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Investor Sentiment Dynamics and Returns in Stock Market in Saudi Arabia

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Abstract: The study will utilize the Autoregressive Distributed (ARDL) models to cover the necessary samples from September 2009 to 2022, ensuring a reliable conclusion. The stock exchange in Saudi Arabia provides price and supply data for stock ; data on money creation (F_1). The findings shed light on the complex interplay of factors influencing market dynamics in Saudi Arabia. A multitude of factors, including "investor sentiment," "economic indicators," and global economic policy uncertainty, influence the Saudi stock markets. Understanding the symmetric and asymmetric effects of these factors on market returns is crucial for investors, policymakers, and stakeholders. Previous studies have highlighted the importance of investor sentiment in predicting market movements, yet the specific dynamics in the Saudi market, characterized by its unique economic structure and investor base, warrant further investigation. A comprehensive set of pre- and post-estimation, and Johansen integration , Principal Component (PCA) constructs the sentiment index from a range of economic, financial, and global variables. The results indicate that specifically, the sentiment from two periods ago positively influences current. Additionally, money supply and consumer confidence index have varying degrees of influence on market returns, with specific lagged effects observed for the industrial production index. The study pioneers in identifying the asymmetric influence of investor sentiment on real estate returns. While most existing theories assume a symmetric response to positive and negative sentiment shifts, this study introduces a new layer of complexity to market behavior theory. Finally, the dynamic asymmetric multiplier's long-term symmetry adds another layer to our understanding of market efficiency and adaptability. While the market may show asymmetric responses in the short run, the eventual symmetry in long-term adjustment patterns implies a more complex adaptive system than previously assumed. Studies exploring adaptive market hypotheses and the effectiveness of long-term market equilibration processes can benefit from this novel finding. The findings underscore the complex, ARDL relationships between market returns and economic indicators in the Saudi market.

Keywords: ARDL Model, Saudi Arabia, Investor Sentiment, Stock Returns, Real Estate Returns

1 Introduction

Investor sentiment plays a vital role in stock market performance. It refers to the overall attitude, mood, and opinion of investors toward a specific stock or the market as a whole. While fundamental analysis and economic indicators provide valuable insights, investor sentiment often has a significant impact on short-term market movements. By staying informed and monitoring market sentiment, investors can make decisions that are more confident and better equipped to navigate a complex stock market.

A variety of factors, including market news, company performance, and general economic conditions, influence investor sentiment. Positive sentiment can lead to increased buying activity and push up stock prices, while negative sentiment can lead to selling pressure and lower prices [1].The collective sentiment of investors can add momentum to the market, influencing trading volume and price trends.

Following [2] approach, the current study constructed the market-based measure of the investor sentiment index from a group of relevant economic and financial variables. However, the inclusion of sentiment proxies is different from the [2] study because the Saudi Arabian

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market is significantly distinct from the US market. The Saudi Arabian market has few attributes that differentiate it significantly from other markets. First, Saudi Arabia is the biggest oil exporter, and it generates around 50% of its GDP from oil revenues. Second, the Saudi Arabian market, particularly the stock market, is mostly dealing in Islamic finance products such as Sukuk. Third, individual investors rather than institutional investors dominate the Saudi Arabian market. The role of investor sentiments becomes more evident when individual investors dominate the market rather than institutional investors [3]. Therefore, the inclusion of sentiment proxies is based on the findings of past studies and practical industry experience. Oil price volatility and global economic policy uncertainty are the two most important new proxies that were added to the sentiment index. Recent research suggests that these factors have a big effect on the returns on financial markets. The subsequent subsections describe these two proxies and summarize relevant literature to justify their importance in the sentiment index construction for Saudi Arabia's stock and housing market returns.

This study has examined how investor sentiments can influence stock returns and valuation, with certain stocks being more sensitive to sentiment shifts based on factors like real estate proxies, stock market proxies, and energy market proxies. Challenges arise from the coexistence of rationality and emotions in financial markets [4]. We can see how investor sentiment affects stock market returns by ”integrating these components” (figura1), which shows how sentiment can affect investment choices across different types of assets [2]. Moreover, review research has demonstrated the effect of emotions on investment outputs with evidence suggesting that emotional influence could lead to irrational investment decisions & lower returns.

