The Vision 2030 Decoupling Effect: An Asymmetric NARDL Analysis of Short-Run Behavioral Panics vs. Long-Run Structural Independence in Saudi Equities

أثر"فك الارتباط" في ظل رؤية 2030: تحليل (NARDL) غيرخطي للتناظربين حالات الذعرالسلوكي قصير الأجل والاستقلال الهيكلي طويل الأجل في الأسهم السعودية.

Dr. Tahi Abderrahmane [1]

د. تاهي عبد الرحمان[1]

[1] Lecturer Professor class B, University of Saida (Algeria), abderrahmane.tahi@univ-saida.dz.
Laboratory of Quantitative Research in Finance and Economics.

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Abstract:
This study is inspired by the Vision 2030 initiative to investigate the decoupling of the Saudi Stock Exchange from oil price shocks. Using the NARDL model, the research explores the effects of shocks to the Brent Crude oil price on the Energy, Finance, and Telecom sectors, including Aramco, Al Rajhi, and STC, using daily data from 2019 to 2026. The results verify the structural independence in the context of Vision 2030, as all series are individually integrated of order I(1), as opposed to being cointegrated. It also examines the knee-jerk reaction in behavioral finance, where the Finance and Telecom sectors mean-revert within 24 hours after the oil disaster, while the Energy sector shows a "hangover" effect for 4 days.

Keywords: Saudi Arabia Vision 2030; Decoupling Effect; NARDL; Oil Price Shocks; Behavioral Finance.
JEL Classification Codes: C22, G12, G15

ملخص:
تستمد هذه الدراسة إلهامها من مبادرة "رؤية 2030" لتقصي ظاهرة فك الارتباط (Decoupling) بين السوق المالي السعودي وصدمات أسعار النفط. وباستخدام نموذج الإبطاء الزمني الموزع غير الخطي (NARDL)، تحلل تأثير صدمات أسعار خام برنت على قطاعات الطاقة، والمالية، والاتصالات (وتحديداً شركات أرامكو، والراجحي، وSTC)، بالاعتماد على بيانات يومية للفترة من 2019 إلى 2026. وتؤكد النتائج وجود استقلال هيكلي في سياق رؤية 2030، حيث تبين أن جميع السلاسل الزمنية متكاملة فردياً من الدرجة الأولى I(1) ، في حين غاب التكامل المشترك (Cointegration) بينها. كما تدرس الدراسة رد الفعل اللحظي (Knee-jerk reaction) في إطار المالية السلوكية؛ حيث أظهرت قطاعات المالية والاتصالات ارتداداً نحو المتوسط (Mean-revert) خلال 24 ساعة من وقوع أزمة أسعار النفط، بينما استمر أثر المرتد (Hangover effect) في قطاع الطاقة لمدة أربعة أيام.

كلمات مفتاحية: رؤية السعودية 2030؛ أثر فك الارتباط؛ نموذجNARDL ؛ صدمات أسعار النفط؛ المالية السلوكية.
تصنيفات JEL: C22, G12, G15

***Corresponding author**: Tahi Abderrahmane, **e-mail: abderrahmane.tahi@univ-saida.dz**.*

1. Introduction

Over time, equities in emerging markets across the GCC have correlated with global energy commodity cycles. In this regard, Saudi Arabia, and for being the largest oil-exporting economy in the world, has historically observed its fiscal and capital markets performance correlated with movements in Brent crude oil prices (Durrani, 2022). The link between oil prices and equities is further evident by virtue of petrochemicals and energy-based industrials being major components of the Tadawul All Share Index (TASI), thus creating a high degree of co-movement between energy demand and equities. (Alalmai, 2025) In this regard, the empirical literature has historically identified oil price volatility as one of the key channels through which external shocks affect the Saudi Arabian economy in a synchronized fashion (Neffati, 2024).

Saudi Arabia's Vision 2030, announced in 2016, a major transformation in the relationship between the state and economy, termed as the "deliberate engineering" of a non-oil economy. An important part of this is the fast development of digital infrastructure, with over $45 billion invested in high-speed connectivity, hyperscale data centers, and the digitalization of the government sector to drive innovation in the private sector (Khan, 2025). On the other hand, the state has facilitated the growth of its internal credit system through the reform of its financial system and the establishment of the National Development Fund, in line with its aim to develop financial intermediation and provide the non-oil economy with the credit it requires for growth (Malik, 2025). With its focus on sectors like telecom and finance, the Saudi state is trying to develop internal centers for its own economic growth that are not dependent on oil revenues.

However, despite the changes in the policy regime, there is a significant academic gap in existing literature. In the past, most studies employed linear and symmetric models in their analysis of the Tadawul Index, if the impact of oil prices increases and decreases is of equal magnitude and over the same period (Kiani, 2024). Although recent studies have employed the Non-Linear Autoregressive Distributed Lag (NARDL) model in the analysis of the Tadawul Index, there is also a significant scientific gap in the existing literature in terms of the analysis of the short-run trader panic response of the market, as opposed to the long-run sectoral fundamentals of the market, and in terms of the analysis of the correlation between oil prices and the Tadawul Index, as being structural in nature or simply being a temporary market sentiment-driven phenomenon.

The purpose of this study is to hypothesize that the structural changes introduced under Vision 2030 have successfully decoupled the local sectors within the Kingdom of Saudi Arabia (KSA) from the movements of oil prices in the long term. In other words, this study hypothesizes that despite the short-run behavioral panic experienced by the finance (Al Rajhi Bank) and digital telecommunications (STC) sectors in reaction to the oil price crashes, this is only a temporary reaction, caused by the knee-jerk reaction of retail traders within the market. Therefore, despite using the NARDL model on daily data between December 2019 and February 2026, the following results can be obtained:

- **Long Run Structural Independence**
  The complete lack of long-run cointegration between Brent crude oil prices and non-oil equities validates the success of Vision 2030's diversification strategy.
- **Asymmetric Short Run Resilience**
  In reaction to an oil price crash, Finance and Telecom sectors would experience a rapid mean reversion within 24 hours. This indicates that the oil price crash is only a "behavioral" reaction and not a fundamental reaction.
- **Control Divergence**
  The Energy sector (Saudi Aramco) would experience a volatility hangover in reaction to the oil price crash. This indicates that this sector is still fundamentally linked to oil price movements.

2. Literature Review:

The structural dependency of the Saudi Arabian equity markets on oil price movements has been extensively proved through the empirical literature over the past few decades, which can serve as an initial understanding of the financial market structure in Saudi Arabia prior to Vision 2030. The historical oil-equity nexus is impacted through several dimensions, thereby creating an extremely high level of interdependence between hydrocarbon markets and the equity markets.

