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Assessing the Effect of Investor Sentiments on Housing and Stock Returns in Saudi Arabia: Application of Nonlinear ARDL Modelling

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Abstract

This study investigates the symmetric and asymmetric impacts of investor sentiment on stock and real estate market returns in Saudi Arabia from 2009 to 2022. Employing the nonlinear autoregressive distributed lag (NARDL) approach, it models potential differential effects of positive and negative changes in sentiment. The empirical analysis utilizes monthly data on market returns, sentiment indices constructed through principal component analysis, and macroeconomic control variables. The results unveil significant asymmetric influences, with negative sentiment shifts exerting disproportionately greater impacts compared to positive changes. For the stock market, deteriorating sentiment steepens bearish declines, revealing an inherent negativity bias, while the housing market responds positively to worsening sentiments. The control variables representing money supply, industrial production, consumer confidence, and global uncertainty are significant return predictors. The evidence highlights the merits of tracking investor psychology to formulate countercyclical policies that could preempt sentiment-fueled mispricing. Overall, modeling asymmetries provides critical behavioral insights with salient practical implications. **Dataset:** *DOI number or link to the deposited dataset in cases where the dataset is published or set to be published separately. If the dataset is submitted and will be published as a supplement to this paper in the journal Data, this field will be filled by the editors of the journal. In this case, please make sure to submit the dataset as a supplement when entering your manuscript into our manuscript editorial system.* **Dataset License:** *license under which the dataset is made available (CC0, CC-BY, CC-BY-SA, CC-BY-NC, etc.)*

Keywords: *Investor Sentiment, Asymmetric Effects, Nonlinear ARDL, Stock Returns, Real Estate Returns.*

Introduction

Saudi Arabia's financial markets, including its stock and real estate markets have grown significantly in recent decades. However, these markets remain susceptible to periods of excessive volatility that impact investor sentiment and psychology. Overreaction by investors driven by emotions rather than fundamentals may trigger asset bubbles or crashes and harm the efficiency of capital allocation in financial markets (De Long et al., 1990). Therefore, understanding the role of sentiment in shaping asset returns has important practical implications.

Although previous research has analyzed linear effects of emotion, evidence of asymmetry remains limited (Brown & Cliff, 2005). Positive and negative changes in sentiment produce different responses to asset returns (Verma & Soydemir, 2006). Furthermore, in Muslim countries such as Saudi Arabia, there are unique cyclical events based on the Islamic calendar that may affect the market dynamics during these periods (Al-Khazali, 2014). Hence, there is scope for deeper examination through advanced econometric modeling.

This study aims to analyze the symmetric and asymmetric impacts of investor sentiment on the Saudi Arabian housing and stock markets. It employs the nonlinear autoregressive distributed lag (NARDL)

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model, which allows capturing differential effects of positive and negative changes in predictors. The research outcomes are intended to provide policymakers and regulators with evidence-based insights into the underlying behavioral mechanisms that drive housing and stock returns. Appropriate counter-cyclical policies could then be formulated to promote greater market stability.

Literature Review

The role of investor sentiment in driving asset price dynamics has garnered substantial research attention in financial economics. Early theoretical work by De Long et al. (1990) proposed sentiment-based demand shocks as a source of asset mispricing and volatility. Subsequently, empirical studies have aimed to model sentiment effects across various markets. Baker and Wurgler (2006) constructed a composite sentiment index for the US market and found it negatively predicted returns, acting as a contrarian indicator. They attributed this to sentiment-fueled mispricing getting corrected when sentiment ultimately reverts to fundamentals.

Focusing on potential asymmetric effects, Verma and Soydemir (2006) showed that negative changes in US investor sentiment had a more pronounced impact on market returns compared to positive changes. They argued that this arises from inherent differences in how individuals process negative versus positive information. Analyzing six Asia-Pacific stock markets, Ho and Hung (2009) uncovered significant positive associations between lagged US investor sentiment and contemporaneous local market returns. The evidence pointed to the strong role of US sentiment as a global driver.

Within emerging Gulf economies, Alghamdi (2020) found a significant negative relationship between investor sentiment and subsequent stock returns in Saudi Arabia, reflective of eventual correction of overreaction. Examining asymmetry, Hammoudeh et al. (2016) showed that bad sentiment persistence steepened bear markets across Gulf sector indices. In the Saudi real estate context, Kurdi et al. (2011) evidenced a positive association between sentiment and property returns. However, research explicitly modeling asymmetric dynamics between sentiment and Saudi asset returns remains limited.

