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Impact of Oil Price Shocks on GCC Stock Markets: Tail-Driven MTNARDL Evidence

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Abstract

This paper examines the asymmetric impact of recent oil price fluctuations on stock markets in the Gulf Cooperation Council (GCC) region from 2019 to 2024, a period marked by the COVID-19 pandemic and the prolonged Ukrainian crisis. Using the Nonlinear Autoregressive Distributed Lag (NARDL) and an enhanced Multiple Threshold Nonlinear Autoregressive Distributed Lag (MTNARDL) framework, the study examines whether extreme positive and negative shocks in oil prices, S&P 500, Bitcoin, and gold induce heterogeneous transmission effects on GCC equity indices. The empirical findings show that both extreme positive and negative oil price shocks exert a stronger and more persistent influence on GCC stock markets than fluctuations in global equities, cryptocurrencies, or precious metals. This confirms the dominant role of oil as a key driver of financial dynamics in oil-dependent economies, particularly during periods of heightened uncertainty. The main contribution of this study lies in the improvement of the MTNARDL specification, which allows for a clearer identification of tail-risk behavior and asymmetric volatility spillovers. The enhanced model captures multi-threshold nonlinearities more effectively than conventional approaches, offering a robust framework for policymakers and investors to better understand shock transmission mechanisms in hydrocarbon-based markets.

Keywords:
Oil Price Shocks;
GCC; Stock Markets;
MTNARDL;
Extreme Tail;
NARDL.

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1- Introduction

Oil is one of the most traded commodities worldwide, and it is a crucial factor in many industries. The oil price fluctuations can significantly impact investor confidence, corporate profits, and the economy through multiple channels. The relationship between oil price movements and stock market performance has been widely researched, especially given oil's strategic role in the global economy. Through these means, the movements of oil prices are revealed by empirical evidence proving that their effects on gross domestic product (GDP) growth can be problematic and context-dependent. As an illustration, some studies have argued that 1% increases in crude oil prices lead to zero economic growth or a negative impact, while others consider that it leads to a substantial positive impact on economic growth in the short and long phases, as noted by Musa et al. (2019) [1] and Deyshappriya et al. (2023) [2]. The complexity of how oil price dynamics impact various economic indicators across the world makes this a critical subject for economists and policymakers.

Historically, the fluctuations in oil prices influenced stock market indices in all emerging and developed markets [3, 4]. This is especially significant because of the notable differences in the economic structures of resource-rich and resource-poor regions and how they respond to the volatility in oil prices. In the Middle East and North Africa (MENA)

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region, the economic effects of oil price changes are relevant, and in many cases, there is vast heterogeneity among different countries, which exposes their stock markets and economic mechanisms [5]. In this regard, oil-exporting countries benefit directly, as high oil revenues allow increased government spending [6]. However, countries with less economic diversification and higher dependency on oil revenues tend to be more exposed to fluctuations and volatility in oil prices and, therefore, do not reap the benefits most of the time. Among the MENA region, the Gulf Cooperation Council (GCC) countries take the lead because of the availability of oil resources and significant economic power. The GCC, which includes Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE, represents a relatively more developed subset of the MENA region. These countries have strong financial and economic relationships, which are evidenced by the high intra-GCC trade and investment, as well as coordinated economic policies that foster development in the regional border of the GCC region [7].

The GCC region is among the foremost in the international energy market. This region tends to experience higher oil prices simultaneously with stock market booms as stock returns respond positively to the increase in oil prices [8]. Oil revenues are the main component of this region's economic framework. All the GCC countries are, as a block, amongst the world's top producers and exporters of crude oil, making this region highly resource-rich and immensely dependent. Remarkably, Saudi Arabia (11%), the UAE (4%), and Kuwait (3%) are among the top ten oil producers in the world, as indicated by the Energy Information Administration (EIA). The total revenue and GDP of GCC countries are primarily a result of the oil revenue, which in turn increases the consequences of oil price movements on the state of financial markets and the country's economic security. According to the World Bank, the GDP in the GCC countries is at least 20% of oil revenue. The over-dependence on oil revenues to cover government budgets, public investments, and economic activities makes the financial markets of these countries and their economic stability more sensitive to oil price shocks. That's why oil price movements tend to closely correlate with the performance of the GCC region's stock markets [9]. From an economic perspective, upward oil price shocks (positive shocks) usually accelerate increased government budgets and improved corporate profitability, mainly in oil-related sectors. On the contrary, downward oil price shocks (negative shocks) can reduce revenues, fiscal deficits, and economic volatility. Figure 1 illustrates the map and geographic location of the six GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and UAE).

Figure 1. GCC countries' map

Oil price fluctuations can be caused by supply or demand changes, as well as geopolitical tensions. Such changes can be attributed to either fundamental or speculative factors and can have an impact that is polarized on the stock markets and then the global economy [10, 11]. For example, supply-side shocks like OPEC production cuts or geopolitical disputes in oil-rich areas tend to increase oil prices at a much higher level than other types of shocks [12]. Such changes would influence the energy sector and other sectors differently as well. On the other hand, demand-side shocks caused by positive or negative growth in oil economies may have a broader effect on investor appetite and expectations. In other words, oil market-specific demand shocks can worsen economic policy uncertainty, affecting the stock market's performance [13, 14].

Apart from oil price shocks, other factors are likely to affect the GCC's stock markets, including the movements of the S&P 500 indexes. As noted by Cheikh et al. (2021) [15], emerging markets like the GCC capital markets tend to follow the sentiment of the global economy, represented by the movements of the S&P 500 index. Furthermore, Bitcoin ranked first out of all 10,679 active cryptocurrencies listed on CoinMarketCap and has also become the most valuable cryptocurrency investment, carrying the highest market capitalization in the crypto market of over $2 trillion by the beginning of 2025. Its trading and investment prospects have significantly grown, providing diversification and speculative opportunities. With more than 12 trillion in market capitalization, gold remains the most important precious metal and a long-trusted haven during uncertain times, which makes it quite stable and appealing as an investment asset. Both Bitcoin and gold provide unparalleled insights into investments during troubled market conditions and global crises [16-18]. Figure 2 demonstrates the stock market performance in GCC countries over the period of study. It can be noticed that the markets' returns have been subject to tremendous declines in the wake of the COVID-19 pandemic; however, the indices exhibit a swift recovery in 2021.