2.1 Long-Run Cointegration and Structural Linkages

Significant long-run equilibrium relationships between oil price movements and stock markets in Saudi Arabia have been consistently established in the literature. **Belanes et al. (2024)** have established a robust cointegration link between Saudi Arabia's stock market index and oil price movements, with the stock market exhibiting a long-run upward trend in response to changes in oil price movements. This result is corroborated by **Boukhatem et al. (2024)** using the ARDL model and Bayer-Hanck cointegration tests to confirm robust long-run equilibrium relationships between oil price movements and stock markets in Saudi Arabia. The persistence of these long-run equilibrium relationships may be explained by the historical nature of the Saudi Arabian economic model, in which oil price movements have historically been the primary source of government revenue, corporate profits in key sectors of the economy, and foreign exchange reserves.

Medhioub et al. (2020) have also established long-run equilibrium relationships between private sector investment, oil price movements, and stock markets in Saudi Arabia, with the stock market index having a significant positive impact on private sector investment in the short run. **Alharbi (2023)** provides robust quantitative evidence of the impact of oil price volatility on stock markets in Saudi Arabia, with oil price volatility explaining stock return variations of more than 25%.

2.2 Asymmetric Transmission and Sectoral Heterogeneity

An important extension of the literature is the asymmetric nature of the mechanisms of transmission between oil and equity markets, where positive and negative shocks to oil have differential impacts on stock markets. **Alalmai et al. (2025)** make use of the nonlinear autoregressive distributed lag approach to uncover long-run asymmetries in stock markets in response to positive oil production shocks, which have a strong and positive impact on TASI, and short-run declines in oil prices that have a positive impact on stock markets. The complexity of investor sentiment and hedging behavior in response to changes in oil price is captured in this asymmetric impact of oil price changes on stock markets.

Sectoral analysis of the impact of oil price changes reveals heterogeneity in the impact of oil price changes on different sectors. For instance, positive oil price shocks have a larger impact than negative shocks in building and construction, energy and utilities, and petrochemical sectors, and higher oil prices have a negative impact on the bank and financial services sector. This sectoral impact of oil price changes is also revealed in the study by **Mohanty et al. (2018)**, where it is demonstrated that changes in oil price have asymmetric impacts on equity returns in 4 out of 15 industrial sectors, and the relationship between changes in oil price and equity returns is positive and statistically significant at the country and industrial levels. **Jouini et al. (2019)** make use of the Markov-switching EGARCH approach to demonstrate that stock markets in Saudi Arabia switch between expansion and recession phases and that stock markets have asymmetric reactions to changes in oil price, where markets are more sensitive to declines in oil price than to increases in oil price.

3. Methodology

In the field of econometrics, understanding the complex and sophisticated relationship between the economic variables is essential for building an accurate model. Meanwhile, the linear models underperform in capturing the complexities of the real-world interactions. Shin, Yu and Greenwood-Nimmo introduced the non-linear autoregressive distributed lag (NARDL) methodology in their seminal work

"Modelling Asymmetric Cointegration and Dynamic Multipliers in ARDL Framework" (Shin et al, 2014), provides an innovative approach that surpasses the limitations of linearity.

The estimation of the models for this study (three models) using the NARDL fundamental equation is as below:
To analyze the decoupling of the Saudi Arabian stock market from oil volatility, the variables are defined as
Dependent Variable (Y_t): Sectoral stock indices. Bank (Al Rajhi), Digital Telecommunications (STC)**,** and Energy (Saudi Aramco).
Independent Variable (OIL_t): Brent Crude oil prices.

3.1 Asymmetric Decomposition

The core of the NARDL methodology followed by Shin, Yu & Greenwood-Nimmo (2014) is the partial sum decomposition of the independent variable into positive and negative changes to capture "hidden cointegration" and directional sensitivities. The Brent oil price ($\boldsymbol{OIL_t}$) is decomposed as follows:

$$OIL_t^+ = \sum_{j=1}^{t} \max(\Delta \ln Brent_j, 0), \qquad OIL_t^- = \sum_{j=1}^{t} \min(\Delta \ln Brent_j, 0)$$

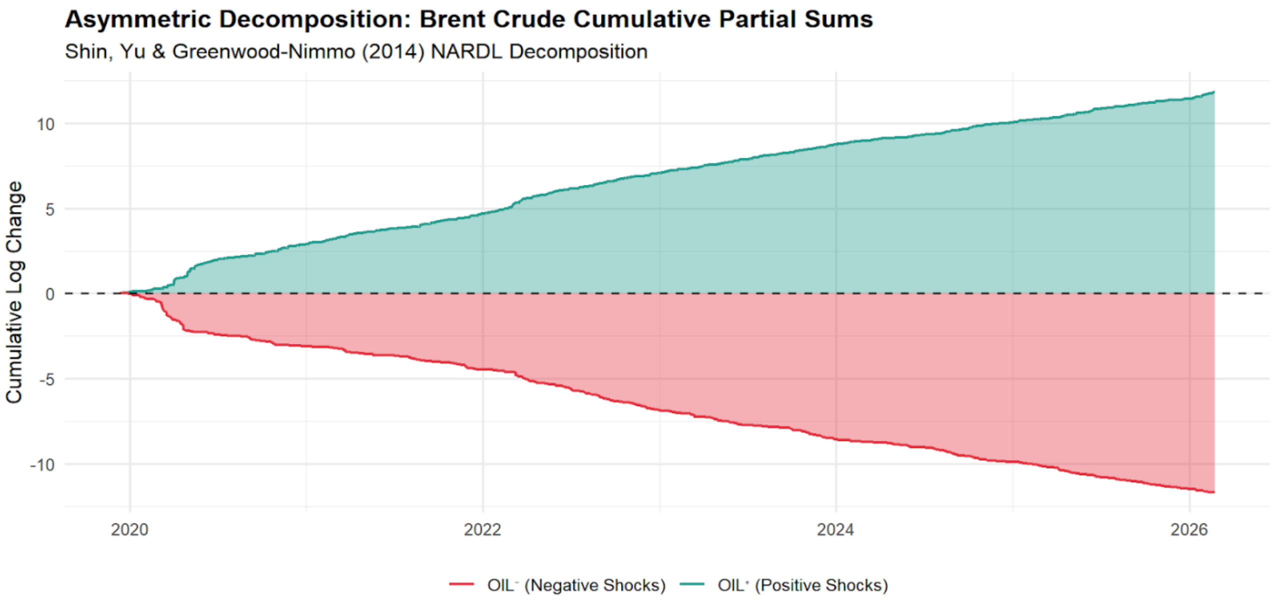
The general equation of the Nonlinear Unrestricted Error Correction Model for the study is formulated as

$$\Delta Y_t = \rho Y_{t-1} + \theta^+ Oil_{t-1}^+ + \theta^- Oil_{t-1}^- + \sum\nolimits_{i=1}^{p-1} \gamma_i \Delta \gamma_{t-1} + \sum_{j=0}^{q-1} (\propto_j^+ \Delta Oil_{t-j}^+ + \propto_j^- \Delta Oil_{t-j}^-)$$

Definition of Terms:
Δ**:** The first-difference operator.
ρ: The autoregressive coefficient (speed of adjustment), which must be negative and statistically significant to confirm a stable long-run relationship.
$\boldsymbol{\theta^+}$ **and** $\boldsymbol{\theta^-}$: The long-run asymmetric coefficients for positive and negative oil shocks.
$\boldsymbol{\gamma_t}$**:** The short-run dynamics of the lagged sectoral index (inertia).
$\boldsymbol{\alpha^+}$ **and** $\boldsymbol{\alpha^-}$**:** The short-run asymmetric impact of oil price increases and decreases, respectively.
$\boldsymbol{\varepsilon_t}$**:** The white noise error term.