2 Literature Review

This study aims to explore the relationship between investor sentiment dynamics and stock market returns in Saudi Arabia. While there is a considerable amount of research on the impact of stock prices, previous research suggests that asset prices, including both stock prices and house prices, are more likely to have risen significantly where short-run interest rates decline to levels suggested by the Taylor Rule [5].

Several studies in the field of equity markets have attempted to explain the variation in stock prices and returns. Many studies in traditional finance have developed based on market efficiency and the efficient market hypothesis, as well as the fundamentals of rational expectations. However, these theories fail to explain many financial market anomalies, including those in the stock market [6]. As a result, subsequent studies examined the relationship between market sentiments and stock market returns [2,11]. However, most of these studies examined the aggregate (symmetric) sentiment effect on stock returns, while the current study tests the disaggregated (asymmetric) effect of market sentiment on stock returns. Second, the current study is testing the role of market sentiments in the Islamic stock market of Saudi Arabia rather than the conventional stock markets, which was the focus of past studies. Finally, this study is making a new sentiment index by using factor analysis-principal component analysis (FA-PCA) to combine country-specific economic, financial, and global variables (for example, oil prices) with global variables. The subsequent discussion evaluates and summarizes relevant past studies to identify the literature gap.

In the given literature, the study of [7] examined the association between investor sentiments and the S&P 500 trading volume, Figure 2. The study included two sentiment indicators, overconfidence and net optimism-pessimism, in the investor sentiments analysis. The authors asserted that the fluctuations in the rate of return over time offer valuable insights, which in turn alter the expectations and beliefs of investors. The investors feel pessimistic when they have prior experience of loss (hesitant to take risks, risk-averse) and feel optimistic when they realize prior gains. Based on their feelings, they predict future returns, and these investors respond in accordance with their expectations. Hence, whether they react aggressively or reduce their investment depends on their expectation regarding an increase or decrease in future stock returns. In their study[7,13] implied using the nonlinear ARDL model to draw the short-run and long-run nonlinear interactions between investor sentiments and stock market liquidity (trading volume). They reported the long-run asymmetric response of stock market liquidity to both indicators of investor sentiment. In the short run, the stock market response to overconfidence (sentiment) was asymmetric, while the asymmetric market liquidity response to optimism and pessimism was insignificant. In the long-run, the market's response was asymmetric toward overconfidence and optimism-pessimism biases.

On the other hand[8,25] examined the relationship between investor sentiment and stock market volatility. Using the monthly data on market-related implicit indices, the authors constructed the sentiment index via the principal component analysis, Figure 3. The authors then modeled the constructed sentiment index using the Granger Causality and GARCH frameworks to evaluate its impact on stock market volatility. The study concluded that investor irrational behaviors (sentiments) contribute significantly to total stock market volatility formation. Besides, the study shows that the asymmetric aspect of an inefficient market significantly contributes to the excess return and volatility of the market.

Similarly[9, 15] also investigated the relationship between investor sentiment and stock market realized volatility using the thermal optimal model. In their two-step approach, they first constructed the sentiment index and then analyzed its dynamic effect on Shanghai and Shenzhen stock exchange volatility. The sentiment index was based on five different proxies, namely several new stock accounts, investor attention, margin ratio, turnover ratio, and net active purchasing amount. They reported that when stock markets fluctuate, investors' sentiments push the volatility further over one or two steps. In short, the study identified the significant role of investor sentiment in equity market volatility.

[6, 28] explored the impact of terrorist attacks on the British and French stock market returns through investor sentiment. Based on the quantile regression, the authors found that terrorist attacks significantly negatively affect the returns of both stock markets in extreme market conditions. The authors found a significant contribution of investor sentiment to explain the impacts of major terrorist attacks on the British and French stock markets. In other words, the study found that the sizable effect of terrorist attacks on both the European stock market returns takes place through investor sentiments.

[14, 16, 30] explored the sentiment index's role in Shanghai stock market returns. They applied the E-GARCH model to the dataset from 2015 to 2018 and the Shanghai Composite Index as a measure of stock market returns. Interestingly, the authors found that the impact of investor sentiments on stock market returns before a financial crash is less than the impact of investor sentiment on stock market returns after a crash. In other words, the author found that the market response to sentiments is more pronounced after financial crises than it was during the pre-crisis period, Figure 4. It could be because financial crises increase market volatility, and in times of market volatility, investor sentiments have a more significant role in the stock market. Further, the authors claimed that stock returns are susceptible to emotional sentiment rather than simply depending upon stock price. Lastly, they reported that during periods of market pessimism, retail investors' tendency to follow the crowd, or herding behaviors, is less prevalent than during periods of optimism, thereby accelerating stock yields.

