSent_t$	**$Small_t$**
Constant	Bull	0.888*	0.032*
	Bear	-0.893*	-0.013
$InvSent_{t-1}$	Bull	0.689	1.011*
	Bear	0.046	0.704*
$InvSent_{t-2}$	Bull	-0.403	-0.204
	Bear	0.142	0.079
$Small_{t-1}$	Bull	-0.027	0.032*
	Bear	-0.009	-0.007
$Small_{t-2}$	Bull	-0.628*	0.070
	Bear	0.142	0.103*
		$InvSent_t$	**$Medium_t$**
Constant	Bull	0.902*	0.014
	Bear	-0.892*	-0.011
$InvSent_{t-1}$	Bull	0.369	0.780*
	Bear	0.027	0.618*
$InvSent_{t-2}$	Bull	-0.479	0.079
	Bear	-0.040	0.148*
$Medium_{t-1}$	Bull	-0.018	0.026*
	Bear	-0.009	-0.011
$Medium_{t-2}$	Bull	-0.426	0.061
	Bear	0.153	0.106*
		$InvSent_t$	**$Large_t$**
Constant	Bull	0.905*	0.015
	Bear	-0.886	-0.015
$InvSent_{t-1}$	Bull	0.337	0.808*
	Bear	-0.317	0.138
$InvSent_{t-2}$	Bull	-0.258	-0.114
	Bear	0.194	0.087*
$Large_{t-1}$	Bull	-0.027	0.031*
	Bear	-0.011	-0.009
$Large_{t-2}$	Bull	-0.553*	0.179*
	Bear	0.201	0.087*

Notes: ** Denotes significance at the 5 percent level of significance.*

Source: Authors' estimation (2021).

It can be observed that investor sentiment was significantly affected by the second lag of Small HPIsand large HPIs in the bull regime. This evidence, consistent with Lin et al. (2017), suggests that delayed

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returns of these housing price indices drove investor behavior in the real estate industry in bullish market conditions only. However, investor sentiment was not responsive to changes in the prices of medium houses across bull and bear market conditions. This implies that investors are sensitive to changes in the prices of small and large houses, but do not react to price fluctuations of mid-range houses.

As can be observed from Table 7, lagged HPIs (small, medium and large) exert varying influences on subsequent changes in HPIs across different market conditions. From the table, lag 1(t-1) had a significant positive coefficient in regime 1 across the 3 segments, while lag 2 (t-2) had significant positive coefficients in regime 2. These findings imply that changes in the previous period affect the current housing prices in the bull regime, while the response of current prices to previous price changes in the bear regime is delayed. These switching lag-effects findings are consistent with prior evidence from Ling et al. (2022), which suggests that past returns of the housing price indices exert predictive influences on the direction of subsequent indexed returns. However, Fei et al. (2010) explained that the predictors of real estate returns are more closely linked to grapevine information flow and lack of investor sophistication than the forces of demand and supply and regulatory policies. This is because the average investor's stock-picking and redemption actions under changing market conditions are largely driven by bounded rationality, which allows them to yield to varying influences rather than established financial planning principles as explained by the AMH (Lo, 2012).

From the same table, the results show that investor sentiment in time t-1 exerted a significant positive impact on the prices of small and medium houses across the bull and bear markets. However, this effect varied across different market conditions in large HPI; it was positive and significant in the bull regime and insignificant in the bear regime.This implies that, generally, small and medium housing market segments are more linked to investor sentiment than the large housing market segment. In this context, sentiment-related risks can be diversified across two (small and medium) segments than the larger segment of housing markets. Moreover, as can be observed from Table 7, there exists a recognizable difference in the size of the coefficient of the various market segment variables across bull and bear markets. From the table, the coefficients of these variables are higher in bull conditions than in bear conditions, and they are generally higher for the small HPI than the medium and large HPIs. However, large HPI coefficients are higher than medium HPI across the different market conditions. This evidence affirms the prevalence of high investor sensitivity during upper periods of the market, relative to prices of the different housing segments, compared to lower periods of the market in South Africa. However, it should be noted that the effect of investor sentiment on housing returns vis-à-vis market conditions differs across corporate investors and retail investors. Huerta-Sanchez et al. (2018) explained that corporate investor sentiment exerts a highly significant influence on HPI returns compared to their retail counterparts, where swings in corporate investor sentiment drive significant changes in the direction of HPIs returns in bearish markets than in bullish markets. This can possibly explain the observed varying effect of investor sentiment on the HPI of large houses across the bull and bear market conditions.