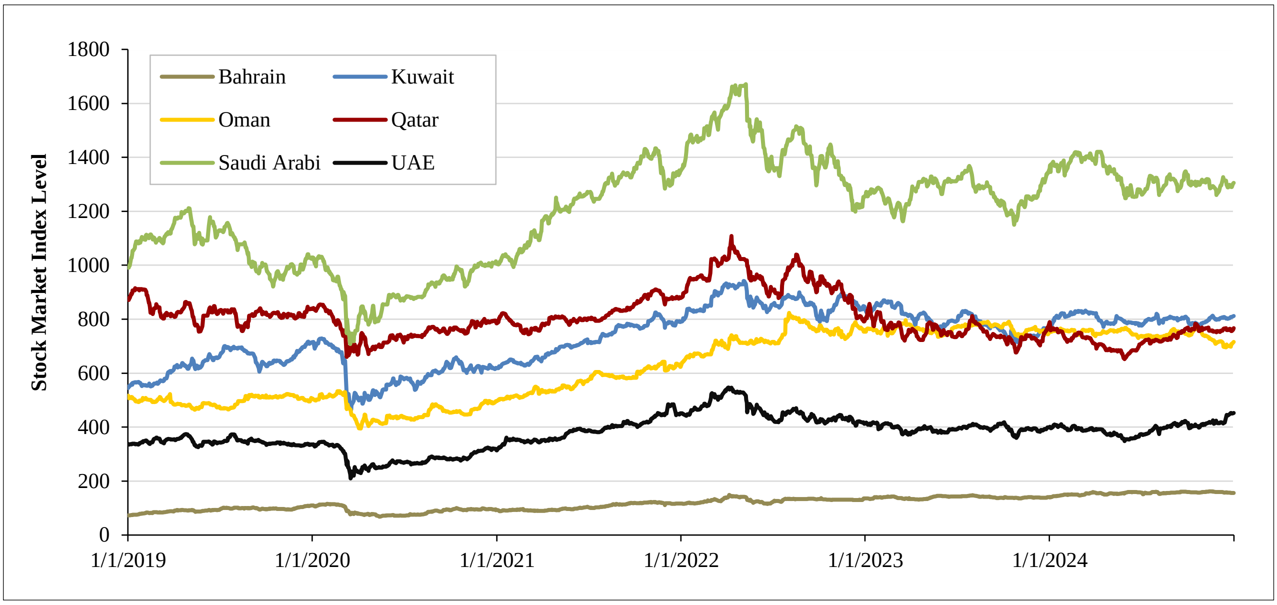

Figure 2. GCC stock market indices (2019-2024)

This paper aims to investigate the impact of extreme movement in oil price shocks along with global stock markets represented by the S&P500 index, the cryptocurrency market (represented by bitcoin), and precious metals (represented by gold) on stock markets in GCC countries. We follow Ready (2018) [19] in decomposing the oil price shocks into demand, supply, and risk shocks to assess the nature of oil shocks that lead to significant responses of the GCC stock indices. To accomplish that, we employ the nonlinear ARDL model that depicts the asymmetric effects of independent variables in the system on the GCC stocks. We also apply the Multiple Thresholds NARDL to depict the extreme tail effects of oil price shocks on these markets. This paper is believed to contribute to the existing literature as follows: First, this paper utilizes a dataset that covers a period of time from 2019 until late 2024, where the oil market has witnessed different types of shocks, including significant demand shocks during the COVID-19 pandemic, and the dataset also covers the noticeable oil supply shock caused by the Russia-Ukraine conflict. Second, this paper compares the reaction of GCC stock markets to shocks in oil prices (which their economies are heavily dependent on as the main source of income) with shocks in financial and investment assets such as the S&P 500, gold, and cryptocurrency markets, and this will shed light on the nature of the financial connectedness of the GCC markets with main commodities and investment securities. Third, in the foregoing studies, multiple thresholds were generally set at relatively moderate quantiles, such as 20%, 40%, 60%, and 80% thresholds, or 30% and 70% in particular, with a view to appropriately sketching the nonlinear pattern in time series data.

Placed within these lines is the work of Pal & Mitra (2015) [20], for instance, who categorized the series into deciles ranging from the 10th percentile to the 90th percentile to explore tail impacts on the series. However, these approaches generally ignore the most dramatic fluctuations in financial series, which in turn play pivotal roles in finance and economics to induce major market activities in practice. To address this gap, we propose a relatively novel formulation in the proposed MTNARDL. Specifically, the new strategy in the extreme tail MTNARDL outlines its financial series decomposition into five partial series with tailored thresholds fixed at relatively more dramatic subsets, namely 2.5%, 5%, 95%, and 97.5% percentiles in particular, to more closely elucidate the dramatic tail impact of oil-price costs, namely demand, supply, and risk in particular, generally dismissed in traditional MTNARDL settings. By targeting these dramatic percentiles in financial series decomposition, we provide a more refined interpretation of rare but significant market activities in GCC stock markets with precision using our improved MTNARDL model for the first time, to the best of our knowledge, with novel implications in the MTNARDL strategy for the scientific treatment for complex financial series with more profound implications for financial time series research in general.

The remainder of this paper is organized as follows: Section two demonstrates the literature review, Section three displays the data and variables used in this research, Section four explains the methodology and model specifications, Section five demonstrates the main results and discussion, and Section six concludes the paper.

2- Literature Review

The reliance of oil-producing countries on oil revenues in their national income has raised a lucid question about the effect of oil price shocks on the financial system in general and stock markets in particular. Over the last decades, oil crises have raised the question of whether GCC stock markets are resilient to sharp rises and/or declines in oil prices. This has given rise to a booming literature measuring the performance of GCC stock markets in the wake of various price shocks and to a main strand of research depicting the oil shocks' spillover to financial markets in major oil-producing countries. Extensive empirical work has been conducted to measure the effect of oil price shocks on major oil-importing countries. The outcomes of this work were diverse and sometimes contradictory; many research outcomes found a clear linkage between oil prices and stock market returns in these countries, that an increase in oil price results in higher net revenues and economic growth, leading to better stock market performance for exporting countries [8, 21-26].