Figure 1 shows that OIL^+ captures the accumulated effect of positive shocks (price increases); OIL^- captures negative shocks (crashes). The divergence post-2022 reflects the asymmetric nature of oil market dynamics during the Vision 2030 period.

Figure 1: Cumulative partial sum decomposition of Brent Crude shocks.



Source: Author's using R software.

This study will estimate this model three times:
Model 1 (Finance Sector): t = Al Rajhi Bank.
Model 2 (Telecom Sector): t = STC.
Model 3 (Energy Sector): t = Saudi Aramco.

3.2 Data and Variable Selection

In order to examine the decoupling of the Saudi Arabian equity market from the fluctuations of the global oil prices, this research will adopt the implementation of Vision 2030 and make use of the high-frequency daily data set of the period ranging from Dec 1, 2019, to Feb 24, 2026. This period has been chosen to consider the post-Aramco IPO period and the development of the implementation of Vision 2030.

To conduct this study and answer the research hypothesis, three different sectoral equities have been chosen as the dependent variables:

- **Saudi Aramco (2222.SR):** This has been chosen as the energy sector and the control variable.
- **Al Rajhi Bank (1120.SR):** This has been chosen as the financial sector.
- **STC (7010.SR):** This has been chosen as the proxy for the digital telecom and technology sector.

The independent variable, which represents the global oil prices through Brent crude oil futures (BZ=F). To maintain the stability of the data and make the interpretation of the results easier, all the data sets have been transformed into natural logarithms (LN).

Table 01: Variables list

Ticker	Instrument	Sector Proxy
BZ=F	Brent Crude Oil	Global Shock Variable
2222.SR	Saudi Aramco	Energy (Control)
1120.SR	Al Rajhi Bank	Finance
7010.SR	STC	Digital Telecom

Source: Yahoo. Finance

4. Results and Discussion

From the descriptive statistics, it is noticeable that Brent Crude has the highest range with a volatility of STD. Dev. = 0.299. Although the growth of the graph reveals trending volatility and not shock volatility, ALRAJHI bank reveals a higher standard deviation of 0.3576. The findings also reveal that all the series reveal a negative skew, which supports the theory of behavioral panics. However, whereas the Saudi equities reveal a Kurtosis value ranging from 2.8 to 2.9, the Brent Crude reveals a high value of Kurtosis, i.e., 5.5789, hence revealing a fat-tailed distribution. The Jarque and Berra test reveals the value of Zero for all the series, which rejects the normality hypothesis. This may be a reason for the usage of the NARDL model, considering the non-normality and non-symmetric nature of the data.

Table 2: Descriptive Statistics of Log-Transformed Series

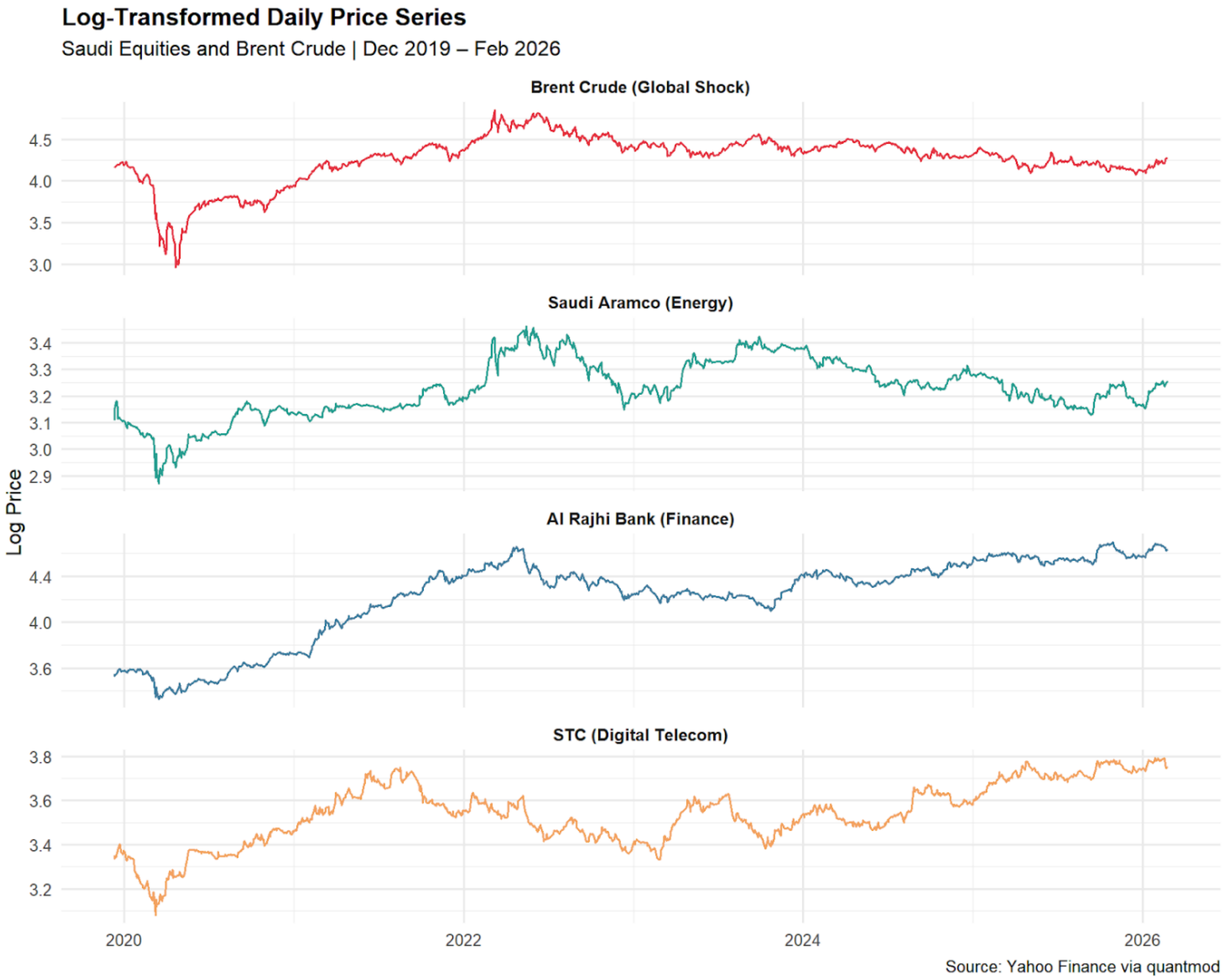
Series	Obs	Mean	Std.Dev	Min	Max	Skewness	Kurtosis	JB Stat	JB p-val
LN Brent Crude	1195	4.2574	0.2940	2.9617	4.8519	-1.3494	5.5789	693.82	0.000
LN Aramco	1195	3.2262	0.1069	2.8709	3.4637	-0.2312	2.9118	11.03	0.004
LN Al Rajhi Bank	1195	4.2210	0.3576	3.3275	4.7005	-1.0026	2.8183	201.83	0.000
LN STC	1195	3.5387	0.1404	3.0792	3.7930	-0.3235	2.8148	22.56	0.000