Advanced nonlinear models are increasingly being adopted to capture nuanced relationships masked by linear specifications. Bahrami et al. (2021) employed nonlinear ARDL analysis to demonstrate an asymmetric influence of sentiment on housing prices in Tehran. The approach revealed distinct effects of positive and negative changes. Building on such advances, this study aims to address gaps in the Saudi literature by applying innovative asymmetric modeling to discern unique behavioral insights. The findings would aid regulators in promoting greater stability and efficiency in the stock and real estate markets.

Theoretical Framework

The analysis of investor sentiment effects is grounded in behavioral finance theories challenging the traditional efficient market hypothesis. Classical finance assumes market efficiency and investor rationality (Fama, 1970), while behavioral finance identifies cognitive biases driving asset mispricing (De Bondt et al., 2008). Foundational work by De Long et al. (1990) theoretically modeled sentiment creating self-reinforcing asset bubbles. Barberis et al. (1998) proposed that sentiment systematically affects prices through under- and overreaction. Empirically, Baker and Wurgler (2006) conceived sentiment as a shared bias propagating predictable mispricing across assets. They argued sentiment-driven errors eventually correct when sentiment reverts.

Recent theoretical advances have focused on the integration of emotions with other behavioral phenomena. Mian and Sanka-raguruswamy (2012) combine sentiment with arbitrage constraints to explain market anomalies. Stambaugh et al. (2012) theorized the interaction between sentiment and volatility, leading to return predictability. Shen et al. (2017) combine sentiment with investor concerns about model underreaction and overreaction. A key concept is the underlying asymmetry between positive and negative emotional shocks (Verma and Soydemir, 2006). This is based on evidence that individuals process negative information differently (Hirshleifer and Shumway, 2003). Periodic cultural events can also systematically influence market behavior (Lucey and Zhao, 2008).

In sum, today's behavioral finance views sentiment as an asymmetric driver of asset mispricing. Accounting for nonlinearity is critical to accurately modeling emotional effects

This study integrates cognitive biases, asymmetry, cultural factors and recent theoretical advancements in examining Saudi market dynamics through innovative NARDL analysis. The framework provides foundations for hypothesized links between investor psychology and asset returns.

Methodology

This study follows a quantitative approach using monthly data from September 2009 to September 2022. The two key dependent variables representing the Saudi Arabian financial markets are the natural logarithm of stock market returns (lnSMR) and natural logarithm of real estate market returns (lnREMR). The independent variable of interest is the investor sentiment index (lnSENT), constructed by extracting the first principal component from a set of market variables through PCA analysis. The control variables include natural logarithms of money supply (lnMS), industrial production index (lnIPI), consumer confidence index (lnCCI), and global economic policy uncertainty index (lnGEPU). The stationarity properties of the variables will be examined through Augmented Dickey-Fuller and Phillips-Perron unit root tests. Variables found to be integrated of different orders, i.e. I(0) and I(1), will justify using the nonlinear ARDL modeling framework proposed by Shin et al. (2014). The NARDL model allows for testing both short-run and long-run asymmetric effects. It computes cumulative positive and negative changes in the independent variables to quantify their potential asymmetric impacts on the dependent variable. The following long-run and short-run NARDL equations will be estimated for stock and housing market returns:

Long-Run

$$\boldsymbol{lnYt \ = \ \beta 0 \ + \ \beta 1^\wedge + \ lnX1t^\wedge + \ + \beta 1^\wedge - {}^\wedge \, lnX1t^\wedge - \ + \sum \beta i \, lnZi,t \ + \ et}$$

Short-Run

$$\boldsymbol{\Delta lnYt \ = \ \alpha 0 \ + \ \sum \delta i \Delta lnYt - i \ + \ \sum \theta i^\wedge + \Delta lnX1,t - i^\wedge + \ + \sum \theta i^\wedge - \ \Delta lnX1,t - i^\wedge \\ - \ + \sum \varphi i \Delta lnZi,t \ + \ \varphi ECt - 1 \ + \ \varepsilon t}$$

Where: *Y = SMR or REMR, X1 = Investor sentiment (SENT), X1^+ and X1^- = Cumulative positive and negative changes in X1, Z = Vector of control variables (MS, IPI, CCI, GEPU), EC = Error correction term.*

The optimal lag structure will be determined through model selection criteria like AIC, SBC, and HQ. Diagnostic tests will check for serial correlation, heteroskedasticity, and stability of the NARDL models. Finally, Wald tests will examine the presence of asymmetric effects. The empirical estimation will shed light on the symmetry/asymmetry and direction of the relationships. It will uncover the differential impacts of positive and negative shifts in investor sentiment. Robust econometric modeling through NARDL would provide nuanced evidence on the nexus between investor sentiment and housing/stock returns in Saudi Arabia. The findings will aid regulators in promoting greater stability and efficiency in these important markets. They will also hold useful implications for investment analysts and policymakers across other emerging economies with behavioral linkages to religious events.