Research regarding GCC stock markets and oil price movements has evolved quickly in recent years. For instance, Lahiani & Arouri (2010) [27] pointed out that while oil price shocks tend to affect stock market returns directly, the responses depend heavily on prevailing market conditions and other factors. Mohanty et al. (2011) [28] found that oil price shocks spillover to the majority of GCC stock market indices, where the price shocks generate positive stock market returns in the region. Similarly, Arouri et al. (2010) [29] employed VAR models and showed that Saudi Arabia and Oman could forecast higher oil prices. Cheikh et al. (2018) [30] further noted that, when considering some of the GCC countries, such as Saudi Arabia and Kuwait, a strong relationship exists between oil prices and stock market volatility. Alqahtani et al. (2019) [31] revealed that oil market uncertainty had negative impacts on GCC stock returns, showing that some stock markets do not react to fluctuations in oil prices. El-Chaarani (2019) [32] found that negative shocks in oil prices have a far greater unfavorable impact on stock market returns than positive shocks experienced in several GCC countries.

In line with the need to incorporate recent insights, newer studies have emerged over the last two to three years. Ziadat & McMillan (2022) [33] indicated that oil price fluctuations significantly affect the risk-return relationship in GCC stock indices, with clear evidence of asymmetric responses to both positive and negative shocks. Bashir (2022) [34] discussed oil supply and demand shocks, stating that demand shocks are believed to have a strong nexus to the region's economic performance; they tend to have a greater impact on the stock market than supply shocks. This is relevant in the context of GCC countries, where Alotaibi & Morales (2022) [35] proved that oil-price volatility dramatically influences the risk and return features of the GCC stock indices, revealing asymmetric responses to positive and negative shocks.

Recent studies have further reinforced and extended these findings by applying refined and more sophisticated methodologies. Building on recent GCC-focused evidence, Bensaïda et al. (2024) [36] uncover regime-dependent spillovers between crude oil and GCC equities, underscoring pronounced nonlinearities; together with Sezen's (2025) [37] time- and frequency-varying causality for GCC markets, these findings reinforce the need for flexible, tail-sensitive models such as our tail-driven MTNADL framework. Afşar et al. (2025) [38] further advanced the literature by employing a quantile-on-quantile connectedness approach to examine dynamic oil–stock linkages in emerging economies. Their results reveal that the strength and direction of dependence vary significantly across quantiles and intensify during extreme market conditions, confirming that crisis episodes amplify tail co-movements. Extending such a tail-sensitive framework to the GCC context provides valuable regional insight into the asymmetric transmission of oil shocks. Moreover, Al-Fayoumi et al. (2025) [39] highlighted those geopolitical shocks—such as the Gaza conflict—further amplify volatility transmission between oil and GCC stock markets. Their evidence shows that during periods of geopolitical tension, the sensitivity of GCC equities to oil-price fluctuations rises sharply, illustrating how external risk factors deepen the tail dependence in oil–stock interactions. Collectively, these studies demonstrate the growing relevance of nonlinear, tail-sensitive, and crisis-responsive models in explaining oil–stock dynamics. Tien & Hung (2022) [40] applied a wavelet-based asymmetric DCC model and revealed significant volatility spillovers between oil and GCC stock markets, particularly during periods of extreme price movement. Hussain & Rehman (2023) [41] showed how global oil price volatility drives volatility spillovers within GCC stock markets, emphasizing the role of global uncertainty in shaping intra-regional market dynamics.

A recent strand of research has examined additional dimensions, such as political instability and tail-risk behavior. Bouri et al. (2023) [42] studied the effect of geopolitical risk indices on GCC stock markets and noted that political uncertainty increases the responsiveness of these markets to oil price shocks. Abdelaziz Eissa et al. (2025) [43] reached a similar conclusion, confirming that geopolitical-risk asymmetries amplify the effect of oil shocks on GCC equities. Such findings highlight the integration between political and economic risks in oil-dependent regions and underline the need for political sustaining investor confidence. Significant global events, such as the COVID-19 pandemic, have also been shown to influence the oil-stock relationship. Shamsudheen et al. (2022) [44] studied the dual impact of fiscal packages and declining oil prices during the pandemic and discovered that GCC stock indices were positively affected by crude oil prices but suffered from global oil market instability. This demonstrates how external shocks alter the oil-stock relationship. Similarly, Yousaf et al. (2022) [45] examined volatility spillover and hedging relationships among GCC stock markets and global financial variables, revealing significant shifts in spillover intensity between normal periods and crises, including the COVID-19 pandemic and the global financial crisis. The literature indicates that this relationship exhibits asymmetrical behavior. Reinvestigating this linkage, Ebadi (2024) [46], for instance, used a regime-switching cointegration approach and revealed that GCC investors react more optimistically toward positive oil shocks rather than negative ones. These findings collectively confirm that the oil-stock relationship exhibits nonlinear and asymmetric patterns that intensify under stress conditions.

Recent publications have analyzed the integration of global financial markets with GCC economies. Hussain and Rehman (2023) [41] studied the spillover impacts of international equity markets, particularly the S&P500, which they note as a leading indicator of GCC stock market performance. This interconnectedness shows that local oil price fluctuations interact with global market movements. Yousuf & Zhai (2022) [47] explored the financial interconnectedness between global equity markets and oil, emphasizing the critical role of crude oil prices in driving co-movement and systemic risk in GCC financial systems. Their findings support the growing need for robust diversification strategies in oil-dependent markets. Das et al. (2020) [48] examined the correlations between oil, cryptocurrency, and gold, emphasizing the growing role of alternative assets as hedges during economic instability [49]. Innovations in econometric modeling have helped explain the asymmetric nonlinear effects of oil price shocks [50]. Ziadat & McMillan (2022) [33] analyze extreme movements in oil prices and their tail effects on the stocks of emerging markets, especially the GCC ones. Their results indicated that negative oil price shocks have a disproportionately larger impact on market volatility than positive shocks, underscoring the asymmetric nature of investor reactions to oil price fluctuations.

