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-RESEARCH ARTICLE-

MODELLING EFFECT OF INVESTOR SENTIMENTS ON THE HOUSING: CASE STUDY OF SAUDI MARKET VOLATILITY

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—Abstract—

In recent years, there has been growing attention on investor psychology, irrational behaviour, and their influence on housing returns in Saudi Arabia. Accordingly, this study seeks to examine the extent to which irrational behaviour and investor sentiment

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affect housing market returns within the Saudi context, with particular focus on the asymmetrical effects of investor attitudes over the period from September 2009 to September 2022. The relationship between investor mood and the performance of both the Saudi stock and real estate markets is analysed using the Nonlinear Autoregressive Distributed Lag (NARDL) model. The findings indicate that negative shifts in investor mood are significantly associated with higher housing returns, whereas positive shifts exert minimal influence. The autoregressive component reveals that, aside from the fourth lag which has a negative impact, previous returns generally have a positive effect on current returns. The model accounts for approximately 99.77% of the variation in real estate returns, reflecting a strong overall fit. These results underscore the importance of comprehensively understanding the dynamics of the Saudi housing market, as investor sentiment may have a lagged influence and the interactions between market returns and economic factors are multifaceted.

Keywords: Market Volatility, Irrational Conduct, NARDL Model, Saudi Arabia, Investor Sentiment, Stock Returns, Real Estate Returns.

INTRODUCTION

The Saudi Arabian stock market has historically experienced persistent volatility, with a decline of 15% and an average negative annual return of -3.7% since the 2014 oil crisis. Represented by the Tadawul All Share Index (TASI), the Saudi stock market is recognised as one of the region's most expansive, diverse, and volatile financial markets (Tadawul). Saudi Arabia also plays a pivotal role in global oil markets. Following structural reforms in the Saudi Stock Exchange (Tadawul), TASI was restructured in March 2021 under a holding company named the Saudi Tadawul Group, now a wholly owned subsidiary. Tadawul remains the principal stock exchange in Saudi Arabia and is considered one of the largest markets in the Middle East. It ranks as the ninth largest among the 67 exchanges affiliated with the World Federation of Exchanges and serves as the dominant financial market within the Gulf Cooperation Council (GCC) (Al-Hosaini et al., 2023).

Trichilli et al. (2020) identified that investor sentiment, often marked by irrationality and cognitive bias, substantially influences stock valuations and returns. The attitude of investors exerts a significant impact on market behaviour, reflecting their general outlook, perceptions, and responses towards individual firms or the broader market. Investor sentiment plays a crucial role in shaping short-term price fluctuations, which are driven by factors such as financial news, corporate performance, and macroeconomic indicators. Optimistic sentiment typically stimulates buying activity and drives up stock prices, whereas pessimistic sentiment tends to prompt selling pressure and depress prices (Al-Hajieh et al., 2011; Alrabei et al., 2023; Saleh et al., 2021). The aggregate mood of investors can generate market momentum, thereby affecting both trading volume and price trajectories. A nuanced understanding of

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investor psychology offers valuable insight into future market developments.

This study presents an in-depth analysis of the relationship between investor sentiment and stock market performance in Saudi Arabia through the application of linear Autoregressive Distributed Lag (ARDL) models. The findings suggest that positive shifts in sentiment contribute to increased market returns following a two-month lag. However, this effect diminishes over time, potentially due to initial overreactions being corrected subsequently. The research employs a hybrid methodology, integrating robust ARDL modelling with economic reasoning and practical insights to explore the dynamic interplay between investor sentiment and market volatility.

LITERATURE REVIEW

Investor sentiment represents the overall outlook of investors regarding individual stocks or the broader market. Numerous studies have affirmed that sentiment has a substantial and enduring impact on asset prices in financial markets (Baker & Wurgler, 2006; Bathia, D., & Bredin.,2016; Cai, Z., & Chen). Traditional financial theory posits that stock prices mirror the discounted value of anticipated future cash flows and that irrational behaviours are counterbalanced through arbitrage. For example, the Capital Asset Pricing Model (CAPM), a principal component of traditional finance, maintains that markets are efficient and largely unaffected by psychological factors. According to this theory, rational investors are capable of correcting pricing errors, thereby aligning market prices with their intrinsic values (Bathia, D., & Bredin., 2018 de Sousa-Gabriel**)**.