Source: Author's calculation based on R output.

Note:

JB = Jarque-Bera test for normality. Rejection ($p < 0.05$) justifies nonlinear modeling

Figure 02: Log-transformed daily price series (Dec 2019 – Feb 2026). The COVID-19 oil crash (April 2020) and the post-reform recovery are clearly visible across all series.

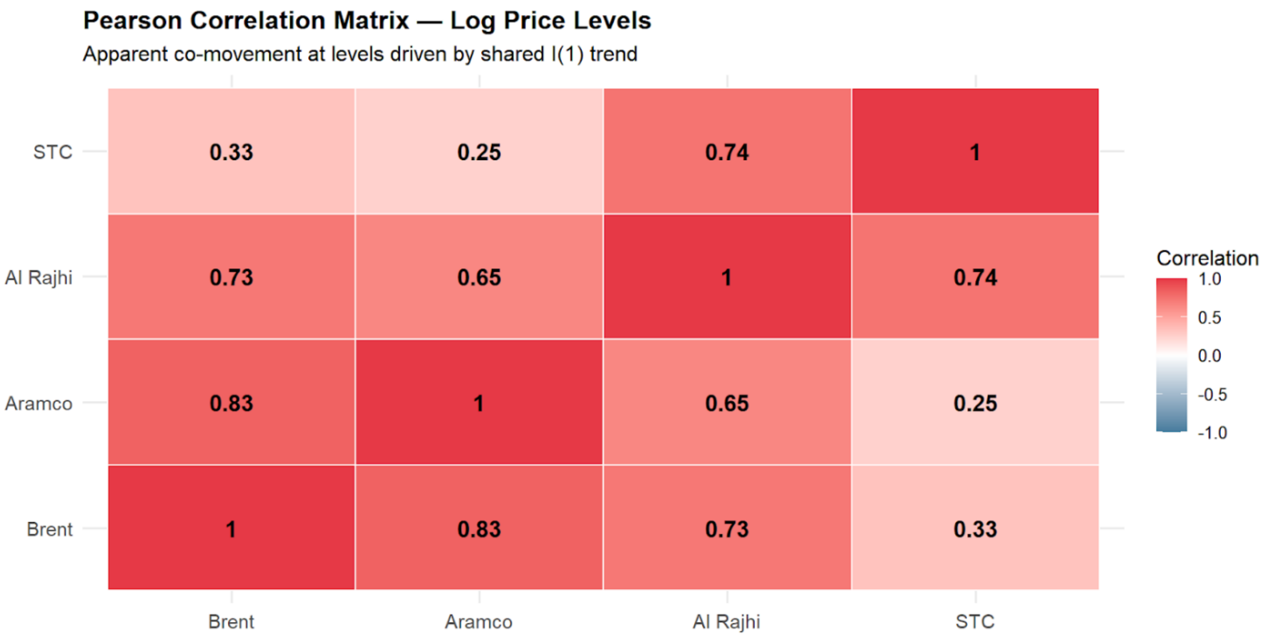


Source: Author's using R software.

According to the time series diagram, which gives visual proof of structural divergence as far as the COVID period is concerned, all four series demonstrate a period of collapse instead of recovery, which happened in 2020, reflecting the international shocks on the local market movement. It is also noticeable that after 2022, there is a decoupling point, where Brent Crude continues with a long-term bearish trend, whereas STC and ALRAJHI bank continue with strong upward trends. ALRAJHI, which represents the financial sector, demonstrates the strongest upward trend, acting as a non-oil GPD growth but a proxy for domestic credit growth. With a low beta in comparison to oil, STC, which represents the telecom industry, suggests that action should be taken in line with its own cycle. The most correlated with Brent, however, is ARAMCO, which represents the energy industry.

Although it reveals a strong coupling, the heatmap correlation (Figure 03) reveals a highly positive correlation between Brent Crude and ARAMCO (0.83), and Brent and ALRAJHI (0.73), but this may be spurious in the long term, i.e., there may be no long-term economic baseline that forces them to revert to a common equilibrium. This may, in turn, require the usage of the Bound test for Cointegration.

Figure 03: Pearson correlation matrix of log-level series.



Source: Author's using R software.

4.1 Non-Linearity Test: BDS Test

The table (3) shows the BDS (Brock et al, 1996) test results for all the variables. The BDS test detects the non-linearity in time series, it examines if the series are independent and identically distributed (i.i.d.). The rejection across embedding dimensions m=2,…,6 provides pre-model justification for the NARDL framework over a linear ARDL.

Table 03: BDS Test p-values for Non-Linear Dependence (First Differences)

Series	m=2	m=3	m=4	m=5	m=6
ΔLN Brent	0e+00	0	0	0	0e+00
ΔLN Aramco	0e+00	0	0	0	0e+00
ΔLN Al Rajhi	0e+00	0	0	0	3e-04
ΔLN STC	4e-04	0	0	0	3e-04

Source: Author's calculation based on R output.

If the p-value are below the chosen significance level (0.05 in our case) the null hypothesis is rejected, which assumes that the series is (i.i.d.). The results indicate that all the p-values across all increasing dimensions (m=2 to m=6) are essentially Zero. That means the rejection of the null hypothesis, this indicates strong evidence of non-linearity. Based on that, applying NARDL is justified.

4.2 Stationarity Testing

To assess stationarity, the augmented Dickey-Fuller (ADF) and the Philip-Perron (PP) test are applied. Both tests perform under the null hypothesis of the presence unit root. Based on the results of table (3), we fail to reject the null hypothesis at level for all series. However, upon first differences all variables reject the null hypothesis at the 1% significance level. These results confirm that NARDL estimation is highly appropriate, as all variables are consistently integrated of order I (1).