Existing empirical studies attempt to measure the nexus between oil price shocks and GCC stock market movements. The outcomes of these studies are generally based on econometric techniques; however, several gaps remain. First, most empirical studies focus on large oil-price movements and often overlook the effect of marginal fluctuations on financial markets. Second, empirical literature rarely differentiates between different demand, supply, and risk-related shocks or fully accounts for the asymmetric effects of these shocks. Third, many studies rely on linear or traditional nonlinear models that may not capture extreme tail behavior. These limitations highlight the need for a more nuanced and granular approach to studying the oil-stock relationship in GCC economies. In this paper, we fill these gaps by focusing on the impact of tiny (or very small) changes in oil prices on GCC stock markets. We advance the MTNARDL approach to depict extreme-tail impacts of time series, imposing restrictions that allow us to track the influence of extremely positive and negative changes in oil-price prices on GCC stock indices. Hence, this research contributes to the existing literature by shedding light on the extreme-tail effects of various oil-price shocks (demand, supply, and risk shocks) in GCC stock markets using the extreme-tail-adjusted MTNARDL methodology.

3- Data

This study utilizes a daily stock market indices dataset for GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and UAE). We also use the daily observations for the main stock market index of the U.S.A. S&P500 index and gold prices[*]. For the oil shocks, we follow Ready (2018) [19], where the percentage change of the nearest maturity New York Mercantile Exchange crude oil futures contracts is used to proxy for oil prices. We also use the VIX index, which indicates investors' fear, and the World Integrated Oil and Gas Producers Index. The data is collected mainly from the DataStream database, in addition to the coins market database and Yahoo Finance. In this study, we consider a data sample that covers the period from the beginning of 2019 until the end of October 2024. We believe that throughout this period, important global events have occurred and led to significant changes and contradicting patterns of oil price movement, starting with the COVID-2019 pandemic that had spread over the world in late 2019 and lasted until 2021. The pandemic period is believed to be the best representative of the oil demand shock. Also, the world witnessed a major geopolitical shock in early 2022 when the war in Ukraine started. One of the main economic and

[*] By using high-frequency data (daily or intraday), it becomes possible to better track drastic and extreme values in the prices compared to coarser-frequency data, for instance, weekly/monthly/quarterly observations, which exhibit smoothing effects on daily fluctuations. Higher daily granularity in tracking prices improves the identification capabilities concerning the clusters of volatilities, drastic jumps, and asymmetric adjustment processes that generally lie in the tail events. All these factors play pivotal roles in understanding risk dynamics and portfolio diversification strategies, as indicated by Campbell et al. (1997) [51].

global consequences of this event is the sanctions imposed by the U.S.A. and EU countries on Russian oil exports, which have caused a shock in oil supplies and raised the barrel price to high levels. We assume that the dataset employed in this study best represents the three different types of shocks introduced by Ready (2018) [19]: oil demand shock, oil supply shock, and oil risk shock.

3-1- Oil Price Shocks Identification

In this paper, we decompose the oil price shock into demand shock, supply shock, and risk shock. These variables are created by disentangling the daily oil prices using Ready's approach. According to this approach, the demand shock is determined as the global oil-producing companies' proportion of return that is orthogonal to the volatility index (VIX) of the Chicago Board Options Exchange (CBOE). Then, we constructed the risk shock based on the innovations of the VIX index, and the supply shock is then calculated using the residuals of the risk shock and demand shock [52]. For that, the following autoregressive moving average ARIMA (1,1) specifications are used:

$$X_t \equiv \begin{bmatrix} \Delta p_t \\ R_t^{prod} \\ \zeta_{VIX,t} \end{bmatrix}, H_t \equiv \begin{bmatrix} Su_t \\ De_t \\ Ri_t \end{bmatrix}, A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{1}$$

where, Su_t, De_t, Ri_t denote the supply, demand, and risk shocks, respectively. Δp_t represents the change in oil price, R_t^{prod} shows the return of oil companies, and $\zeta_{VIX,t}$ denotes the unexpected changes to VIX. The Ready's method assures the orthogonality between the three variables.

4- Research Methodology

The research in this paper employs the Autoregressive Distributed Lag (ARDL) method to capture the short and long-run co-movements among the independent variables represented by different oil price shocks, S&P500, bitcoin, and gold, and the list of GCC stock market indices that represent the dependent variables. The main advantage of the ARDL model is that it can be applied whether the variables are integrated in the same or different orders; it can also demonstrate the error correction mechanism, if any, in the long run cointegration relationship [53]. However, it has been widely argued in the literature that the time series variables are known by their nonlinearity, where the time series variables might exhibit an unsynchronized effect on each other depending on whether the change in regressors is positive or negative. In other words, the dynamic transmission of shocks among time series variables could be better captured by a nonlinear econometric framework. In this context, Shin et al. (2014) [54] suggested the nonlinear ARDL model with a single threshold to decompose the time series variables into positive and negative partial sums. This enables testing for the existence of asymmetric impacts of time series on each other through capturing the influence of each escalation or drop of the independent variable on the dependent variable. In the last few years, the NARDL model has been subject to further developments. For instance, Verheyen (2013) [55] introduced the bi-threshold NARDL, where the regressors in the system are decomposed into three partial sums using two thresholds set at the 30th and 70th quantiles. Following that, various research scholars have applied the NARDL with multiple thresholds using different quantiles such as 20th, 40th, 60th, and 80th [52, 56, 57] or using the multiple deciles [20].

The previous developments in the multiple threshold NARDL model have enabled researchers to measure asymmetric impacts through decomposing the independent variables into different and multiple partial sums and assessing whether their effects on the dependent variables remain constant (symmetric relationship) or change from one partial sum to another (asymmetric relationship). However, the current application and utilization of the MTNARDL do not highlight the behavior and potential effects of regressors in their extreme positive and negative values. In this paper, we impose new thresholds to decompose the variables into five different partial sums, focusing mainly on extreme tails of 0 to 2.5%, and 2.5% to 5% (for extremely low values), and 95% to 97.56% and 97.5% to 100% to account for extreme escalation in the value of our variables. However, the middle partial sum represents values between 5% to 95% which we consider as the inner corridor. Henceforth, our paper contributes to existing literature by upgrading the on MTNARDL methodology to enable capturing the extreme tail asymmetric and nonlinear effects among time series variables. By the time of writing this paper, we are not aware of any research work that attempted to upgrade the MTNARDL to capture the extreme tail asymmetric effect among time series variables. Figure 3 illustrates the methodology utilized in this paper and it outlines a three-stage process: data preparation, modelling, and application. In the data preparation stage, relevant financial data such as oil shocks, S&P500, Bitcoin, Gold, and GCC stock indices are collected, cleaned, transformed, and optimized using AIC lag selection. The modelling stage applies ARDL, NARDL, and MTNARDL models to estimate short- and long-run effects, capture asymmetric relationships, and test for extreme-tail impacts. Finally, the application stage performs country-by-country estimations to analyse how markets respond differently under normal and extreme conditions.