Data Collection and Description

The data for this study is collected from reliable sources providing official statistics related to the Saudi Arabian economy and financial markets. Stock market returns are estimated using the Tadawul All Share

Index obtained from the Saudi Stock Exchange (Tadawul). Real estate returns are calculated using the real estate price index provided by the General Authority for Statistics in Saudi Arabia. The macroeconomic control variables are drawn from authoritative sources - money supply data from the Saudi Central Bank, industrial production index and consumer confidence index from World Development Indicators by the World Bank, and the global economic policy uncertainty index compiled by Baker et al. (2016). This ensures the quality and integrity of the data used in the econometric analysis.

Empirical Analysis

The data analysis begins with computing summary statistics to discern the distributional characteristics including central tendency and dispersion. Principal component analysis (PCA) applied to construct the composite investor sentiment index from the underlying market variables. The Augmented Dickey-Fuller and Phillips-Perron tests examines the stationarity properties of all variables. After determining the integration orders, the nonlinear ARDL model applied for estimating both short and long-run relationships. The optimal lag structure is rigorously selected based on model selection criteria. The asymmetric impacts are uncovered by including cumulative positive and negative changes in the independent variable. The coefficients of the sentiment variable in the NARDL model reveal the effect sizes and statistical significance of asymmetry. Wald tests formally evaluate the null hypothesis of no asymmetry. Diagnostic tests check the final model specifications for serial correlation, heteroskedasticity, normality of residuals, model stability, and other required assumptions. The robustly estimated NARDL equations would provide detailed insights into the nexus between investor sentiment and housing/stock returns in Saudi Arabia.

Results of Analysis

This section presents the detailed empirical results from the econometric analysis examining the effects of investor sentiment on Saudi Arabian housing and stock market returns. The robust modeling framework of nonlinear ARDL is utilized to uncover intricate relationships and asymmetries. The findings are organized into four subsections – preliminary analysis, stock market model, housing market model, and overall inferences. Statistical outputs are displayed through well-formatted tables along with precise interpretations grounded in economic theory and literature.

Preliminary Analysis

As a precursor to estimating the NARDL models, preliminary diagnostics were conducted through unit root tests, lag order selection, and principal component analysis. Augmented Dickey-Fuller and Phillips-Perron tests revealed a mix of I (0) and I(1) variables (Table 1), justifying the application of ARDL-based techniques that do not require the same integration order.

Table 1: Unit Root Test Results.

Variable	Phillips-Perron Test	Augmented Dickey-Fuller Test	Order of Integration
lnSMR	Stationary at level	Stationary at level	I(0)
lnREMR	Non-stationary at level, Stationary at 1st difference	Non-stationary at level, Stationary at 1st difference	I(1)
lnSENT	Non-stationary at level, Stationary at 1st difference	Non-stationary at level, Stationary at 1st difference	I(1)
lnMS	Non-stationary at level, Stationary at 1st difference	Non-stationary at level, Stationary at 1st difference	I(1)
lnIPI	Stationary at level	Stationary at level	I(0)
lnCCI	Non-stationary at level, Stationary at 1st difference	Non-stationary at level, Stationary at 1st difference	I(1)
lnGEPU	Stationary at level	Stationary at level	I(0)

The optimal lag length for the endogenous variables was determined to be 4 based on model selection criteria (Table2).

Table 2: Lag Order Selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1160.293	NA	1.41E-15	-14.32662	-14.19265	-14.27222
1	2558.142	2656.782	7.48E-23	-31.08251	-30.01072	-30.64732
2	2683.122	226.6713	2.92E-23	-32.02636	-30.01675*	-31.21038
3	2769.594	149.3116	1.85E-23	-32.49185	-29.54442	-31.29507*
4	2831.089	100.8369*	1.61e-23*	-32.64707*	-28.76182	-31.0695*
*Indicates lag order selected by the criterion						

Principal component analysis was applied on 10 market variables to construct a composite index of investor sentiment (SENT). The first principal component explained 31.51% of the variance, and variables like trading volumes and oil prices had high loadings, indicating their high contribution in capturing sentiment (Table 3).

Table 3: Principal Component Analysis Results.