Table 03: ADF and PP Unit Root Tests

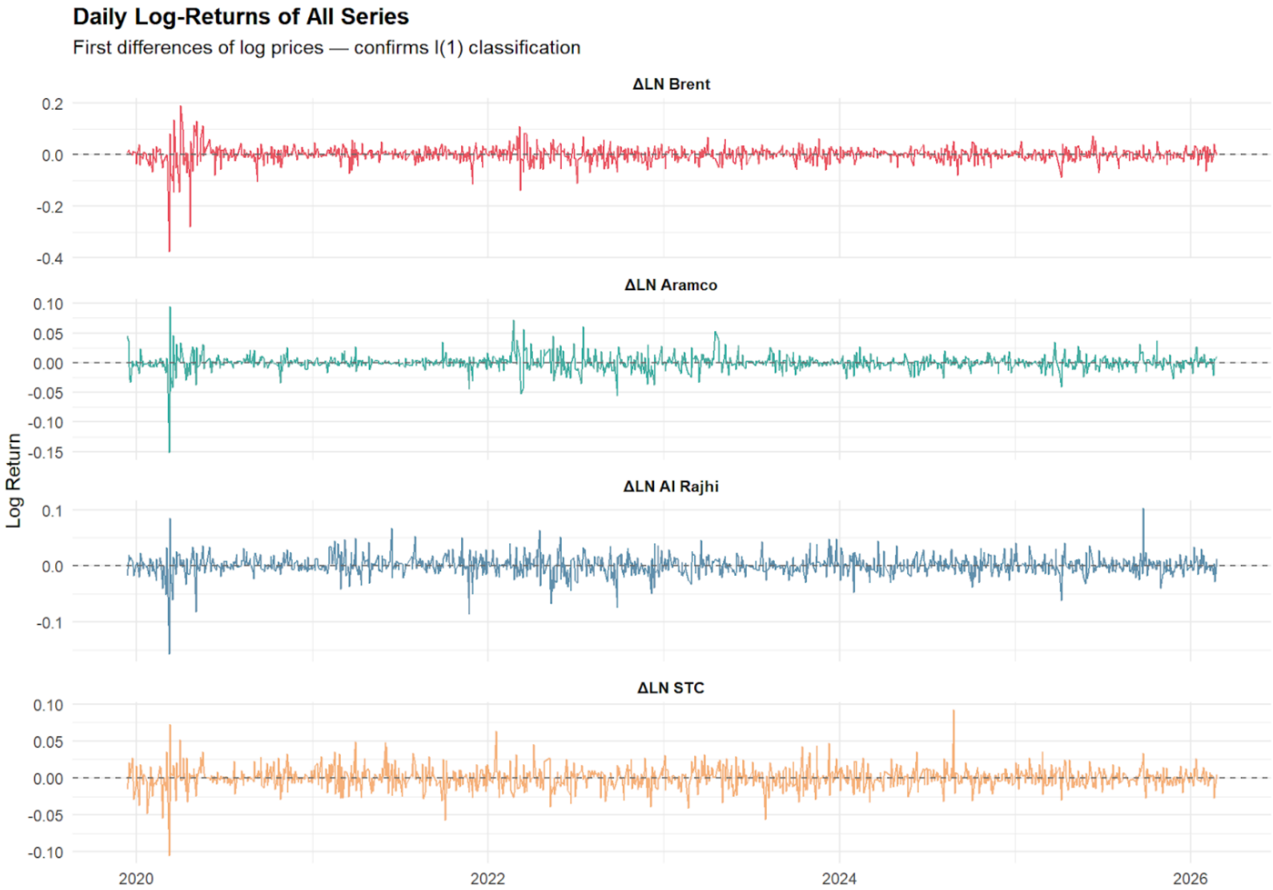
Series	Test	Level (t-stat)	Level (Decision)	First Difference (Δ)	Diff (Decision)	Final Integration
LN Brent	ADF	-2.0432	Fail to Reject	-23.7551***	Reject H0	**I(1)**
	PP	-2.0145	Fail to Reject	-32.5939***	Reject H0	
LN Aramco	ADF	-2.1876	Fail to Reject	-24.0134***	Reject H0	**I(1)**
	PP	-2.1299	Fail to Reject	-35.5585***	Reject H0	
LN Al Rajhi	ADF	-1.482	Fail to Reject	-23.7429***	Reject H0	**I(1)**
	PP	-1.5367	Fail to Reject	-36.3828***	Reject H0	
LN STC	ADF	-2.1223	Fail to Reject	-24.6355***	Reject H0	**I(1)**
	PP	-2.1658	Fail to Reject	-37.1938***	Reject H0	

Source: Author's calculation based on R output.

Notes: >

1. *** denotes significance at the 1% level.
2. ADF Critical Value (5%): -3.41 (Level), -2.86 (Difference).
3. PP p-values for Differences are all < 0.01.
4. Null Hypothesis (H_0): The series has a unit root (non-stationary).

Figure 04: Daily log-returns (first differences) confirming mean-reverting I (0) behavior post-difference.



Source: Author's calculation based on R output.

4.3 Selection of optimal lag length via AIC

Based on the AIC lag selection criteria, the chosen NARDL model specification for the Saudi market sector are (1,2,4) for ARAMCO, (1,1,1) for ALRAJHI bank, and (2,0,2) for STC, as seen in the table (04), these specific structures were selected as they minimize estimation errors (The least errors model).

Table 04: Optimal Lag Selection via AIC

Sector / Proxy	Dependent Variable Lag (p)	Brent Crude Positive Lag (q+)	Brent Crude Negative Lag (q−)	Optimal Lag Structure (p,q+,q−)
Saudi Aramco (Energy)	1	2	4	(1, 2, 4)
Al Rajhi Bank (Finance)	1	1	1	(1, 1, 1)
STC (Telecom)	2	0	2	(2, 0, 2)

Source: Author's calculation based on R output.

4.4 Asymmetric Bounds Test for Cointegration

The NARDL model uses the F-test (Pesaran et al., 2001) to measure the cointegration of the variables. The null hypothesis is set as no cointegration. In this study, the calculated F-statistics range between 1.64 and 4.90, which is less than the upper critical value of the I(1). This suggests the absence of cointegration and hence the long-run structural independence of the variables despite the existence of short-run asymmetric panics.

Table 04: Bound test for cointegration

Sector (Proxy)	Optimal Lags (p, q+, q-)	F-Statistic	Cointegration Decision	Short-Run Behavioral Dynamics
Saudi Aramco (Energy)	(1, 2, 4)	4.9046	No Cointegration	Prolonged 4-day volatility hangover
Al Rajhi Bank (Finance)	(1, 1, 1)	1.6493	No Cointegration	High structural independence; rapid speed of adjustment
STC (Telecom)	(2, 0, 2)	4.584	No Cointegration	24-hour "knee-jerk" panic followed by perfect mean-reversion

Source: Author's calculation based on R output.