In terms of the effect of investor sentiment in time t-2, there are significant positive coefficients under medium and large HPIs in the bearish regime, but insignificant in the bullish regime. These results indicate that, generally, recent as well as delayed investor behavior exerted a positive predictive influence on the prices of medium and large real estate properties, but this relationship is evident only under bearish market conditions. From the literature (Ling et al., 2014), investor sentiment culminates in an increase in short-term returns of private real estate investments. However, adverse effects are derived from an increase in investor sentiment on publicly traded real estate stocks, which is attributable to financial markets' inefficiency.

4.3.3. Smoothed regime probabilities

Figure 3 below plots the smoothed probability of the bullish and bearish states, fitted to the sampled HPIs for the estimated MS-VAR (2) model specification in Equation 9. The HPIs exhibit similar patterns of fluctuations with investor sentiment across both the low volatility (bullish state) and high volatility (bearish state) regimes of the market for the sampled period.

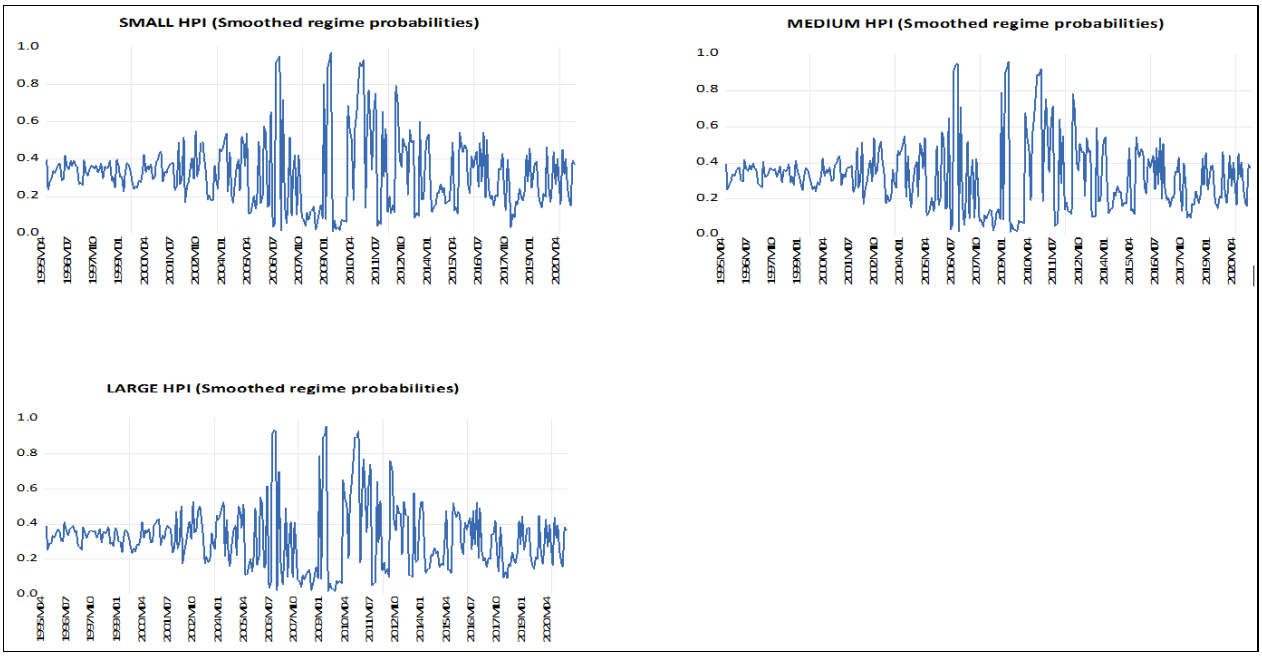


Fig. 3. Smoothed probability of the bullish and bearish states for MS-VAR (2) Model *Source:* Authors' estimations (2022).