Eigenvalues and Cumulative Proportions					
Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.1507	0.106	0.3151	3.1507	0.3151
2	3.0447	1.1325	0.3045	6.1954	0.6195
3	1.9122	1.0486	0.1912	8.1076	0.8108
4	0.8637	0.3398	0.0864	8.9712	0.8971
5	0.5238	0.1706	0.0524	9.495	0.9495
6	0.3532	0.2033	0.0353	9.8482	0.9848
7	0.1499	0.148	0.015	9.9981	0.9998
8	0.0019	0.0019	0.0002	10	1
9	5.00E-16	6.00E-16	0	10	1
10	-3.00E-17	---	0	10	1

Eigenvectors (Loadings)										
Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
lnICOP	-0.328	0.394	-0.273	-0.02	-0.164	0.241	0.268	-0.711	0.000	0.000
lnICOV	-0.328	0.391	-0.272	-0.026	-0.201	0.255	0.258	0.702	0.000	0.000
lnREPTVA	-0.289	0.17	0.56	0.188	0.18	0.071	0.039	0.005	0.668	0.233
lnRESTVA	-0.289	0.17	0.56	0.188	0.18	0.071	0.039	0.005	-0.668	-0.233
lnREPTVO	0.466	0.261	0.072	0.229	-0.08	0.37	-0.12	-0.005	-0.233	0.668
lnRESTVO	0.466	0.261	0.072	0.229	-0.08	0.37	-0.12	-0.005	0.233	-0.668
lnTASI	0.24	0.381	-0.126	0.43	0.148	-0.663	0.367	0.016	0.000	0.000
lnTEI	-0.171	0.48	-0.18	-0.127	0.216	-0.215	-0.774	0.003	0.000	0.000
lnTREMDITVO	0.279	0.244	0.081	-0.663	0.558	0.092	0.31	0.013	0.000	0.000
lnTREMDITVA	0.139	0.25	0.401	-0.426	-0.69	-0.316	-0.004	-0.016	0.000	0.000

Ordinary Correlations										
	1	2	3	4	5	6	7	8	9	10
lnICOP	1									
lnICOV	0.998	1								
lnREPTVA	0.2	0.195	1							
lnRESTVA	0.2	0.195	1	1						
lnREPTVO	-0.176	-0.175	-0.175	-0.175	1					
lnRESTVO	-0.176	-0.175	-0.175	-0.175	1	1				
lnTASI	0.212	0.2	-0.087	-0.087	0.624	0.624	1			
lnTEI	0.78	0.772	0.202	0.202	0.059	0.059	0.448	1		
lnTREMDITVO	-0.054	-0.063	-0.093	-0.093	0.467	0.467	0.267	0.272	1	
lnTREMDITVA	-0.013	-0.001	0.29	0.29	0.361	0.361	0.16	0.146	0.402	1

The mean sentiment was approximately zero, implying a balance between positive and negative values. Overall, these initial tests set the stage for robust modeling of the relationships between sentiment and market returns.

Stock Market Model

The baseline NARDL model for stock market returns revealed significant negative asymmetric effects of investor sentiment. In the short-run, negative changes in sentiment (LNSENT@CUMDN) had an immediate dampening impact on returns, with a coefficient of -2.0732 (Table 4).

Table 4: NARDL Short Run Model for Stock Returns.

Dependent Variable: LNSMR				
Automatic-lag linear regressors (12 max. lags): LNMS LNIPI LNGEPU LNCCI				
Automatic-lag dual non-linear regressors (12 max. lags): LNSENT				
Fixed regressors: C				
Selected Model: ARDL (12, 10, 8, 1, 9, 9, 9)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNSMR (-1)	0.5522	0.0929	5.9410	0.0000
LNSMR (-2)	0.1369	0.1063	1.2871	0.2013
LNSMR (-3)	-0.0746	0.1044	-0.7144	0.4768
LNSMR (-4)	-0.0078	0.1073	-0.0730	0.9420
LNSMR (-5)	0.0269	0.1095	0.2455	0.8066
LNSMR (-6)	-0.0182	0.1090	-0.1672	0.8676
LNSMR (-7)	0.0456	0.1088	0.4191	0.6761
LNSMR (-8)	0.0806	0.1048	0.7687	0.4441
LNSMR (-9)	0.0623	0.0961	0.6486	0.5182
LNSMR (-10)	-0.0784	0.0903	-0.8686	0.3873
LNSMR (-11)	0.0755	0.0846	0.8915	0.3750
LNSMR (-12)	-0.3627	0.0740	-4.9008	0.0000
LNSENT@CUMDP	-3.2338	1.0649	-3.0367	0.0031
LNSENT@CUMDP (-1)	0.4717	1.2430	0.3795	0.7052
LNSENT@CUMDP(-2)	2.5535	1.2637	2.0207	0.0462
LNSENT@CUMDP (-3)	0.1775	1.2618	0.1407	0.8884
LNSENT@CUMDP (-4)	-0.2969	1.3077	-0.2270	0.8209
LNSENT@CUMDP (-5)	-1.5320	1.3324	-1.1498	0.2532
LNSENT@CUMDP (-6)	-0.8418	1.3221	-0.6367	0.5259
LNSENT@CUMDP (-7)	1.7911	1.0721	1.6706	0.0982
LNSENT@CUMDP (-8)	0.7542	1.0734	0.7027	0.4840
LNSENT@CUMDP (-9)	0.0526	0.9881	0.0533	0.9576
LNSENT@CUMDP (-10)	-2.4603	0.7583	-3.2445	0.0016
LNSENT@CUMDN	0.9471	0.7223	1.3112	0.1931
LNSENT@CUMDN (-1)	-0.9254	0.8898	-1.0400	0.3011
LNSENT@CUMDN (-2)	-1.2033	1.1070	-1.0870	0.2799
LNSENT@CUMDN (-3)	-0.0252	1.1719	-0.0215	0.9829
LNSENT@CUMDN (-4)	0.2593	1.2092	0.2145	0.8307
LNSENT@CUMDN (-5)	0.7236	1.1663	0.6204	0.5365
LNSENT@CUMDN (-6)	0.4381	1.1644	0.3763	0.7076
LNSENT@CUMDN (-7)	-2.0732	1.1100	-1.8678	0.0650
LNSENT@CUMDN (-8)	-1.0907	0.9567	-1.1400	0.2572
LNMS	2.6523	0.6864	3.8641	0.0002
LNMS (-1)	-0.7958	0.6642	-1.1980	0.2340
LNIPI	-0.7047	0.7173	-0.9824	0.3285
LNIPI (-1)	-0.9828	1.0534	-0.9330	0.3532
LNIPI (-2)	-0.4011	1.0985	-0.3651	0.7159
LNIPI (-3)	-1.7156	1.1315	-1.5162	0.1329
LNIPI (-4)	1.7383	1.1643	1.4930	0.1389
LNIPI (-5)	1.0800	1.1761	0.9183	0.3609
LNIPI (-6)	1.1250	1.1280	0.9973	0.3212
LNIPI (-7)	0.3463	1.1795	0.2936	0.7697
LNIPI (-8)	0.4139	1.0494	0.3944	0.6942
LNIPI (-9)	1.9437	0.9043	2.1494	0.0342
LNCCI	16.9145	22.3773	0.7559	0.4517