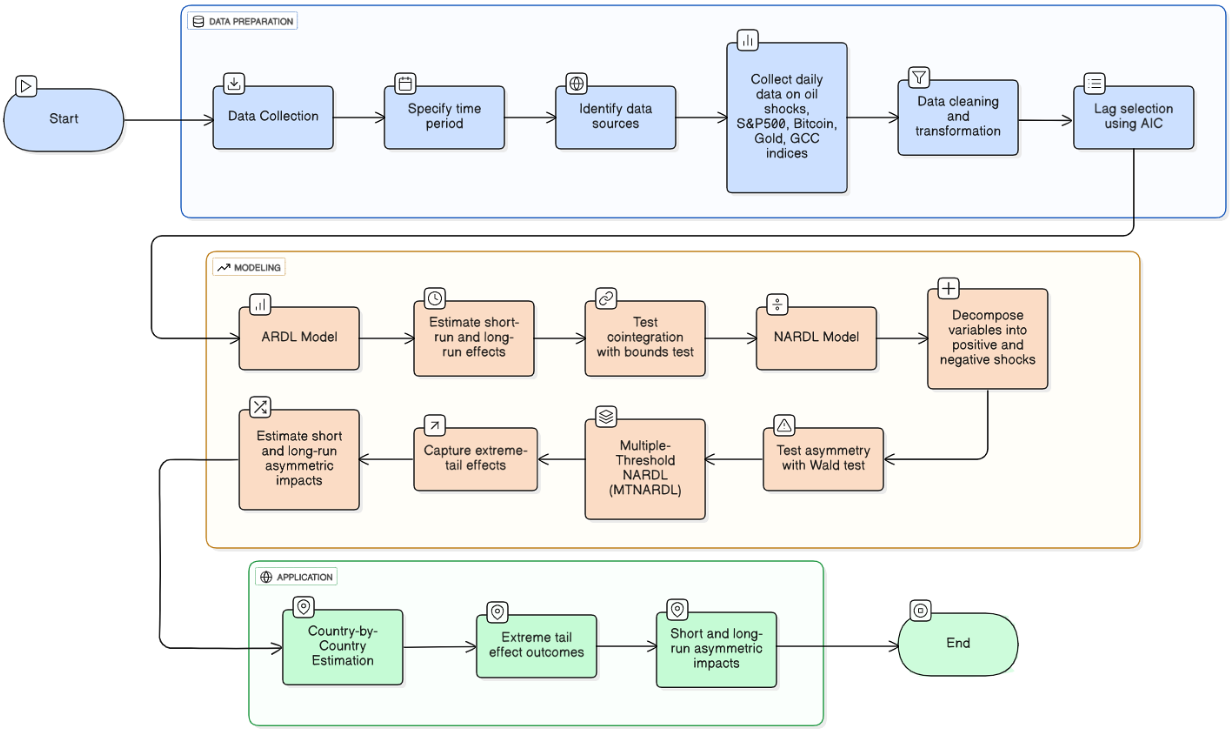

Figure 3. Methodology Process for Oil Shocks and GCC Stock Markets

4-1- ARDL Approach

The ARDL model introduced by Pesaran et al. (2001) [53] suggests that the relationship among variables in the system is represented as follows:

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n} \Omega_{2i} \Delta Y_{t-i} + \delta_1 X_{t-1} + \delta_2 Y_{t-1} + \varepsilon_t \tag{1}$$

where, X_t refers to the stock market indices in GCC countries (separately) at the time t, and Y_t stands for the independent variables of oil shocks, including demand shock, supply shock, and risk shock, in addition to the rest of the independent variables of the S&P500 index, Bitcoin, and Gold prices. The Δ indicates the first difference of the variable, and ε_t is the error term. The ARDL model specifications in this paper are presented as follows:

$$\begin{aligned} \Delta X_t &= \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n} \Omega_{2i} \Delta demandshock_{t-i} + \sum_{i=0}^{n} \Omega_{3i} \Delta supplyshock_{t-i} + \sum_{i=0}^{n} \Omega_{4i} \Delta riskshock_{t-i} + \\ &\sum_{i=0}^{n} \Omega_{5i} \Delta SP500_{t-i} + \sum_{i=0}^{n} \Omega_{6i} \Delta bitcoin_{t-i} + \sum_{i=0}^{n} \Omega_{7i} \Delta gold_{t-i} + \delta_1 X_{t-1} + \delta_2 demandshock_{t-1} + \\ &\delta_3 supplyshock_{t-1} + \delta_4 riskshock_{t-1} + \delta_5 SP500_{t-1} + \delta_6 bitcoin_{t-1} + \delta_7 gold_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

The ARDL model encompasses the measurement of long-run and short-run relationships among the variables. The F-test measures the existence of a long-run effect (cointegration) of independent variables on GCC stock markets. The null hypothesis of no cointegration between the variables in Equation 2 is $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = 0$ against the alternative hypothesis of $H_1: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq 0$. The coefficients Ω_2 to Ω_7 in Equation 2 represents the short-run effect of independent variables on GCC stock market indices. The cointegration outcomes in Equation 2 are determined based on the value of the F-statistic, where the null hypothesis of no cointegration is rejected when the value exceeds the upper bound critical value [53]. The optimum lag length used for the econometric specifications in Equation 1 was determined using the AIC approach.