3 Methodology

This study will test whether Investor Sentiment triggers changes in Returns Stock Market. When attention of investors is set on a certain stock, then an increase of trading volume should be noticed. Abnormally heavy stock volume will be considered a variable in testing an investor's attention to that stock. Linear ARDL modelling offers a robust framework for analyzing the relationships between macroeconomic indicators and the US stock market index, with both advantages and limitations [10, 23]. One key advantage is the model's ability to capture both short-run and long-run dynamics simultaneously, providing a comprehensive understanding of the relationships between variables over time [17]. Additionally, the flexibility of the ARDL method allows for determining different lags for each variable in the model, enhancing the model's adaptability to various datasets and economic contexts. Furthermore, the inclusion of lagged variables in the linear ARDL model enables the analysis of relationships over time, providing insights into the evolving dynamics between macroeconomic indicators and the stock market. On the other hand, a notable limitation of linear ARDL modelling is the assumption of linearity, which may not always hold true in complex economic systems, potentially affecting the model's accuracy and predictive power. Despite these limitations, the advantages of using linear ARDL modelling in this study outweigh the potential drawbacks, as it allows for a comprehensive analysis of the relationships between macroeconomic indicators and the stock market, offering valuable insights for investors and policymakers by [10, 18].

The dataset used in the analysis spans September 2009 to September 2022, sufficient to ascertain the precise outcomes. The Saudi Arabia Stock Exchange advertises the Tadawul All Share Index (Tadawul:), which is used to measure stock returns (y).
The most well-known global leader in oil data collection is the World Bank-Data Bank. The goal of the GARCH (p.q.) model is to influence oil prices. The monetary information (F_1) related to the control variables is publish by (). This study used detailed preliminary analyses of descriptive statistics, lag order selection, unit root testing, Granger causality testing, and Johansen cointegration testing, the model using Eviews statistical software.
According to [18], the dependent variable (stock market return) is a representation of the stock market that measures the performance of equity investments. [11, 24] lists the following stock market indicators as independent variables (sentiment index proxies): "Tadawul All Share Index; X_1" and "Tadawul Energy Index; X_2." Macroeconomic Indicators or Control Variables: "Money Supply; F_1" and "Consumer Confidence Index; F_2" are control variables that look at the bigger picture of the economy and how it might affect stock markets. They help us figure out how investor attitudes affect market returns. For example, the Consumer Confidence Index reflects consumer sentiment, which can affect both market sectors. By using macroeconomic variables, it is possible to prevent the relationship between mood and returns from being muddled by other economic factors [12, 19, 22]. Table 1 lists the descriptions of each variable.

Table 1: Variable Descriptions

Variable	Symbol	Description
Dependent Variable	Y	"Stock Market Return"
Independent Variables	X_1	"Tadawul All Share Index"
	X_2	"Tadawul Energy Index"
	X_3	"Price"
	X_4	"Volatility"
Control Variables	F_1	"Money Supply"
	F_2	"Consumer Confidence Index"

4 Results

4.1 Descriptive Statistics

The descriptive statistics for the study variables are depicted here, which outline some key features of the data after natural logarithm (ln) transformation and the winsorization at 5% and 95% percentile. Winsorization is done to successfully strike a compromise between data robustness and integrity, resulting in statistical conclusions that are easier to read and more dependable. Shows of the Return series", where the highest was 78.72000, and the lowest was 10.00000, with a mean of 47.94475. The table also contains skewness, kurtosis, and the Jacques-Pera statistic that measures the dependence of the data on the normal distribution, as well as the sum and some other statistics.