The dynamics of the HIPs performance show minimal levels of fluctuation between 1996 and 2005. The transition enters a bullish state towards the end of 2005 through to the end of 2006 and plummets significantly between 2007 and 2009. The entry of the system into the bearish state is linked to the global financial melton which happened around the same period (2007- 2009).

The performance of the HPIs recovers from the bearish state at the beginning of 2010, where they enter a bullish state (regime 1) through to the end of 2011. During the period of the global financial crisis, most investors became skeptical about the general performance of benchmarks. This resulted in the withdrawal of significant volumes of investments due to market uncertainty, which caused significant volatilities in the performance of most recognized market indices. As explained by Fratzscher (2012), the increased HPIs volatility is largely attributable to a general surge in capital flight from emerging economies to advanced economies during the period of the global financial crisis, causing instability in the domestic financial market of South Africa. This represents a dynamic form of adaptation to changing market conditions by way of windfall returns on the part of fund managers, which can be explained by the AMH.

4.3.4. Analysis of bullish and bearish conditions of the three housing segments

Table 8 below reports the average transition probabilities and expected durations between different regimes of the system for the sampled housing price indices (HPIs).

Table 8

Regime transition probabilities and expected durations

	Regime 1	Regime 2	Duration	Probability
Regime 1	0.599	0.401	2.67	0.545
Regime 2	0.485	0.514	2.23	0.455

Source: Authors' estimations (2022).

The average probability of staying in the bullish state, regime 1, was 59.9% while the probability of regime 1 transitioning to regime 2, the bearish state, was 40.1%. The probability of staying in regime 2 was 51.4% and the probability of regime 2 transitioning to regime 1 was 48.5%. These results suggest that the bullish state had the highest continuous probability, and hence, is the most stable and persistent regime. It was expected to persist for an average of 2.67 months while regime 2 was expected to persist for 2.23 months on average.

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4.3.5. Impulse-response function based on different regimes

Figures 4 to 6 show the cumulative impulse response of the estimated Markov switching VAR model for the two regimes. They were employed to assess the direction, duration and level of impact of investor sentiment on property and housing prices while comparing the differences in the effect of the underlying short-run dynamics across the bullish and bearish regimes. In the analysis, shocks were introduced to investor sentiment, and the cumulative responses of small, medium and large HPIs were observed over a 10-month period across the bullish and bearish regimes. For the small HPI in regime 1, a shock to investor sentiment elicited a positive response in the changes of small HPIs in the first month. The response gradually increased, with the cumulative response reaching a peak of approximately 1.19 and maintaining a steady momentum through to the tenth month.