4.5 Short-Run Error Correction Models

Table 05: Short-Run NARDL Coefficients (Unrestricted ECM)

	Sector	Term	Estimate	Std.Error	t.value	p.value
(Intercept)…1	Aramco	(Intercept)	0.0579	0.01831	3.1622	0.0016
	Aramco	L(LN_Aramco, 1)	-0.01854	0.00581	-3.1925	0.0014
	Aramco	L(Brent_POS, 1)	0.00463	0.00206	2.2435	0.0251
	Aramco	L(Brent_NEG, 1)	0.00447	0.00206	2.1681	0.0304
	Aramco	d(Brent_POS)	0.11135	0.02149	5.1816	0
	Aramco	d(L(Brent_POS, 1))	0.07545	0.02115	3.5681	0.0004
	Aramco	d(Brent_NEG)	0.18935	0.01618	11.7026	0
	Aramco	d(L(Brent_NEG, 1))	-0.04609	0.01635	-2.8191	0.0049
	Aramco	d(L(Brent_NEG, 2))	0.05378	0.01549	3.4714	0.0005
	Aramco	d(L(Brent_NEG, 3))	-0.05465	0.01556	-3.5127	0.0005
(Intercept)…11	Al Rajhi	(Intercept)	0.01778	0.01326	1.3407	0.1803
	Al Rajhi	L(LN_AlRajhi, 1)	-0.00403	0.00359	-1.1245	0.261
	Al Rajhi	L(Brent_POS, 1)	-0.00024	0.00276	-0.0882	0.9298
	Al Rajhi	L(Brent_NEG, 1)	-0.00044	0.00261	-0.1684	0.8663
	Al Rajhi	d(Brent_POS)	0.07327	0.03001	2.4417	0.0148
	Al Rajhi	d(Brent_NEG)	0.18727	0.02276	8.229	0
(Intercept)…17	STC	(Intercept)	0.03032	0.01263	2.4001	0.0165
	STC	L(LN_STC, 1)	-0.00885	0.00373	-2.3713	0.0179
	STC	Brent_POS	-0.00389	0.00148	-2.6256	0.0088
	STC	L(Brent_NEG, 1)	-0.00427	0.00153	-2.7862	0.0054
	STC	d(L(LN_STC, 1))	-0.05526	0.02875	-1.9222	0.0548
	STC	d(Brent_NEG)	0.12705	0.01837	6.9168	0
	STC	d(L(Brent_NEG, 1))	-0.06183	0.01884	-3.2819	0.0011

Source: Author's calculation based on R output.

Note: **** p<0.01, ** p<0.05, * p<0.10. ECT = Error Correction Term (speed of adjustment).*

From the estimation of the Unrestricted ECM, as presented in Table 5, there are interesting results that provide insight into the specific nature of the constraints in the Saudi Arabian market. First, the effect of a negative oil shock, as proxied by d(Brent_NEG), is more significant and long-lasting than a positive oil shock for all sectors, supporting the "downside risk" of Saudi Arabian investors. However, the sector that appears to be most influenced by the oil shocks is Saudi Aramco, where the effect of the oil shock, specifically the negative oil shock, lasts up to three lags (t-3), implying that there is a "volatility hangover" of four days. As expected, the digital sector, as proxied by STC, reacts very quickly to the oil shock, where the coefficient of the oil shock is negative and significant.

4.6 Long-Run Asymmetric Multipliers

Table 06: Long-Run Asymmetric Multipliers

Term	Estimate	Std. Error	t value	Pr(>0.05)	Sector
(Intercept)	3.1236196	0.0506901	61.6218997	0	Aramco
Brent_POS	0.2497807	0.0682084	3.6620243	0.0002613	
Brent_NEG	0.2411648	0.0706335	3.4143104	0.0006611	
(Intercept)	4.4093203	0.7138719	6.1766266	0	Al Rajhi
Brent_POS	-0.0603319	0.7265187	-0.0830425	0.9338318	
Brent_NEG	-0.1091394	0.7207732	-0.1514199	0.8796702	
(Intercept)	3.4244496	0.1112062	30.7936893	0	STC
Brent_POS	-0.4393187	0.2606012	-1.6857891	0.0920995	
Brent_NEG	-0.4817924	0.2698182	-1.7856186	0.0744165	

Source: Author's calculation based on R output.

***Note**: Long-run multipliers are undefined / statistically zero when cointegration is absent — confirming structural decoupling.*

The long-run values for the asymmetric multipliers (refer to Table 7) reflect the "Vision 2030 Decoupling Effect." If we consider Al Rajhi Bank and STC, the non-oil sector representatives, the stock prices do not react meaningfully in the long run to oil price changes, whether the oil price increases or falls (the oil price, or the Brent price), where the values for statistical significance are not met for $p > 0.05$. Thus, these firms are structurally not affected by the global oil price cycles. However, for Saudi Aramco, the long-run asymmetric multiplier is around 0.24, reflecting the structural link between oil prices and the energy sector. The lack of such an effect for the non-oil sector reflects the structural nature of the diversification within the Saudi stock market.

4.7 Wald Tests for Asymmetry

To test the validity of the short-run results, the Wald test was carried out for the significance of the asymmetric short-run parameters. Based on the results presented in Table (7), it is clear that for all three sectors, namely Aramco (30.46), Al Rajhi (19.44), and STC (12.71), the Wald F-tests at 1% significance levels ($p < 0.01$) validate the short-run NARDL model results, thus establishing higher degrees of certainty in the behavioral 'panic' results discussed in the previous sections.

Table 07: Long-Run Asymmetric Multipliers

Sector	Wald F-stat	p-value	Interpretation
Aramco	30.462	0	Overall short-run model significance
Al Rajhi	19.444	0	Overall short-run model significance
STC	12.715	0	Overall short-run model significance