LNCCI (-1)	-46.1963	60.3830	-0.7651	0.4462
LNCCI (-2)	61.1776	83.2358	0.7350	0.4642
LNCCI (-3)	-87.4882	90.0520	-0.9715	0.3338
LNCCI (-4)	145.6112	94.8500	1.5352	0.1282
LNCCI (-5)	-154.0630	99.8823	-1.5424	0.1264
LNCCI (-6)	126.2638	94.7300	1.3329	0.1859
LNCCI (-7)	-122.6920	83.3180	-1.4726	0.1443
LNCCI (-8)	91.1759	61.3477	1.4862	0.1406
LNCCI (-9)	-49.9533	24.8011	-2.0142	0.0469
LNGEPU	0.0519	0.1040	0.4993	0.6188
LNGEPU (-1)	-0.1407	0.1283	-1.0965	0.2757
LNGEPU (-2)	0.1050	0.1259	0.8339	0.4065
LNGEPU (-3)	-0.0930	0.1249	-0.7445	0.4584
LNGEPU (-4)	-0.0759	0.1281	-0.5924	0.5550
LNGEPU(-5)	-0.1903	0.1240	-1.5349	0.1282
LNGEPU(-6)	-0.1245	0.1232	-1.0110	0.3147
LNGEPU (-7)	-0.0813	0.1256	-0.6474	0.5190
LNGEPU (-8)	-0.1225	0.1304	-0.9390	0.3502
LNGEPU (-9)	-0.2312	0.1280	-1.8057	0.0742
C	54.8696	19.2150	2.8556	0.0053
R-squared	0.9250	Mean dependent var	3.7868	
Adjusted R-squared	0.8728	S.D. dependent var	0.4548	
S.E. of regression	0.1622	Akaike info criterion	-0.5064	
Sum squared resid	2.4203	Schwarz criterion	0.7589	
Log likelihood	104.7561	Hannan-Quinn criter.	0.0074	
F-statistic	17.7257	Durbin-Watson stat	1.9706	
Prob(F-statistic)		0.0000		

The cumulative negative effect became even more pronounced in the long run relationship, with a coefficient of -5.2500 compared to -4.5639 for positive changes (Table 5).