However, the market crash of October 1987 exposed limitations in such theories (Gabbori et al., 2021). Following this, researchers observed that asset prices often underreact to fundamental news or overreact to media narratives, highlighting inconsistencies in investor behaviour (Saleh et al.,2023; Gabriel et al.,2024). The emergence of the 'noise trader' theory suggested that waves of investor optimism or pessimism could drive prices away from fundamental values, occasionally with severe consequences for market stability (Gharaibeh et al,2022). These anomalies have strengthened the case for behavioural finance, which continues to expand in scope.

Baker and Wurgler (2006, 2007) introduced the notion of investor sentiment as broad-based optimism or pessimism that can systematically influence market outcomes. Their research indicated that sentiment not only predicts returns but also affects market volatility. When sentiment is the dominant force, even rational investors might find it challenging to rectify mispricing (Barberis & Thaler, 2003). Supporting this view, Krainer and Paul (2001) demonstrated that deviations from fundamental values can induce non-linear behaviour in key indicators such as the log dividend–price ratio. Past events, including the collapse of the dot-com bubble in 2000 and the subprime mortgage crisis in 2008, offer concrete examples of sentiment-driven distortions in asset pricing. Several empirical investigations confirm the strong relationship between investor sentiment and market volatility. further concluded that investor sentiment remained a significant determinant of market volatility even after post-crisis regulatory changes. In a different approach, P H and Rishad (2020) used principal component analysis to develop a sentiment index from several indirect indicators. This index was then employed in Granger causality and GARCH models to examine its effect on trading behaviour, revealing that sentiment significantly affects both trading volume and price fluctuations.

Although the importance of investor sentiment has been acknowledged, its asymmetric effects have largely been overlooked, especially in the context of Saudi Arabia. This study addresses this shortfall by examining how sentiment may exert uneven influences depending on market conditions and economic structure, particularly given Saudi Arabia's reliance on oil revenues. Prior research predominantly focused on aggregate markets without capturing localised economic factors that might shape sentiment more acutely. Moreover, while much attention has been directed toward equity markets, sentiment in real estate has not been thoroughly explored despite its susceptibility to speculative behaviour. Wang and and Hui (2017), for example, investigated the role of investor sentiment in Hong Kong's housing market, employing a composite index of economic and financial indicators.

Furthermore, many earlier studies assumed linearity in macroeconomic relationships, despite increasing evidence to the contrary. Öcal and Osborn (2000) and Cross (1995) observed that economic variables such as unemployment often respond asymmetrically to positive and negative shocks. Recognising these non-linear patterns, the current study adopts a similar perspective to evaluate asymmetric effects of investor sentiment on both equity and housing markets. (Chau et al.,2016) also found that irrational investor sentiment in commercial real estate can generate long-term repercussions across financial markets, with notable effects estate and equity returns.

Despite the rising interest in behavioural finance, the real estate literature has largely underemphasised the role of psychological factors. Most existing models continue to rely on the assumption of rational behaviour, which does not adequately account for the volatility observed in real estate markets. Hence, this study seeks to investigate how investor sentiment influences housing returns, with a particular focus on the Saudi market. Most empirical work has concentrated on stock markets and emphasised the relevance of sentiment for understanding risk and return. In the Saudi context, although studies have analysed the TASI using various sentiment indicators, the real estate sector has received scant attention. Moreover, despite investor sentiment being a pivotal factor in market behaviour, no universally accepted measure for it has been established.