4-2- NARDL Approach

The ARDL model assumes linearity among time series in the system; however, it has been argued that most of these variables do not exhibit a linear relationship with each other. Hence, the NARDL model was introduced to investigate the existence of asymmetric impacts among time series. The NARDL model is used in this paper, which divides the regressors into positive and negative partial sums to capture the effect of increases and decreases of the aforementioned independent variables on GCC stock markets. Each independent variable of (Y, demand shock, supply shock, risk shock, S&P500, Bitcoin, and gold, separately) is decomposed into positive and negative shocks as per the following:

$$Y_t = Y_0 + Y_t^+ + Y_t^- \tag{3}$$

The Y_t^+ and Y_t^- represents the influence of increases and decreases in independent variables of oil price shocks, S&P500, Bitcoin, and Gold on dependent variables of GCC stock markets. The Y_t^+ and Y_t^- are expressed as:

$$Y_t^+ = \sum_{i=1}^{t} \Delta Y_i^+ = \sum_{i=1}^{t} \max(\Delta Y_i, 0) \tag{3a}$$

$$Y_t^- = \sum_{i=1}^{t} \Delta Y_i^- = \sum_{i=1}^{t} \min(\Delta Y_i, 0) \tag{3b}$$

The NARDL representation of the positive and negative shocks effect of our independent variables is:

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta demandshock_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta demandshock_{t-i}^- + \delta_1 X_{t-1} + \delta_2 demandshock_{t-i}^+ + \delta_3 demandshock_{t-i}^- + \varepsilon_t \tag{4}$$

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta supplyshock_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta supplyshock_{t-i}^- + \delta_1 X_{t-1} + \delta_2 supplyshock_{t-i}^+ + \delta_3 supplyshock_{t-i}^- + \varepsilon_t \tag{5}$$

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta riskshock_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta riskshock_{t-i}^- + \delta_1 X_{t-1} + \delta_2 riskshock_{t-i}^+ + \delta_3 riskshock_{t-i}^- + \varepsilon_t \tag{6}$$

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta SP500_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta SP500_{t-i}^- + \delta_1 X_{t-1} + \delta_2 SP500_{t-i}^+ + \delta_3 SP500_{t-i}^- + \varepsilon_t \tag{7}$$

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta bitcoin_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta bitcoin_{t-i}^- + \delta_1 X_{t-1} + \delta_2 bitcoin_{t-i}^+ + \delta_3 bitcoin_{t-i}^- + \varepsilon_t \tag{8}$$

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \Omega_{2i} \Delta gold_{t-i}^+ + \sum_{i=0}^{n2} \Omega_{3i} \Delta gold_{t-i}^- + \delta_1 X_{t-1} + \delta_2 gold_{t-i}^+ + \delta_3 gold_{t-i}^- + \varepsilon_t \tag{9}$$

Equations 4 to 9 demonstrate the effect of positive and negative shocks in independent variables on GCC stock markets represented by X_t variable separately. For instance, Equation 4 illustrates the impact of positive and negative movements of oil demand shock on stock markets in the GCC region, while Equation 5 measures the effect of positive and negative values of oil supply shock on GCC markets. The same applies to the rest of the independent variables (risk shock, S&P500, bitcoin, and gold).

On top of measuring the impact of positive and negative shocks on GCC indices, the NARDL model investigates the existence of long and short-run asymmetries. In other words, unlike the ARDL model, which assumes that the relationship among variables in the system is best described by a linear form, the NARDL investigates the existence of non-linearity in the short and long-run co-movements among the variables. The short-run asymmetry in Equations 4 to 9 is measured using the Wald test statistic with the null hypothesis of no asymmetry H_0: $\Omega_2 = \Omega_3$. In the same way, the standard Wald test is used to test long-run asymmetries for the null hypothesis of H_0: $\delta_2 = \delta_3$. At last, the existence of a cointegration relationship is tested by the bound test for H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ against the alternative hypothesis of no cointegration.

4-3- Multiple Threshold NARDL (MTNARDL)

The MTNARDL introduced by Pal & Mitra [20] splits the independent variables into different quantiles by imposing multiple thresholds on the time series. This decomposition enables capturing the asymmetric transmission of the regressors with different fluctuations [52]. In this paper, we impose four different thresholds to decompose the regressors into five partial sums or quantiles; however, one of the main contributions of this paper is that we utilize the MTNARDL to measure the extreme tail impacts of shocks in oil, S&P500, bitcoin, and gold on stock markets in the GCC region. For that, we impose thresholds on regressors in the system at 2.5%, 5%, 95%, and 97.5% in order to capture the dynamic transmission and impact of extreme values of these independent variables on GCC stock market indices. The imposition of four thresholds decomposes the regressors into five partial sums as follows:

$$Y_t = Y_0 + Y_t^{(\varphi 1)} + Y_t^{(\varphi 2)} + Y_t^{(\varphi 3)} + Y_t^{(\varphi 4)} + Y_t^{(\varphi 5)} \tag{10}$$

In Equation 10, the $Y_t^{(\varphi 1)}$, $Y_t^{(\varphi 2)}$, $Y_t^{(\varphi 3)}$, $Y_t^{(\varphi 4)}$, and $Y_t^{(\varphi 5)}$ are the five partial sums series of independent variables are generated using the thresholds of $\tau_{2.5}$, τ_5, τ_{95}, $\tau_{97.5}$ at the 2.5, 5, 95, and 97.5 quantiles, respectively. The five partial sums are calculated using the following specifications:

$$Y_t^{(\varphi 1)} = \sum_{i=1}^{t} \Delta Y_i^{\varphi 1} = \sum_{i=1}^{t} \Delta Y_i^{I} (\Delta Y_i \leq \tau_{2.5}) \tag{11a}$$

$$Y_t^{(\varphi 2)} = \sum_{i=1}^{t} \Delta Y_i^{\varphi 2} = \sum_{i=1}^{t} \Delta Y_i^{I} (\tau_{2.5} < \Delta Y_i \leq \tau_5) \tag{11b}$$

$$Y_t^{(\varphi 3)} = \sum_{i=1}^{t} \Delta Y_i^{\varphi 3} = \sum_{i=1}^{t} \Delta Y_i^{I} (\tau_5 < \Delta Y_i \leq \tau_{95}) \tag{11c}$$

$$Y_t^{(\varphi 4)} = \sum_{i=1}^{t} \Delta Y_i^{\varphi 4} = \sum_{i=1}^{t} \Delta Y_i^{I} (\tau_{95} < \Delta Y_i \leq \tau_{97.5}) \tag{11d}$$

$$Y_t^{(\varphi 5)} = \sum_{i=1}^{t} \Delta Y_i^{\varphi 4} = \sum_{i=1}^{t} \Delta Y_i^{I} (\Delta Y_i > \tau_{97.5}) \tag{11e}$$