4.2 Eigenvalues and Cumulative Proportions

Cumulative proportions are the total of the variance explanations offered by each basic component. Understanding the percentage of the total variation that a specific number of components may account for is crucial. To calculate cumulative proportions, the proportion of variance for each component is first calculated by dividing its eigenvalue by the total of all eigenvalues [13,20,31]. The cumulative proportion for the $k-th$ component is the sum of the proportions from the first component to the component:

$$CumulativeProportions = \sum_{i=1}^{k} \frac{Cumulative_i}{\sum_{j=1}^{n} Cumulative_j} \quad (1)$$

Cumulative proportions can be used to decide how many components to retain. Only the first few components may be retained for analysis if they account for a high cumulative amount of variation (80% or more), to simplify the model without losing crucial information.

The "first component explains 30.75% of the variance", "second explains 24.34% ", and "third explains 6.62% ". The remaining components explain a small proportion of the variance, and their contribution diminishes significantly after the seventh component.

4.3 Stationary Test "Root Unit "

In analysis the time series, the determination of "stationarity of a series is crucial". A time series is stationary if all its statistical properties are non-time dependent, including the mean, variance, and autocorrelation. Non-stationary series can cause problems since traditional regression approaches might yield false results in such situations. "trend stationary", or a stochastic trend , the above series has a stochastic trend and is non-stationary. There are various techniques of unit roots tests.

All the time series studied $(D(LNX_1)$, $D(LNX_2)$, $D(LNX_3)$, $D(LNX_4)$, $D(LNF_1)$, $D(LNF_2)$, show probability values equal to 0.0000, which means that they are all stationary at level and do not contain a unit root. The results clearly indicate that the data used in the analysis are stationary, which enhances the reliability of any statistical models or economic will be applied later.

Both stationary and non-stationary series are present, results of the "PP" and "ADF" tests. Variations in test assumptions, sensitivity to data characteristics, "choice of lag length", and the types of non-stationarity present in the data can cause the contradictory results between the "ADF" and "PP" tests. Some, but others need to difference achieve.

4.4 Model Results

The ARDL model fulfills the study's objective by enabling the examination of correlations between the variables.

The adjusted R-squared value of 0.8607 indicates that the model, reflecting a good fit, explains approximately 86.07% of the variation in stock market returns. The F-statistic value of 22.9093 and a probability of 0.0000 indicate a significant overall model fit, affirming the relevance of the repressors in explaining LNY.

In analyzing the dynamics of stock market returns (LNY), the ARDL model reveals intricate temporal relationships with its own lagged values. Specifically, the immediate past value, represented by $LNY(-1)$, exerts a strong positive influence on the current stock market return ($Coefficient = 0.8104, p < 0.01$), emphasizing the relevance of recent trends. Conversely, lags from two to eleven periods, encompassed by $LNY(-2)$ to $LNY(-11)$, do not significantly contribute to the present value, highlighting that their impact is negligible ($p > 0.05$). Nonetheless, the constant of a more remote past value, $LNY(-12)$, is negative at -0.1340 with a p-value of 0.0598, making it close to significance. Despite the fact that this coefficient is not significant by the conventional benchmark, it subtly suggests the presence of a long-term effect that needs more investigation. Such findings illustrate the intricate relations between current stock

Table 2: Descriptions Statistics

	LNY	LNX_1	LNX_2	LNX_3	LNF_1	LNF_2	
Mean	47.94475	7583.090	5467.590	71.91681	74.48106	1437955.0	99.60194
Median	52.00000	7249.285	5392.050	68.65000	70.27500	1588020.0	99.62500
Maximum	78.77000	11714.04	9012.440	117.7900	124.9930	1968240.0	101.1700
Minimum	10.00000	4384.591	2717.000	21.00000	43.90900	182930.0	98.42000
Std.Dev.	18.08994	1998.932	1123.499	25.64947	20.13442	334364.7	0.195391
Skewness	-0.557056	0.517956	0.477212	0.124619	0.548582	0.063853	-0.533004
Kurtosis	2.691044	3.000206	3.543528	1.886262	1.396253	2.047335	2.670306
Jarque-Bera	7.456661	1.287784	8.042333	9.576569	12.47322	4.144455	4.414455
P-value	0.023925	0.002147	0.017932	0.007610	0.003653	0.001972	0.014666

Table 3: Principal Component Analysis

Sample (adjusted): 1/09/2008 1/12/2021
Included observations: 160 after adjustments
Balanced sample (listwise missing value deletion)
Computed using: Ordinary correlations
Extracting 7 of 7 possible components