Recently, the influence of macroeconomic variables such as oil prices, exchange rates, and financial uncertainty has attracted increasing scholarly interest. For instance, Gong et al.,2022) examined the asymmetric impact of exchange rates on Vietnam's trade

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flows, while Ashraf (2020) explored similar asymmetries in fiscal policy outcomes. Hammoudeh & Nguyen.,2016) analysed the effect of US economic uncertainty on the Dow Jones Index, and Liu et al.,2022) studied asymmetries in financial market dynamics. Against this backdrop, the present study contributes to the literature by investigating the asymmetric role of investor sentiment in shaping the performance of equity and real estate markets in Saudi Arabia.

METHODOLOGY

Conducting sentiment analysis presents greater challenges than volatility analysis. As noted by Baker and Wurgler (2007), there remains no universally accepted metric for measuring investor sentiment. A considerable body of research has relied on proxies to approximate sentiment within financial markets (Baker & Wurgler, 2006; Rupande et al., 2019). The use of proxies is appealing due to their ease of identification, and their real-time observability offers insight into prevailing bullish or bearish attitudes among market participants. However, these proxies are inherently imperfect. The rationale underpinning them is often debated, as they tend to encompass both emotional and non-emotional elements, making their theoretical foundation contentious (Rupande et al., 2019).

The extensive use of diverse sentiment proxies in existing literature underscores the absence of a consistent, comprehensive, and dependable conceptualisation of investor sentiment (Baker & Wurgler, 2006). To address this complexity, the present study adopts the Consumer Confidence Index (CCI) as a surrogate for investor sentiment across different sectors. The CCI data are derived from the OECD principal economic statistics database. Furthermore, stock price movements in both developed and emerging markets are influenced by a complex array of domestic and international financial, economic, and socio-political factors. To incorporate the effects of such local and global informational determinants, this study employs a multivariate framework. In addition, this study extends beyond the conventional linear or symmetric ARDL model by employing a nonlinear or asymmetric ARDL framework, as proposed by Tita and Opperman (2022). In essence, the core independent variable—namely, the sentiment index—is decomposed into its positive and negative components, thereby enabling an evaluation of the distinct effects of increasing versus decreasing sentiment. This decomposition follows the nonlinear modelling approach developed by Shin et al. (2014), in which the sentiment variable (SenT) is disaggregated to capture potential asymmetries in its impact.

$$SenT_t^+ = \textstyle\sum_{j=1}^{t} \Delta SenT_j^+ = \sum_{j=1}^{t} \max(\Delta SenT_j, 0) \quad (1)$$

$$SenT_t^+ = \sum_{j=1}^{t} \Delta SenT_j^+ = \sum_{j=1}^{t} \max(\Delta SenT_j, 0)$$

$$SenT_t^- = \sum_{j=1}^{t} \Delta SenT_j^- = \sum_{j=1}^{t} \min(\Delta SenT_j, 0) \quad (2)$$

A growing body of research has decomposed realised variance into positive and negative return variances to improve volatility forecasting (Patton & Sheppard, 2015), explain asset return variations (Zouaou et al.,2011), and analyse asymmetric volatility across markets (Baruník et al., 2016). Applying this method using RSt +, provides a clearer understanding of price dynamics in the Saudi housing market.

In mathematical terms, variables are considered cointegrated when they share a stationary linear combination or exhibit a long-run equilibrium relationship. Traditional approaches for assessing cointegration include the Engle-Granger and Johansen methods. Nevertheless, both the maximum-likelihood Johansen technique and the two-step residual-based Engle-Granger method may lead to biased outcomes when examining long-term associations among variables that are integrated at levels I(0) or I(1) (Naik, 2013). To address these limitations, Shin et al. (2014) introduced the ARDL model, which combines DL and AR terms (Mokoena & Nomlala.,2021). The ARDL(1,1) form is widely used to model variable relationships in time series analysis (Rim & Zha.,2025).

$$Yt = \alpha 0 + \alpha 1 \cdot Yt{-}1 + \beta 0 \cdot Xt + \beta 1 \cdot Xt{-}1 + \varepsilon t. \quad (3)$$