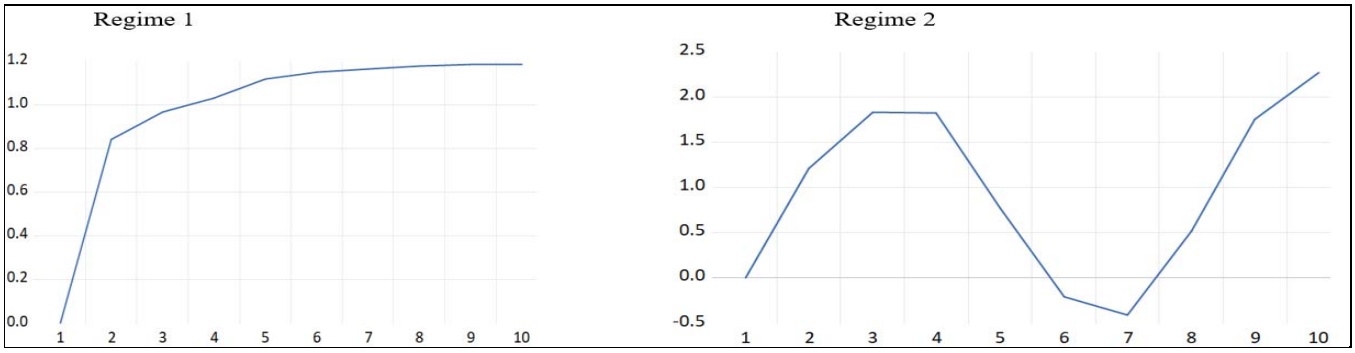


Fig. 4. Cumulative response of Small HPI to Investor Sentiment under two regimes. *Source:* Authors' estimations (2022).

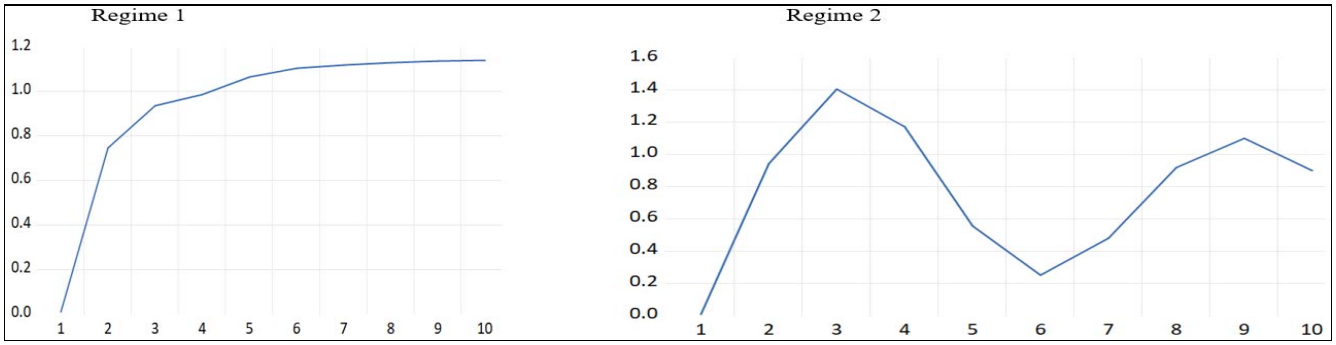


Fig. 5. Cumulative response of Medium HPI to Investor Sentiment under two regimes. *Source:* Authors' estimations (2022).