Where the $I(.)$ is a dummy variable that equals 1 when the conditions stated within (.) are satisfied, else zero. The decomposition of each oil shock series into partial sums over distinct thresholds, MTNARDL, can help reduce collinearity issues related to linear combinations because it models regime-specific effects separately. Based on the specifications above, the multiple threshold NARDL at the 2.5, 5, 95, and 97.5 quantiles is denoted as follows:

$$\Delta X_t = \sum_{i=1}^{n1} \Omega_{1i} \Delta X_{t-i} + \sum_{j=1}^{5} \sum_{i=0}^{n2} \Omega_{ki} \Delta Y_{t-i}^{\varphi_j} + \delta_1 X_{t-1} + \sum_{j=1}^{5} \delta_k Y_{t-1}(\varphi_j) + \varepsilon_t \quad (12)$$

where, $k = j + 1$. The cointegration among the variables is tested by the bound test for the null hypothesis H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$ against the alternative hypothesis H_1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq 0$ of no cointegration. The short-run asymmetry is assessed using the null hypothesis of H_0: $\Omega_2 = \Omega_3 = \Omega_4 = \Omega_5 = \Omega_6 = 0$, while the long-run asymmetry is assessed with H_0: $\delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$. The optimal lag length in Equation 12 is determined using AIC to better capture the dynamic relationships in the data, which reduces autocorrelation in residuals. This leads to more reliable parameter estimates and valid statistical inference.

Before the application and display of Equation 12 outcomes, we would like to reaffirm that the above regression is used repeatedly to measure the impact of extreme tails movement of independent variables of oil demand shock, oil supply shock, oil risk shock, S&P500 index, bitcoin, and gold, on stock markets in the GCC region (representing dependent variables) separately. For more clarification, the MTNARDL presented in Equation 12 is applied six different times to capture the effect of extreme tails of oil demand shock, oil supply shock, oil risk shock, S&P500 index, bitcoin, and gold, on stock market in Bahrain, then another six different times to capture the effect of extreme tails of same six variables on stock market in Kuwait, and so on so forth.

5- Results and Discussion

In this paper, we assess the order of integration among the variables by conducting the Augmented Dickey-Fuller and Phillips-Perron tests proposed by Dickey & Fuller (1979) and by Phillips & Perron (1988), respectively [57, 58]. The results of unit root testing are presented in Table 1. The results indicate that all variables are integrated of order I(0) in their levels, except for the supply shock, which has significant t-statistics at the 5% level, and the risk shock, which has a 1% level of significance. However, all series become stationary in their first differences I(1). The main advantage of the ARDL model is that it can be applied regardless of whether the variables are all integrated of the same or mixed orders. Hence, in the next section, we proceed to apply the ARDL approach to test for the cointegration among the variables. Following the confirmation of stationarity in the first differences of all variables, we proceed to test for long-run cointegration among the variables using the ARDL approach. The results in Table 2 present the outcomes of the linear ARDL model.

Table 2 demonstrates the outcomes of the ARDL model for long and short-run associations among the variables. The outcomes of the F-statistics are presented in the last row of the table, indicating the long-run cointegration among the variables. The F-statistic is compared with the upper and lower bound critical values estimated by Pesaran et al. (2001) [53] to test for the potential rejection of the null hypothesis of no cointegration. Column (3) in Table 2 demonstrates the outcomes of the ARDL cointegration test presented by Equation 2 above. Where the stock market returns in Bahrain are the dependent variables and placed on the left side of the equation, whereas the price shocks (demand, supply, and risk), along with S&P500 returns, bitcoin, and gold are the independent variables. Panel A in Table 2 demonstrates the outcome of short and long-run effects of oil demand shock on stock market returns in Bahrain. The outcomes reveal that the movement and changes in global oil demands can influence the performance of the Bahraini stock market in the near future and in the long run, and this is indicated by the significant coefficients of ΔD and $D(-1)$ for short and long-run horizons, respectively. Panels B and C demonstrate the outcomes pertinent to of global supply and risk shocks (respectively) coefficients. The outcomes in panels B and C are in line with the findings for oil demand shock, where the stock market in Bahrain seems to be influenced by uprisings and declines in oil supplies and uncertainty pertinent to global oil prices.

On the other hand, the results in panels D, E, and F measure the potential effect of S&P500, bitcoin, and gold price changes on stock market performance in Bahrain. The outcomes indicate for negligible influence of running from this set of variables on the stock market of Bahrain. The last row in Table 2 displays the F-statistic results for long-term cointegration among the independent variables in the system and the Bahrain stock market return. It can be noticed that the F-statistic is significant at 5% level, which indicates for cointegration relationship among the independent variables of Equation 2 and the stock market performance in Bahrain. The rest of the columns in Table 2 demonstrate the effect of independent variables in Equation 2 on the rest of the GCC stock indices. That column (4) in Table 2 demonstrates the outcomes of the long and short-term association among the three oil price shocks, as well as other dependent variables in the system, on stock market performance in Kuwait. The outcomes indicate financial connectedness and influence from the three oil price shocks, in addition to the S&P500 index, on the Kuwaiti stock market. Column (5) displays the outcomes pertinent to stock market performance in Oman. It can be noticed that the coefficients of short and long-run impacts are significant for the oil demand and supply shocks. The stock index in Oman appears to be influenced by the performance of the S&P index in the short run, whereas this influence does not carry on over a long-run horizon. Columns (6) and (7) for Qatar and Saudi Arabia indices, respectively, seem to be quite similar to each other and to their GCC counterparts, where the markets are significantly affected by the oil price changes and volatility; however, the effects of bitcoin and gold price changes on the two markets are more noticeable than in previous ones. The last column in Table 2 shows that the UAE stock index follows the same pattern as its GCC counterparts in terms of responsiveness to oil price shocks. In general, it can be noticed that the GCC stock markets are more gravitating and influenced by shocks in global oil prices, and this is somewhat plausible since these nations relay heavily on oil exports as a main economic growth engine and source of income, with respect to the recent attempts by regulatory authorities in Saudi Arabia, UAE, and Qatar to globalize their economies and adopt financial openness policies. The outcomes of the ARDL test support the findings of Naifar et al. (2013) [50] and Ziadat & McMillan (2022) [33], who affirmed the financial connectedness and volatility transmission among oil prices and GCC stock markets.