Here, ARDL (1,1) denotes that both the dependent and independent variables are included with one lag. Under this specification, the regression coefficient of X in the long-run equation is defined as follows:

$$k = \beta 0{+}\beta 1/1{-}\alpha 1. \quad (4)$$

The ARDL-based ECM in its basic form, ARDL (1,1), is specified as follows:

$$\Delta Yt = \alpha 0 + (\alpha 1 - 1) \cdot (Yt{-}1 - k \cdot Xt{-}1) + \beta 0 \cdot \Delta Xt{-}1 + \varepsilon t. \quad (5)$$

The ARDL model is often stated as $ARDL\ (p0, p1, p2, p3 \ldots, pn)$ for a single dependent variable (Y) and a selection of independent variables $X1$, $X2$, …, Xn. For $ARDL$ ($p0$, $p1$, $p2$, $p3$, …, pn), the formula is:

$$Yt = \alpha. + \sum (\beta 0{,}i \cdot Yt{-}i) + \sum (\beta 1{,}j\ X1{,}t{-}j) + \sum (\beta 2{,}k \cdot X2{,}t{-}k) + \sum (\beta 3{,}t \cdot X3{,}t{-}l) + \\ + (\beta n{,}m \cdot Xn{,}t{-}m) + \varepsilon t. \quad (6)$$

The ARDL model begins with a testing procedure to identify the presence of cointegration among the variables (P H, H., & Rishad.,2020) The structure below presents the UECM form of the ARDL framework:

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$$\Delta Yt = \alpha + \sum (\beta 0,i \cdot \Delta Yt{-}i) + \sum (\beta 1,j \cdot \Delta X1,t{-}j) + \sum (\beta 2,k \cdot \Delta X2,t{-}k) + \sum (\beta 3,t \cdot \Delta X3,t{-}l) + \ldots + \sum (\beta n,m \cdot \Delta Xn,t{-}m) + \lambda 0 \cdot Yt{-}1 + \lambda 1 \cdot X1,t{-}1 + \lambda 2 \cdot X2,t{-}1 + \lambda 3 \cdot X3,t{-}1 + \ldots + \lambda n \cdot Xn,t{-}1 + \varepsilon t \,. \quad (7)$$

The NARDL model extends the ARDL framework to effectively capture asymmetric relationships between variables. Asymmetry, in this context, indicates that the dependent variable may respond dissimilarly to increases and decreases in the explanatory variables. Owing to its complexity, the NARDL model is particularly suitable for modelling our dependent variable (W).

RESULTS

Data Analysis

The descriptive statistics for the variables employed in this study are presented following a natural logarithm (ln) transformation and winsorisation at the 5th and 95th percentiles. Winsorisation is implemented to balance data robustness with integrity, enhancing the clarity and reliability of statistical inferences. Table 1 summarises the descriptive statistics for all variables used. Among these, Real Estate Primary Trading Volume records the lowest mean value (44.94475), whereas Real Estate Primary Trading Value exhibits the highest average (7583.090). These findings imply that the dataset reflects substantial market influence, potentially attributable to elevated transaction costs arising from opportunistic behaviour, data asymmetries, and growing investor uncertainty. The statistically significant outcome of the Jarque-Bera test confirms that the residuals do not follow a normal distribution. Under such conditions, traditional linear regression models become inappropriate due to their reliance on the assumption of normally distributed errors. In contrast, non-linear models are more suitable. Specifically, the NARDL model is well-suited in this context, as it accommodates non-linear dynamics, making it an appropriate approach when confronted with non-normality in the data, as indicated by the Jarque-Bera statistic.

Table 1: Descriptions Statistics

Mean	44.94475	7583.090	5467.590	71.91681	74.48106	1437955.0
Median	52.00000	7249.285	5392.050	68.68500	70.27500	1588020.0
Maximum	78.72000	11704.14	9012.440	117.7900	124.9300	1962842.0
Minimum	10.00000	4384.590	2771.620	21.04000	23.34000	793118.0
Std.Dev	18.08994	1498.992	1123.499	23.95910	25.64974	342368.7
Skewness	-0.505765	0.671386	0.477212	0.214219	0.300663	-0.490165
Kurtosis	2.689104	3.200066	3.543528	1.868662	1.896235	2.047353
Jarque-Bera	7.465661	12.28707	8.042333	9.756569	10.53260	12.45722
P-Value	0.023925	0.002147	0.017932	0.007610	0.00563	0.001972

A composite index of investor sentiment is developed through the application of PCA, a statistical technique used to reduce the dimensionality of datasets while retaining the

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maximum possible variance.