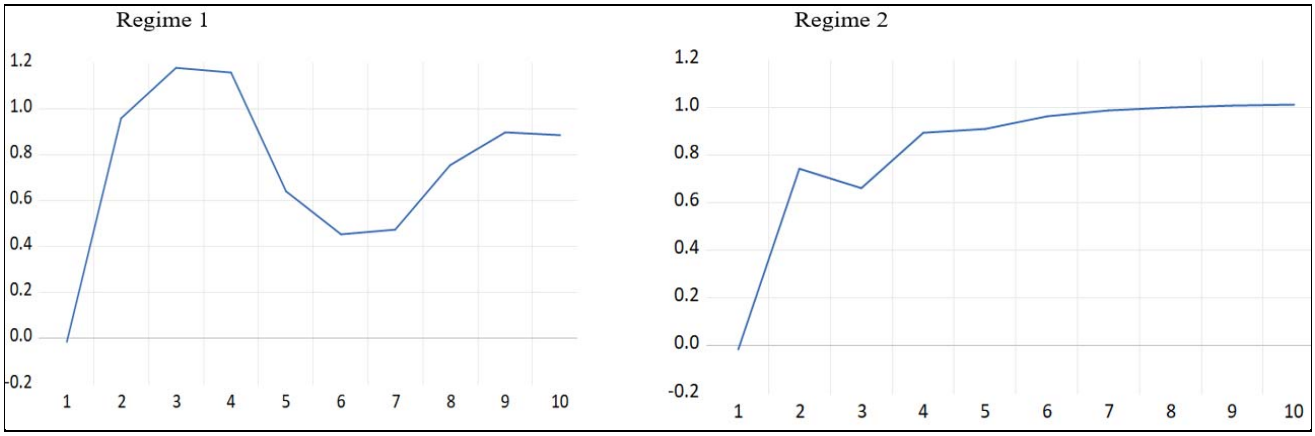


Fig. 6. Cumulative response of Large HPI to Investor Sentiment under two regimes. *Source:* Authors' estimations (2022).

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In regime 2, the response of the small HPI was negligible in the first month, but assumed an increasing trend from the second month, with the cumulative response reaching a peak of approximately 1.8 in the third month before sharply declining until the seventh month where it assumed a negative response of -0.5. The cumulative response began to accelerate once again from the end of the seventh month through to the tenth month, reaching a peak of approximately 2.3. It is apparent that investor sentiment exerts varying impacts on the small HPI across different periods, where it is generally positive in regime 1 and negative in regime 2. The overall results imply that increase in investor sentiment under bull conditions of the market results in high returns of small HPIs, while a similar increase in sentiment under bear conditions leads to a decline in the returns of small HPIs. As such, a significantly sharp increase in investor cumulative skeptical impulses negatively affects the prices of small-cap property and housing investments.

Similar dynamics observed between small HPIs' and investor sentiment were apparent between investor sentiment and the medium HPI. A shock to investor sentiment resulted in a positive incremental trend in medium HPI, a trend sustained until the tenth month of the innovation and peaking at approximately 1.18. This was just lower than the peak of 1.19 reported in respect of small HPIs. In regime 2, a positive incremental response of medium HPIs to investor sentiment was observed from the first month through to the third month, where it reached a peak of 1.4 and began to decline fast to a low of 0.2 in the sixth month. Subsequently, the response increased slowly to reach an approximate peak of 1.17, but assumed a decreasing trend thereafter into the tenth month. These results show that, in general, the time-varying sentiment of real estate investors produces a positive response in the prices of medium-cap housing portfolios in the short-run of the business cycle. However, the response declines in the long run.

Lastly, for the large HPI in regime 1, a shock to investor sentiment caused a positive response from the first month to reach a peak of approximately 1.19 in the middle of the second month. The response began to decline at a moderate speed from the end of the fourth month through to the beginning of the sixth month and then assumed a gradual rise from the seventh month to a peak of 0.8 in the ninth month. In regime 2, the cumulative response of large HPI reached an initial peak of approximately 0.7 in the second month and declined slightly in the third month before assuming a positive incremental response from the fourth month through to the tenth month to a peak of 1.0. The results show that investor sentiment elicits a similar trend of response in large HPI across different regimes, where the short-run dynamic impact of investor sentiment on large housing prices property is positive.

Overall, the impact of investor sentiment on the small, medium and large HPIs was generally positive and more pronounced in the bullish state of the market than in the bearish state. Noh (2020) explained that housing price uncertainty shocks in bull regimes result in housing price hikes, but vice versa for similar shocks in bear regimes. This implies that investor sentiment is a systemic instability driver of fluctuations in housing prices. In this context, the creation of a stable macroeconomic environment represents an effective means of promoting positive investor sentiment. Evidence by Simo-Kengne et al. (2013) shows that the returns on real estate investments in South Africa decline significantly under bear market conditions than in bull markets. This implies the existence of an asymmetric relationship between the prices of houses and macroeconomic shocks. As such, the sensitivity between housing returns and investor sentiment increases after periods of market downturns. This indicates that a shock to housing prices is likely to have a significant long-term impact on housing sentiment and macroeconomic dynamics, as explained by André et al. (2021).