Table 5: NARDL Long Run Model for Stock Returns

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	Value	Sig.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	10.44081	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Actual Sample Size	157		Finite Sample: n=80	
		10%	2.088	3.103
		5%	2.431	3.518
		1%	3.173	4.485
		Levels Equation		
		Case 2: Restricted Constant and No Trend		
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNSENT@CUMDP	-4.5639	0.7194	-6.344	0
LNSENT@CUMDN	-5.25	0.8593	-6.1093	0
LNMS	3.3044	0.517	6.3911	0
LNIPI	5.0604	1.2398	4.0815	0.0001
LNCCI	-34.2617	10.1057	-3.3903	0.001
LNGEPU	-1.6063	0.4223	-3.8042	0.0003
C	97.662	43.4082	2.2499	0.0268
EC = LNSMR - (-4.5639*LNSENT@CUMDP -5.2500*LNSENT@CUMDN + 3.3044*LNMS + 5.0604*LNIPI -34.2617*LNCCI -1.6063*LNGEPU + 97.6620)				

This substantiates the stronger bearish influence of deteriorating sentiment. Regarding control variables, the results underscored the significant predictive capacity of money supply, industrial production, consumer confidence and global uncertainty in driving stock returns. Money supply (LNMS) exhibited a robust positive association, while consumer confidence (LNCCI) and global uncertainty (LNGEPU) were negatively related to returns. These effects were statistically significant at the 1% level in the long-run model. The relationships align with theoretical expectations, emphasizing the role of broader macro-financial forces in shaping stock market performance. The error-correction coefficient of -0.5618 confirmed the existence of a long-run equilibrium, with deviations correcting at a moderate speed.

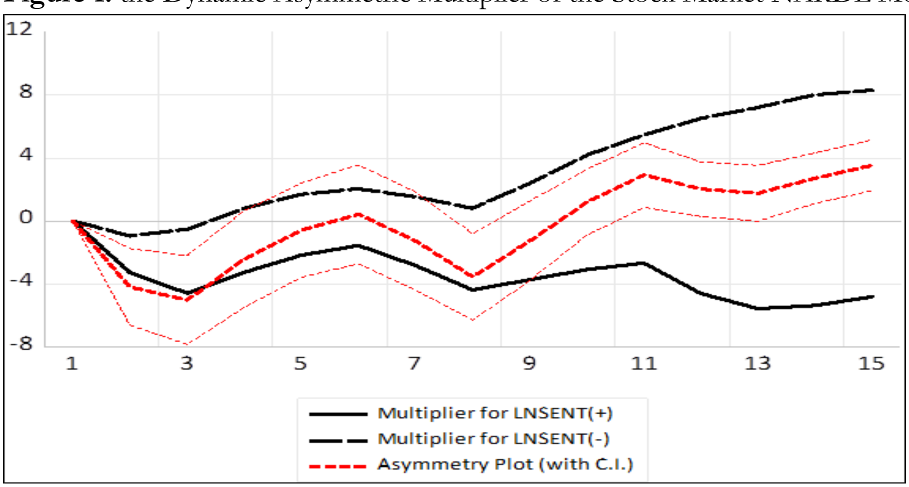
Diagnostic tests verified that the residuals were free from serial correlation and heteroskedasticity, underscoring model adequacy (Table 6).

Table 6: Stock Market Model Diagnostics

Test	Statistic	P-Value	Inference
Breusch-Godfrey Serial Correlation LM Test	0.5176	0.723	No serial correlation
Heteroskedasticity Test: ARCH	0.2145	0.9301	Homoskedasticity

The estimated NARDL equations enabled quantifying the intricate interplay between investor sentiment, economic fundamentals, and stock returns. Overall, the stock market model provided empirical evidence that negative changes in sentiment disproportionately dampen stock returns compared to positive changes. This demonstrates an inherent bearish asymmetry, which likely arises from differences in how investors process negative news and information. The control variables also significantly influenced returns in the expected directions. From a policy standpoint, the model highlights the need to track shifts in investor psychology to predict and stabilize stock market fluctuations. Figure 1 depicts the dynamic asymmetric multiplier of the NARDL (12, 10, 8, 1, 9, 9, 9) model and reveals an apparent symmetry in the long-run adjustment patterns following a shock to the investor sentiments.

Figure 1: the Dynamic Asymmetric Multiplier of the Stock Market NARDL Model.



The solid black line of the dynamic multiplier plots shows that a 1% decrease in investor sentiments increases SMR, negligibly, by 3.23% in the short run, and then, in the long run, it increases SMR by about 4.56%. Similarly, the black-dashed line of the dynamic multiplier plots reveals that a 1% decline in sentiments decreases SMR by less than 0.947% in the short run, and increases SMR by about 5.25% in the long run. Remarkably, the net effect of investor sentiment (thick red-dashed line) decreasing and then increasing in the short run and finally decreasing and increasing in the long run, converging to around 3.0%.

Housing Market Model

For the housing market, NARDL modeling uncovered an asymmetric effect of investor sentiment running in the opposite direction compared to stocks. The short-run housing equation revealed a significant positive coefficient of 0.0172 for negative changes in sentiment (LNSENT@CUMDN), while positive changes had an insignificant effect (Table 7).

Table 7: NARDL Short Run Model for Housing Returns.