The construction of investor sentiment through PCA involves the aggregation of multiple variables that influence market sentiment into a single representative measure. As noted by Shin et al. (2014), this method enables the identification of underlying sentiment patterns by examining various indicators that collectively shape investor outlook in financial markets.

NARDL Results

Table 2 presents various statistical indicators that reflect the model's strong overall goodness of fit. The R-squared value of 0.9977 indicates that approximately 99.77% of the variation in LNW is accounted for by the model, suggesting a high level of predictive accuracy. The results pertain to the Nonlinear Autoregressive framework applied to real estate market returns (LNW) and several explanatory variables within the Saudi Arabian context. These findings uncover complex linear and nonlinear relationships. The autoregressive structure of LNW plays a critical role in the model's explanatory power. Notably, the first, third, and fourth lags exhibit statistically significant coefficients (0.8057, 0.5941, and -0.5241, respectively). The positive coefficients for the first and third lags suggest that past returns exert a favourable influence on current returns, while the negative coefficient for the fourth lag reflects a reverse effect at that specific temporal interval.

Table 2: NARDL Model (W) Short -Run

Variable	Coefficient	Std. Error	T-Statistic	Prob.*
LNW(-1)	0.806	0.070	11.59	0.000
LNW(-2)	-0.008	0.083	-0.09	0.927
LNW(-3)	0.594	0.083	7.17	0.000
LNW(-4)	-0.524	0.066	-7.00	0.000
LNR@CUMDP	-0.008	0.007	-1.21	0.230
LNR@CUMDN	0.017	0.008	2.25	0.026
C	0.4363	0.222	1.97	0.051
R	0.99			
R^2	0.99			
S.E.	0.004			
Sum	0.003			
Log Likelihood	665.9			
F-Statistic	5984.4			
Mean	4.51			
S.D.	0.09			
Akaike	-7.93			

Moreover, the analysis highlights the asymmetric effect of investor sentiment (LNR) on real estate returns. This asymmetry is evident in the differentiated significance of sentiment changes: while the coefficient for positive changes in sentiment (LNR@CUMDP = -0.0079, $p > 0.05$) is statistically insignificant, the coefficient for negative changes (LNR@CUMDN = 0.0172, $p < 0.05$) is both significant and positive.

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These results indicate that negative shifts in investor sentiment are associated with higher real estate returns, whereas positive changes do not exert a meaningful influence. This differential impact provides new insights into the functioning of the Saudi real estate market, suggesting that it responds more acutely to negative sentiment. The differential response to sentiment dynamics—particularly the insignificant impact of positive sentiment changes contrasted with the statistically significant effect of negative sentiment—demonstrates that investor reactions are not uniform. These findings underscore the market's sensitivity to adverse sentiment, further validating the use of asymmetric modelling techniques in capturing nuanced investor behaviour.

As shown in Table 3, a notable observation is the coefficient of the Cointegrating Equation (CointEq(-1)), which is -0.1320 for the error correction term. The associated p-value, which is highly significant (approximately 0.0000), confirms the existence of a long-run equilibrium relationship among the variables.