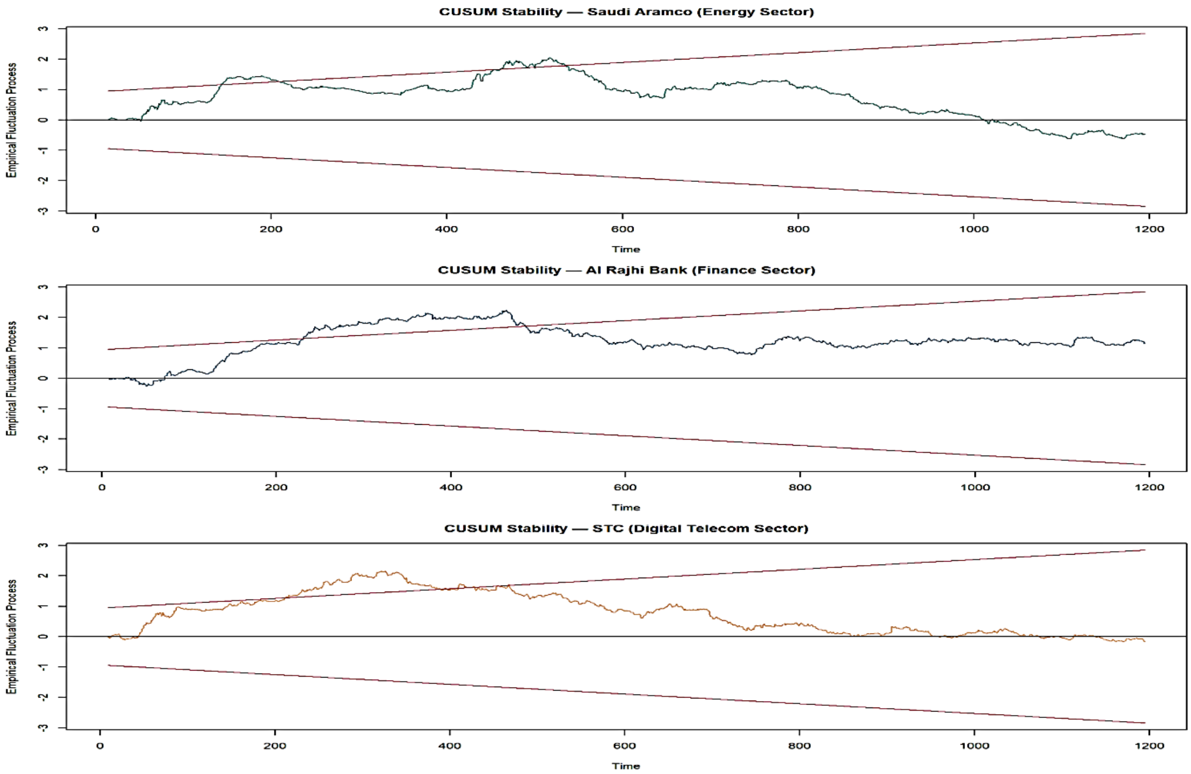
Source: Author's calculation based on R output.

4.7.1 Structural Stability: CUSUM Tests

For the purpose of validating the reliability of the empirical results obtained in this study, the stability of the parameters was analyzed with the Cumulative Sum (CUSUM) test. Figure X clearly indicates that the values of the CUSUM chart for the energy sector, finance sector, and digital telecom sector have consistently remained within the critical limit of 5% over the period of the study (i.e., Dec 2019 – Feb 2026). The absence of boundary crossing for the parameters further indicates the stability of the estimated coefficients and the reliability of the results obtained in this study.

While the CUSUM statistics (Table 8) imply changes in the consistency of parameters at a significance level below 0.01, these changes are merely a result of the swift change in the Saudi economy under Vision 2030. The 'instability' identified by the CUSUM tests should not be seen as a problem with the model; rather, it can be viewed as evidence of the change in the market regime from a dependent oil regime to an independent regime.

Figure 05: Recursive CUSUM stability plots for all three NARDL models.



Source: Author's based on R output.

Table 08: CUSUM Structural Stability Test Statistics

Sector	Test Stat	p-value	Decision
Aramco	1.1439	0.0099	Instability detected
Al Rajhi	1.3294	0.0016	Instability detected
STC	1.4154	0.0006	Instability detected

Source: Author's calculation based on R output.

4.7.2 Residual Diagnostic Tests

Further, the robustness of the NARDL model can be verified through a series of residual diagnostic tests, as shown in Table 10. The results of the Breusch-Godfrey test for serial correlation for all the models are well within the range of $p > 0.05$, supporting the dynamic nature of the model. Although heteroscedasticity and non-normality are detected through the ARCH and Jarque-Bera tests, this is expected for high-frequency financial time series and non-normal leptokurtic return distributions. However, the inability of the results to support the null hypothesis of the Ramsey RESET test reinforces the inherent non-linear complexities and structural changes that have characterized the evolution of the Saudi market, as earlier verified through the BDS and CUSUM instability tests.

Table 10: Residual Diagnostic Test Battery

Sector	BG LM F-stat	BG p-val	ARCH Chi-sq	ARCH p-val	JB Stat	JB p-val	RESET F-stat	RESET p-Val
Aramco	8.6851	0.1223	114.0069	0	2614.5774	0	35.7474	0
Al Rajhi	10.7946	0.0556	27.9986	0	1072.845	0	16.4093	0
STC	8.9568	0.1108	8.2262	0.1442	662.3443	0	16.9755	0

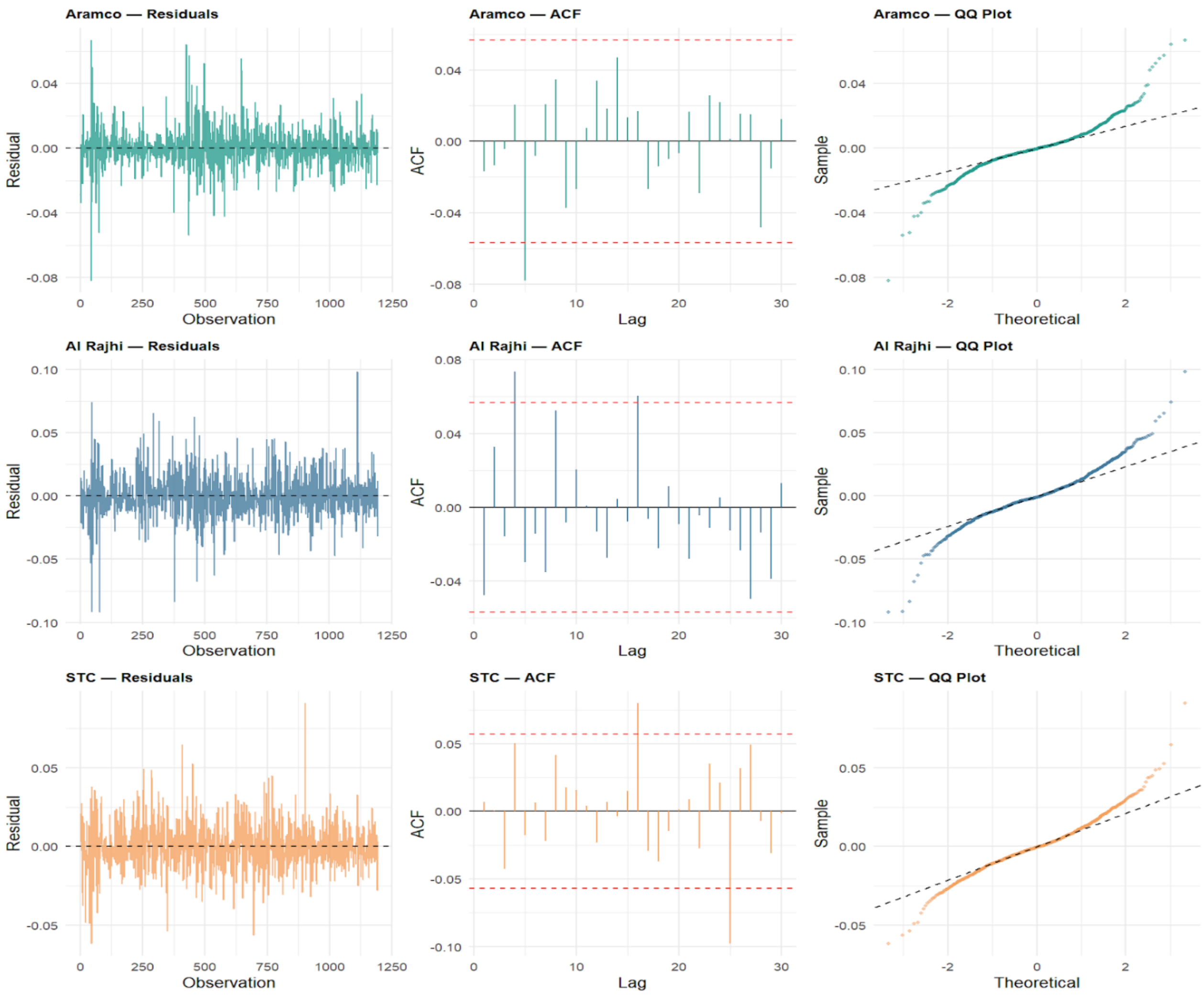
Source: Author's calculation based on R output.