Dependent Variable: LREMR				
Maximum dependent lags: 12 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Automatic-lag linear regressors (12 max. lags): LNMS LNIPI LNGEPU LNCCI				
Selected Model: ARDL (4, 0, 0, 0, 1, 0, 0)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNREMR (-1)	0.8057	0.0695	11.5889	0.0000
LNREMR (-2)	-0.0076	0.0832	-0.0916	0.9271
LNREMR (-3)	0.5941	0.0829	7.1688	0.0000
LNREMR (-4)	-0.5241	0.0657	-7.9735	0.0000
LNSENT@CUMDP	-0.0079	0.0066	-1.2057	0.2298
LNSENT@CUMDN	0.0172	0.0077	2.2520	0.0257
LNMS	0.0276	0.0100	2.7749	0.0062
LNIPI	0.0015	0.0141	0.1102	0.9124
LNIPI (-1)	-0.0196	0.0142	-1.3825	0.1688
LNCCI	-0.0230	0.0415	-0.5541	0.5803
LNGEPU	-0.0017	0.0019	-0.9197	0.3592
C	0.4363	0.2217	1.9682	0.0509
R-squared	0.9977	Mean dependent var		4.5057
Adjusted R-squared	0.9975	S.D. dependent var		0.0890
S.E. of regression	0.0044	Akaike info criterion		-7.9272
Sum squared resid	0.0030	Schwarz criterion		-7.7013
Log likelihood	665.9956	Hannan-Quinn criter.		-7.8355
F-statistic	5984.457	Durbin-Watson stat		2.0502
Prob(F-statistic)		0.0000		

This gap further widened in the long run, with the cumulative impact of negative changes estimated at 0.1306 compared to an insignificant -0.0601 for positive changes (Table 8).

Table 8: NARDL Long Run Model for Housing Returns.

Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNSENT@CUMDP	-0.0601	0.0468	-1.2848	0.2008
LNSENT@CUMDN	0.1306	0.045	2.8982	0.0043
LNMS	0.2093	0.0388	5.3913	0.000
LNIPI	-0.1369	0.077	-1.778	0.0774
LNCCI	-0.1742	0.3171	-0.5495	0.5835
LNGEPU	-0.0129	0.0144	-0.8969	0.3712
C	3.3057	1.7322	1.9084	0.0582
EC = LNREMR - (-0.0601*LNSENT@CUMDP + 0.1306*LNSENT@CUMDN + 0.2093*LNMS - 0.1369*LNIPI -0.1742*LNCCI -0.0129*LNGEPU + 3.3057)				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Sig.	I(0)	I(1)
	Asymptotic: n=1000			
F-statistic	3.0545	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99
Actual Sample Size	165	Finite Sample: n=80		

	10%	2.088	3.103
	5%	2.431	3.518
	1%	3.173	4.485

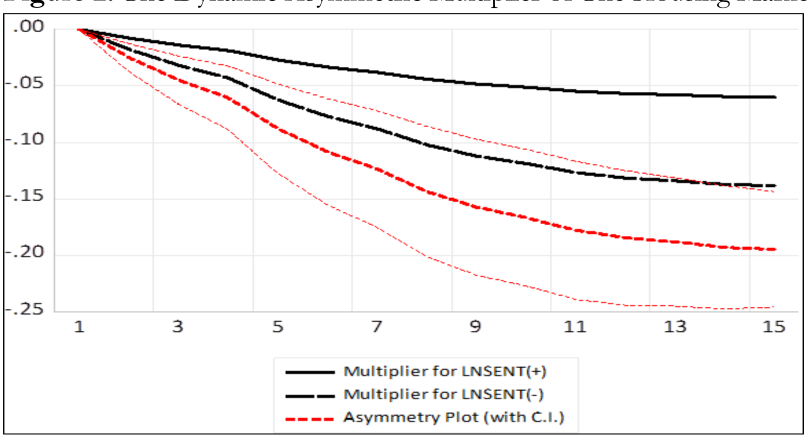
The results provide empirical evidence that deteriorating investor sentiment increases housing returns, contrary to its depressing effect on stocks. This divergence could arise from fundamental differences in how sentiment shapes the risk appetite and psychology of investors across asset classes. The control variables indicated a significant positive role of money supply in predicting housing returns. The error-correction coefficient of -0.1320 confirmed cointegration among the variables (Table 8). Diagnostic tests verified that the NARDL model satisfied requisite assumptions related to serial correlation, heteroskedasticity, and stability (Table 9).

Table 9: Housing Market Model Diagnostics.