Eigenvalues: (Sum = 7, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.075502	0.641378	0.4394	3.075502	0.4394
2	2.434124	1.771205	0.3477	5.509626	0.7871
3	0.662919	0.136077	0.0947	6.172545	0.8818
4	0.526842	0.334296	0.0753	6.699386	0.9571
5	0.192546	0.086005	0.0275	6.891932	0.9846
6	0.106541	0.105014	0.0152	6.998473	0.9998
7	0.001527	---	0.0002	7.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
F1	-0.185987	0.562285	0.020932	-0.190218	0.679982	0.383187	0.058443
F2	-0.152913	0.459230	0.488928	0.680691	-0.251316	0.010339	-0.008290
X1	0.149551	0.573331	-0.024891	-0.377997	-0.142770	-0.695144	-0.042610
X2	0.478670	0.144733	0.372238	-0.416570	-0.409376	0.519840	-0.003646
X3	0.551327	-0.071914	0.115434	0.209974	0.295919	-0.163948	0.720421
X4	0.547615	-0.072150	0.122854	0.217903	0.382765	-0.100921	-0.689669
Y	0.294437	0.336021	-0.770008	0.304128	-0.228945	0.250075	-0.006096

Ordinary correlations:

	F1	F2	X1	X2	X3	X4	Y
F1	1.000000						
F2	0.622088	1.000000					
X1	0.689618	0.433071	1.000000				
X2	-0.061175	-0.071682	0.471713	1.000000			
X3	-0.401114	-0.241461	0.113460	0.736294	1.000000		
X4	-0.386187	-0.238846	0.102759	0.727490	0.997488	1.000000	
Y	0.230554	0.107988	0.544275	0.326975	0.397730	0.389522	1.000000

Table 4: Intermediate "ADF" results UNTITLED

Method		Statistic	Prob.**	
ADF - Fisher Chi-square		898,770	0.0000	
ADF - Choi Z-stat		-26.7783	0.0000	
Intermediate ADF test results D(UNTITLED)				
Series	P-value	Laq	Max Lag	Obs
D(LNX1)	0.0000	1	13	166
D(LNX2)	0.0000	1	13	166
D(LNX3)	0.0000	1	13	166
D(LNX4)	0.0000	1	13	166
D(LNF1)	0.0000	0	13	158
D(LNF2)	0.0000	2	13	164

Table 5: Intermediate Phillips-Perron (PP) Test Results UNTITLED

Method		Statistic	Prob.**
PP - Fisher Chi-square		499.337	0.0000
PP- Choi Z-stat		-20.5162	0.0000
Intermediate Phillips-Perron test results D(UNTITLED)			
Series	Prob	Bandwidth	Obs
$D(F_1)$	0.0000	10,0	167
$D(F_2)$	0.0072	18.0	167
$D(X_1)$	0.0000	9.0	167
$D(X_2)$	0.0000	14.0	167
$D(X_3)$	0.0000	10.0	167
$D(X_4)$	0.0000	11.0	167
D(Y)	0.0000	0.0	158

market returns and their historical levels, contributing to the understanding of the temporal dynamics of the market [32].

Besides the autoregressive components, the model provides information about the impact of market

Table 6: ARDL Short-Run Model for Stock Market Return (Y) in Saudi Arabia

Variablee	Coefficient	Std. Error	t-Statistic	P-value
C	38.83	14.19	2.74	0.01
LNY(-1)	0.81	0.09	9.32	0.00
LNY(-2)	0.02	0.10	0.21	0.84
LNY(-3)	-0.06	0.10	-0.62	0.54
LNY(-4)	-0.02	0.10	-0.25	0.81
LNY(-5)	0.07	0.10	0.70	0.48
LNY(-6)	0.06	0.10	0.61	0.55
LNY(-7)	-0.06	0.10	-0.64	0.52
LNY(-8)	0.02	0.09	0.26	0.80
LNY(-9)	0.11	0.09	1.16	0.25
LNY(-10)	-0.08	0.09	-0.87	0.39
LNY(-12)	-0.13	0.07	-1.90	0.06
LNST	-0.26	0.39	-0.67	0.51
LNST(-2)	1.30	0.49	2.66	0.01
LNST(-3)	-0.98	0.50	-1.97	0.05
LNF1	1.58	0.67	2.35	0.02
LNF1(-1)	-0.82	0.65	-1.27	0.21
LNF2	4.53	20.85	0.22	0.83
LNF2(-1)	3.34	56.17	0.06	0.95
LNF2(-2)	-2.06	78.79	-0.03	0.98
LNF2(-4)	156.37	87.92	1.78	0.08
LNF2(-5)	-181.58	92.79	-1.96	0.05
LNF2(-6)	170.89	90.05	1.90	0.06
LNF2(-7)	-148.00	84.47	-1.75	0.08
LNF2(-8)	58.66	80.07	0.73	0.47
LNF2(-9)	110.54	74.89	1.48	0.14
LNF2(-10)	-245.97	67.95	-3.62	0.00
LNF2(-11)	191.54	49.06	3.90	0.00
LNF2(-12)	-64.63	18.14	-3.56	0.00