Table 3: NARDL Error Correction Regression for (W)

Variable	Coefficient	Std. Error	T-Statistic	Prob.
D(LNW(-1))	-0.0623	0.0584	-1.0673	0.2875
D(LNW(-2))	-0.0699	0.0598	-1.1695	0.2440
D(LNW(-3))	0.5241	0.0606	8.6481	0.0000
D(LNE)	0.0015	0.0126	0.1233	0.9020
CointEq(-1)*	-0.1320	0.0261	-5.0551	0.0000
R	0.4414	Mean		-0.0012
R^2	0.4274	S.D		0.0057
S.E.	0.0043	Akaike		-8.0121
Sum	0.0030	Schwarz		-7.9179
Log Likelihood	665.9956			

This negative and statistically significant coefficient indicates that around 13.20% of the disequilibrium in the dependent variable is corrected in each time period, thereby restoring the system towards its long-term equilibrium path.

The coefficients in the Table 4 show how the log of Real Estate Market Return (LNSMR) is related to a number of important economic variables over the long term using the NARDL model:

Positive Dynamic (LNR@CUMDP): It has a t-statistic of -1.2848 (p-value = 0.2008) and a coefficient of -0.0601, indicating a weak and statistically insignificant negative association with LNSMR under positive market sentiment.

LNR@CUMDN: When sentiment is negative, the relationship becomes positive, with a coefficient of 0.1306 and a t-statistic of 2.8982 (p-value < 0.01), highlighting the significant influence of negative sentiment on real estate returns.

Indicator of Industrial Production (LNE): A coefficient of -0.1369 and a t-statistic of -1.7780 (p-value < 0.1) imply that higher industrial production correlates with a

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decline in real estate market returns.

Constant (C): The constant term is 3.3057, with a t-statistic of 1.9084 (p-value < 0.1), capturing the impact of unobserved or omitted variables.

Table 4: NARDL Long- Run Regression for (W)

Variable	Coefficient	Std. Error	T-Statistic	Prob.
C	0.436	0.22	1.97	0.05
LNW(-1)*	-0.132	0.034	-3.86	0.00
LNR@CUMDP**	-0.008	0.007	-1.21	0.22
LNR@CUMDN**	0.017	0.008	2.25	0.02
LNMS**	0.028	0.010	2.77	0.00
LNE(-1)	-0.018	0.009	-2.01	0.04
D(LNW(-1))	-0.062	0.066	-0.95	0.34
D(LNW(-2))	-0.070	0.067	-1.05	0.29
D(LNW(-3))	0.5241	0.0657	7.97	0.00
D(LNE)	0.0015	0.0141	0.1102	0.91

The Bound testing approach, shown in Table 5, is crucial for confirming a long-run equilibrium among variables. It suits the NARDL framework, which allows for differing integration orders among variables. In the present case, the F-statistic obtained from the Bound test is 3.0545. To interpret this outcome, reference is made to the critical value bounds established for different significance thresholds, with specific attention to asymptotic values appropriate for a sample size of 165 observations. If the F-statistic exceeds both the lower (1.99) and upper (2.94) bounds, a long-run relationship is confirmed. In this case, the F-statistic surpasses the upper bound at the 10% level, indicating cointegration and justifying model estimation.

Table 5: NARDL Bound Test for (W)

Bounds		Null Hypothesis		
	Value	**Sig.**	**I(0)**	**I(1)**
n=1000				
F	3.0545	10%	1.99	2.94
K		5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Sample Size	165	n=80		
		10%	2.088	3.103
		5%	2.431	3.518
		1%	3.173	4.485

CONCLUSION

This study examined the asymmetric effects of investor sentiment on housing returns in Saudi Arabia. Unlike findings in other markets, sentiment was found to have limited influence, likely due to substantial government intervention through subsidies and housing distribution. These measures appear to dampen sentiment-driven fluctuations, reinforcing a self-perpetuating return pattern in the short term. The findings reveal distinct market dynamics, with negative sentiment having a stronger effect than positive sentiment, reflecting behavioural tendencies where losses weigh more heavily than gains. However, any deviations from fundamentals are corrected over time, possibly due to state intervention mitigating supply constraints during downturns. Overall, the Saudi real estate market demonstrates resilience to sentiment shocks, shaped by institutional and policy frameworks. Future research should explore these institutional roles further and apply the model to other datasets, such as Tadawul's closing prices or insurance-related data, to extend understanding of market behaviour.

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