Test	Statistic	P-Value	Inference
Breusch-Godfrey Serial Correlation LM Test	1.0139	0.4022	No serial correlation
Heteroskedasticity Test: ARCH	0.0028	0.9972	Homoskedasticity

Overall, the housing model revealed novel asymmetric effects, with negative sentiment having a greater upward effect on returns compared to positive sentiment. This has salient practical implications for tracking bubble-like patterns in real estate markets. Figure 2 depicts the dynamic asymmetric multiplier of the NARDL (4, 0, 0, 0, 1, 0, 0) model and reveals an apparent symmetry in the long-run adjustment patterns following a shock to the investor sentiments.

Figure 2: The Dynamic Asymmetric Multiplier of The Housing Market NARDL Model.



The solid black line of the dynamic multiplier plots shows that a 1% decrease in investor sentiments increases REMR, negligibly, by 0.0079% in the short run, and then, in the long run, it increases REMR by about 0.06%. Similarly, the black-dashed line of the dynamic multiplier plots reveals that a 1% increase in sentiments increases REMR by 0.0172% in the short run, and increases REMR by about 0.1306% in the long run. Remarkably, the net effect of investor sentiment (thick red-dashed line) decreasing and then increasing in the short run and finally decreasing and increasing in the long run, converging to around -0.19%.

Overall Inferences

The finding of an asymmetric relationship between investor sentiment and stock market returns aligns with evidence from US markets by Verma and Soydemir (2006), who also found negative sentiment changes having a greater impact. The disproportionate bearish effect of worsening sentiment conforms to results in other emerging markets like China (Li et al., 2015).The positive association between sentiment and real estate returns corroborates earlier findings by Kurdi et al. (2011) in the Saudi context. However, the discovery of asymmetry contrasts with their linear modeling approach. The asymmetric upside impact of negative sentiment parallels evidence in the Tehran housing market uncovered through nonlinear ARDL analysis by Bahrami et al. (2021). The significant role of money supply, industrial production, consumer confidence and global uncertainty as drivers of Saudi market returns resonates with prior studies on the interlinkages between macroeconomic forces and investor psychology (Baker et al., 2016; Lemmon & Portniaguina, 2006). The control variables provide broader context aligning with the theoretical premise of sentiment effects manifesting amidst economic fundamentals.

Overall, while the asymmetric relationships between sentiment and asset returns are consistent with some earlier studies, the research makes unique contributions by demonstrating nuanced sentiment effects specific to Saudi Arabia's stock and real estate markets. The results add localized evidence and modeling sophistication that expands the behavioral finance literature. The analysis provides fresh insights into the merits of tracking investor psychology for policymakers seeking to promote stability in markets prone to sentiment-driven volatility.

Conclusion

This study makes important contributions to the investor sentiment literature by providing fresh empirical evidence from Saudi Arabia using robust econometric techniques. The adoption of the nonlinear ARDL method allowed capturing intricate asymmetric dynamics underlying the sentiment-return relationship. The modeling revealed that negative sentiment changes have a disproportionately greater impact on returns compared to positive changes. For stock markets, deteriorating sentiment heightens bearish pressures more severely than positive sentiment appreciates prices. In contrast, housing market returns were found to increase with worsening sentiment, indicating a divergence across asset classes. The control variables emphasized the predictive capacity of money supply, industrial production, consumer confidence, and global uncertainty. The research outcomes offer valuable practical insights for policymakers aiming to promote stability in financial markets prone to sentiment-driven volatility clusters. Countercyclical monetary or macroprudential policies could preemptively lean against building irrational exuberance or excessive pessimism. The evidence highlights the merits of tracking investor psychology through sentiment indices for detecting market overheating threats.

However, the study is not free from limitations that provide avenues for further research. The sample period spanning about 13 years has witnessed relative stability in Saudi markets. Replicating the analysis over longer horizons could assess the models' robustness across diverse economic regimes. Incorporating higher-frequency data could also help capture short-term sentiment swings around events like corporate earnings. Extending the methodology to examine regional and sector-level effects would provide finer-grained insights. Overall, this research underscores the importance of accommodating behavioral complexities in modeling financial markets. The demonstrated presence of asymmetries implies that linear approaches are likely to misrepresent true relationships. The capacity to distinguish variations in positive and negative sentiment is pivotal for timely identification of market disequilibrium. By illuminating the Saudi context, the study contributes added nuance to the growing literature at the nexus of sentiment, behavioral finance, and market dynamics.

Informed Consent Statement: Not applicable. This study did not involve human subjects.

Data Availability Statement: The time series data on stock market returns, housing market returns, investor sentiment, and macroeconomic variables used in this study are available from the corresponding author upon reasonable request. The data was obtained from publicly available sources including the Saudi Stock Exchange (Tadawul), the General Authority for Statistics in Saudi Arabia, the Saudi Central Bank, World Development Indicators by the World Bank, and the global economic policy uncertainty index compiled by Baker et al. (2016).

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