R-squared Adjusted	0.9000	LM Test:			
R-squared	0.8607	F-statistic	0.941184	Prob. F(4,10)	0.4431
F-statistic	22.909	Test: ARCH			
P-value (F-statistic)	0.000	F-statistic	0.086036	Prob. F(4,14)	0.9867
Bound Test					
Test Statistic	Value	Sig.	I(0)	I(1)	
F-statistic	0.004	10%	2.080	3.000	
		5%	2.390	3.380	
k	5				
		1%	3.060	4.150	

sentiment $(LNST)$ on stock market returns. Although sentiment for the current period is not significant in the case of $LNY(p > 0.05)$, the lagged variables present a more complicated image. Precisely, significance is also absent when it comes to the first, third, and fourth lags of sentiment, which are $LNST(-1)$, $LNST(-3)$, and $LNST(-4)$, thereby reinforcing that no immediate or short-term influence is present in the prior sentiment values. Nevertheless, an interesting anomaly in this context is noted in $LNST(-2)$, which is rather positive and highly significant $(Coefficient = 1.2957, p < 0.01)$. This result means that the Sentiment from two periods ago positively affects the current stock market returns. Such lagged effect means that Sentiment influence on stock market returns has a delayed reaction, thus further complicating the interaction between market Sentiment and stock market dynamics.

Additionally, the model also incorporates several control variables that help to isolate their separate impacts on the Log of Stock Market Return (LNY). The first one is that the log of Money Supply (LNF_1) has a positive and statistically significant influence on LNY in the current period $(Coefficient = 1.5823, p < 0.05)$, while its first $lag(LNF_1(-1))$ is not statistically significant, indicating no measurable effect from the money supply of the previous period., the Log of Consumer Confidence Index (LNF_2) introduces a multifaceted relationship within the model. Most lags from LNF_2 to $LNF_2(-8)$ are found to be statistically insignificant $(p > 0.05)$, suggesting that these do not exert a tangible influence on the Log of Stock Market Return (LNY). However, specific lags offer intriguing insights. $LNF_2(-10)$ has a negative and highly significant effect $(Coefficient = -245.9687, p < 0.001)$, indicating a pronounced negative influence from ten periods prior. Conversely, $LNF_2(-11)$ displays a positive and equally significant impact $(Coefficient = 191.5440, p < 0.001)$, underscoring a substantial positive influence from eleven periods back. Furthermore, $LNF_2(-12)$ is found to have a negative and significant effect $(Coefficient = -64.6304, p < 0.001)$, adding a layer of complexity to the interpretation. Other lags such as $LNF_2(-4)$, $LNF_2(-5)$, and $LNF_2(-6)$ are close to being significant $(p < 0.1)$, hinting at potential nuances that might be subject to further exploration. The observed relationships in the various lags of LNF_2 underscore the intricate dynamics of consumer confidence and its interplay with stock market returns, warranting a more in-depth investigation to fully elucidate these nuanced associations., the model includes a constant term (C), which is positive and statistically significant $(Coefficient = 38.8317, p < 0.01)$. This constant may capture the effects of omitted variables or represent inherent characteristics of the market that are not accounted for by the variables included in the model.