5. Conclusions and policy recommendations

This study analyzed the constant and time-varying effect of investor sentiment on the housing market in South Africa. Various GARCH models were employed to assess the impact of investor sentiment on the property returns and their conditional volatility, while the effect of investor sentiment on price indices of different housing segments under different market conditions (the bullish and bearish states) was tested with a Markov switching VAR model. GARCH results showed that property returns increased with positive changes in investor sentiment whereas the conditional volatility of property returns decreased with the same changes in investor sentiment. The inclusion of the sentiment variable in both equations also had a significant impact on the other parameters, particularly the risk premium and the effect of past shock in the mean equation. The model chosen changed from the one with a significant leverage

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parameter to a symmetric model, suggesting that sentiment explains a significant component of asymmetry. The results of the analysis are as follows. First, it was found that prices of large houses exhibit higher levels of variability compared to medium and small houses prices. This implies that housing price indices are generally more volatile in the large housing market segment than in the other categories of the South African housing markets. Second, volatility clustering was found across the property index returns during the sampled period. The volatility clustering was found to be more prevalent during the period of the emergence of the coronavirus pandemic, which was also the period of increased investor apprehension. This indicates that the direction of property index and house prices was largely driven by investor sentiment, which was premised on the uncertainty which surrounded the impact of the global pandemic on financial markets.

From the Markov-switching VAR analysis, it was found that delayed returns of housing price indices generally drive investor sentiment in the real estate industry in bullish market conditions only. This implies that property investment decisions are generally motivated by historical movements in the upper period returns of the benchmark. The study found that recent investor sentiment exerts positive predictive influences on prices of small and medium houses across bullish and bearish market conditions. However, the effect of investor sentiment on prices of the large housing market segment is prevalent in the bullish state of the market only. This makes investments in small and medium houses more susceptible to investor sentiment compared to large houses. This, in turn, means that it is feasible to implement sentiment-related risk diversification across different segments of the South African real estate market. Additionally, it was found that investor sentiment exerts a significant and varying impact under different regimes on the three categories of the housing market in the short run, confirming the role of investor sentiment on the real estate market.

The findings indicate that investors are sensitive to changes in prices of small and large houses under bullish conditions but do not react to fluctuations in prices of medium houses. This implies that prices of small and large segments of the housing market can play a role in predicting investor sentiment but only in bullish market conditions. Thus, the interactions between investor sentiment and housing prices portray adaptive behaviors and it would be optimal to analyze the investor sentiment under the AMH framework. Furthermore, an analysis of bullish and bearish conditions of the three housing segments shows that the housing market is generally less volatile and stays longer in the bullish than in the bearish market condition. Thus, the dynamic impact of investor sentiment on the various housing prices under regime switching conditions can be characterized by ''steady rise'' and ''sharp decline'' periods. This implies that investors allocate more cash to real estate portfolios in the bullish regime, where they are more confident about the expected returns on their investments.

This study provides new findings on the asymmetric and switching interactions between the property market and investor sentiment and such findings contribute to the existing literature on the volatility of the property markets. As a policy recommendation, investors should consult professional investment advisors before finalizing stocking-picking decisions on real estate portfolios as time-varying dynamics of housing price indices have a direct impact on investor assets. Managers of real estate investments should implement policies that consolidate the liquidity positions of their portfolios, as the predictive effect of investor sentiment on housing index returns remains a plausible driver of mass investor redemption actions under conditions of uncertainty. In addition, policymakers should implement policies that create a conducive trading environment as systemic instabilities drive fluctuations in the returns of housing price indices.

This study has a recognizable limitation in terms of the scope of the analysis, as it is only focused on the South African real estate market due to the lack of access to data. Future studies can extend the coverage of the research to other emerging markets as a composite analysis of the dynamics of various markets would engender a more comprehensive generalization about the relationship between investor sentiment and housing prices, while broadening the scope of the extant literature on the subject matter.

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