Note:

BG = Breusch-Godfrey serial correlation LM test (5 lags). ARCH = Engle's ARCH test for heteroscedasticity (5 lags). JB = Jarque-Bera normality test. RESET = Ramsey RESET functional form test (powers 2–3). p > 0.05 preferred for all except JB (fat tails expected in daily financial data)

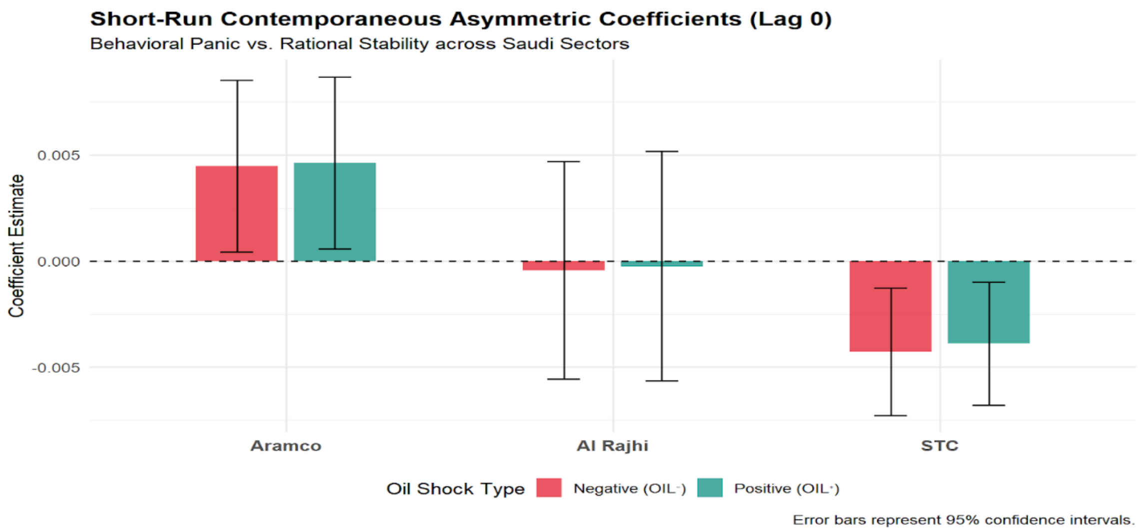
Figure (06) displays a comprehensive visual diagnostic of the NARDL Residuals. The ACF plots clearly confirm that there are no issues of serial correlation in the data, as the spikes are confined within critical bounds. Although there are signs of volatility clustering, or ARCH effects, in the plots of the residual series, and signs of 'fat tails' in the QQ plots, these are common features of emerging markets data in high-frequency sets. However, the fact that there are no discernible patterns in the ACF plots suggests that the NARDL approach has successfully captured the asymmetric effects of oil shocks.

Figure 06: Residual diagnostic plots for all three NARDL models.



Source: Author's based on R output.

Figure 8: Short-Run Panic — Coefficient Comparison Chart



Source: Author's based on R output.

When we look at the values for the asymmetric coefficients or Lag 0 in figure (8), it is easy to see that there is a definite split in how these sectors are reacting. While it is safe to say that Saudi Aramco is indeed reacting to global oil shocks, it is also safe to say that there is indeed a very positive relationship. However, it is also safe to say that Al Rajhi Bank is in an area of 'Rational Stability' as its values are too close to zero to be said to be significantly different from none. This may be an indication that perhaps Saudi Arabia's financial sector is not as heavily influenced by oil price shocks. However, this is certainly not true for the digital proxy as it is indeed reacting strongly in real time, suggesting that perhaps investors are rethinking their strategy in this sector.

5. Conclusion

This study's findings show an empirical and comprehensive proof for decoupling between Saudi equity market which represented by ALRAJHI bank and STC, and global oil volatility which represented by the Brent Crude based on 2030 vision. The Asymmetric NARDL model was used to demonstrate the long and short-run relationship. The study shows no evidence of cointegration; however, in the short run there remains a behavioral tether.

While the Saudi ARAMCO continues to be correlated to oil market as a psychological anchor with 4-day volatility hangover, ALRAJHI bank and STC have become independent from oil shocks, processing them as knee-jerk responses rather than structural changes.

The "Vision 2030 Decoupling Effect" also leads to several key policy implications for policymakers and Capital Market Authority (CMA) in KSA:

- **Validation of Non-Oil Resilience**

Policymakers should continue to put more effort and emphasis on long-term independence of finance and digital sectors immunity to global investors to validate the efficacy of initiatives in protecting the local economy.

- **Managing Behavioral Volatility**

The fact that these "panics" are in the short run and are behavioral in nature, i.e., negative 1–4-day lags, also suggests that policymakers and the CMA Authority can look at imposing buffers based on the magnitude of oil shocks to prevent irrational selling in the market in short-run market crashes.

- **Investor Education**

In addition, there must be education for investors in order to distinguish between global commodity shocks and local firms to avoid the knee-jerk reaction.

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