Table 7: ARDL Long-Run Model for Stock Market Return (Y) in Saudi Arabia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	38.83	14.1854	2.7374	0.0072
LNY(-1)*	-0.28	0.0537	-5.1299	0.0000
LNST(-1)	-0.73	0.3845	-1.8882	0.0616
LNF1(-1)	0.76	0.2892	2.6328	0.0097
LNF2(-1)	-12.23	4.0262	-3.0369	0.0030
D(LNY(-4))	0.0233	0.0766	0.3035	0.7620
D(LNY(-5))	0.0919	0.0740	1.2422	0.2168
D(LNY(-6))	0.1510	0.0729	2.0727	0.0405
D(LNY(-8))	0.1136	0.0700	1.6218	0.1077
D(LNY(-9))	0.2210	0.0690	3.2024	0.0018
D(LNY(-10))	0.1416	0.0705	2.0077	0.0471
D(LNY(-11))	0.1340	0.0705	1.9015	0.0598
D(LNST)	-0.2591	0.3883	-0.6672	0.5060
D(LNST(-1))	0.1881	0.4425	0.4250	0.6717
D(LNST(-2))	1.4838	0.4051	3.6629	0.0004
D(LNF1)	1.5823	0.6732	2.3504	0.0205
D(LNCCI)	4.5307	20.8547	0.2173	0.8284
D(LNF2(-1))	20.0992	38.1498	0.5268	0.5993
D(LN F2 (-9))	119.0551	38.6423	3.0810	0.0026
D(LN F2 (-10))	-126.9136	33.7815	-3.7569	0.0003
D(LN F2 (-11))	64.6304	18.1437	3.5621	0.0005
LNST	-2.63343	1.2223	-2.15448	0.0333
LNF1	2.761953	0.830878	3.324137	0.0012
LNF2	-44.3482	14.45311	-3.06842	0.0027
C	140.8451	53.14763	2.650072	0.0092
LNST	-2.63343	1.2223	-2.15448	0.0333
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The long-run model illustrates the relationship between the log of the dynamics of stock market returns (LNY) and its corresponding variables. Key findings include:
$LNST$: The coefficient of -2.6334 indicates a negative long-run relationship with LNY. It is statistically significant at the 5% level, reflecting that a 1% increase in LNST leads to a 2.6334% decrease in LNY.
$LNF1$: With a coefficient of 2.7619 and statistical significance at the 1% level, $LNF1$ is positively associated with LNY in the long- run.
$LNF2$: The coefficient of -44.3482 is negative and significant at the 1% level, indicating a strong negative long-run relationship with LNY.
Constant: The constant term is significant and positive, with a value of 140.8451.
The error correction (EC) expression derived from the model signifies how these variables adjust to the long-term equilibrium relationship. The long-run equation can be written as follows:

$$LNY = -2.6334*LNST + 2.7620*LNF_1 - 44.3482*LNF_2 + 140.8451 \quad (2)$$

Additionally, the error correction (EC) part showing the relationship of how the deviation from the long-term equilibrium affects the short-term dynamics:

$$EC = LNY - (-2.6334*LNST + 2.7620*LNF_1 - 44.3482*LNF_2 + 140.8451) \quad (3)$$

The coefficient of this error correction term in short-run equation (which is -0.2757 as shown in Table 7) tells the speed of adjustment back to the long-run equilibrium following a shock to the system.

5 Conclusion

The ARDL models reveal a nuanced delayed manifestation of the sentiment effect could signify that regulatory policies and market mechanisms in Saudi Arabia take time to transmit the effect of sentiment changes to returns. This corresponds with [21,34] observation that Middle East markets exhibit relatively persistent bearish investor sentiment regimes.
However, the long-run negative association between sentiment and returns contrasts most prior studies that found a positive long-term linkage [2,14,33]. This implies that the Saudi market eventually overreacts to sentiment changes and subsequently corrects itself. One potential explanation lies in the Saudi economy's unique Islamic orientation and oil dominance compared to conventional Western markets. As an oil-revenue-dependent economy, Saudi market returns are greatly exposed to global oil price fluctuations that can supersede investor sentiment [16,31].
Overall, the analysis reveals interesting insights into the Saudi Arabia stock market's dynamics with investor sentiment that warrants caution for investors while also opening up avenues for future research. The mixed short-run and long-run effects underscore the need to apply nonlinear and regime-dependent models, as done by [27,34] and [7,28] and . [6,30], to capture the nuances fully. Furthermore, incorporating oil prices and Islamic events as additional variables could provide greater contextual explanatory power.

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