Table 1. Unit root testing results

Variables	Augmented Dickey-Fuller	Phillips-Perron
Panel A: Variables at levels	**t-statistics**	**t-statistics**
Bahrain	1.1277	1.0930
Kuwait	1.9050	1.8648
Oman	-0.6731	-0.6953
Qatar	-1.9553	-2.0859
Saudi Arabia	1.4734	-1.5271
UAE	-1.4788	-1.4143
Demand Shock	-1.9177	-1.9608
Supply Shock	-2.1884	-2.9981**
Risk Shock	9.6461***	-9.4977***
S&P500	-0.7031	-0.6865
Bitcoin	-1.4845	-1.4816
Gold	0.1380	0.4445
Panel B: Variables at first difference	**t-statistics**	**t-statistics**
Bahrain	14.3131***	40.5765***
Kuwait	14.8897***	37.7308***
Oman	-39.1911***	-39.1982***
Qatar	-37.7398***	-37.7733***
Saudi Arabia	-15.0464***	-38.8940***
UAE	-36.0053***	-36.0511***
Demand Shock	-41.0330***	-40.9624***
Supply Shock	-27.1587***	92.6628***
Risk Shock	-20.8499***	76.4377***
S&P500	42.2396***	-42.1886***
Bitcoin	-39.8736***	-39.8581***
Gold	-39.5027***	-39.7155

Note: Significant at 10% (*), 5% (**), and 1% (***).

The results of the ARDL model presented in Table 2 establish long-run association among the variables in the system; however, the ARDL approach does not allow for splitting the independent variables into positive and negative sums, which is necessary to assess whether positive and/or negative variations of oil price shocks carry large impacts on GCC stock indices. For that, we proceed to apply the NARDL approach to investigate the existence of asymmetric impacts among time series and to distinguish the different responses of dependent variables of GCC stock indices to shocks, increases, and decreases in oil demand, supply, and risk shocks, along with their counterparts of shocks in S&P500, bitcoin, and gold.

Table 2. ARDL results

Variables	Regressors	Regressands					
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Demand Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔD	0.0123***	0.0906***	0.0318***	0.0005	0.2332***	0.0654***
	$\Delta D(-1)$	0.0009	0.0372***	0.0148***	0.0052**	0.1089***	0.0111***
Long Run	D	0.0000	0.0000	0.0000	0.0002	0.0002	0.0000
	$D(-1)$	0.0016**	0.0025**	0.0025**	0.0930***	-0.0042**	0.0007
Panel B: Supply Shock							
Short Run	ΔS	-0.0548***	-0.1641***	-0.0047**	0.0000	0.0002	-
	$\Delta S(-1)$	-0.0040**	0.0001	-0.0003	-0.0013*	0.0000	0.0000
Long Run	S	0.0001	0.0002	0.0000	0.2315***	0.0232***	0.0002
	$S(-1)$	0.0819***	0.0481***	0.0261***	-0.0352***	-	0.0000
Panel C: Risk Shock							
Short Run	ΔR	-0.0045**	0.1595***	-	-	1.1200***	0.1223***
	ΔR(-1)	0.0003	-0.0001	-	0.0000	0.5389***	0.1408***
Long Run	R	0.0000	0.0000	0.0002	0.0000	0.0002	0.0000
	$R(-1)$	0.0819***	0.453***	0.1755***	-0.0024***	-0.0441***	-0.2388***
Panel D: S&P 500							
Short Run	$\Delta S\&P$	0.0008	-0.0009	-0.0033**	0.0000	0.0004	0.1223***
	$\Delta S\&P$(-1)	0.0020**	-0.0204***	0.0059**	0.0131***	-0.0294***	0.1488***
Long Run	$S\&P$	0.0001	0.0001	0.0000	-0.0002	0.0000	0.0000
	$S\&P(-1)$	0.0003	0.0013**	0.0005	0.0023***	0.0034***	0.0012**
Panel E: Bitcoin							
Short Run	ΔB	0.0023**	-	-	0.0002	0.0002	-
	ΔB(-1)	0.0007	-	0.0001	0.0000	0.0003	-
Long Run	B	0.0002	0.0000	0.0000	0.0001	0.0000	0.0000
	$B(-1)$	0.0005	-0.0001	0.0003	0.0001	0.0002	0.0001
Panel F: Gold							
Short Run	ΔG	0.0000	0.0123***	-	-	0.0176***	-
	ΔG(-1)	0.0000	-	0.0002	-	-	-
Long Run	G	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
	$G(-1)$	0.0005	0.0003	0.0010*	-0.0029***	-0.0061**	0.0029**
	F Statistic	5.61***	3.26*	3.30**	4.23***	2.49	3.79**

Note: Significant at 10% (*), 5% (**), and 1% (***). The F statistic is calculated by the Wald test (where H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = 0$ against the alternative hypothesis of H_1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq 0$).

Table 3 displays the outcomes of the NARDL model that decomposes the fluctuations of the independent variables of Oil demand, supply, risk shocks, as well as the S&P500, Bitcoin, and gold into two partial sums, and investigates the effect of each partial sum on the dependent variable. The NARDL outcomes represent the econometric application of Equations 4 to 9, where each GCC stock market is regressed against the positive and negative shocks of our dependent variables (oil demand shock, oil supply shock, oil risk or precautionary shock, S&P500 shocks, Bitcoin, and gold shocks as well) in short and long run horizons. Before the demonstration of the NARDL outcomes, we would like to affirm that the outcomes of the test range varies between significant coefficient in case the short or long run impacts in found to be influential on the dependent variables, a number with no significance sign which accounts for the existence of the independent variable in the equation without exhibiting any influence on the dependent variable, and finally the cell with dash (-) which indicates that the independent variable/s is eased out or excluded from the equation.

Panel A in Table 3 demonstrates the effect of positive and negative shocks in oil demand shocks on stock markets in GCC countries. The results show that in the short run, the negative shock in oil demand has a significant impact on GCC stock markets at levels also in first difference (except for markets in Oman and UAE). Similarly, the positive shock in demand for oil affects all stock markets except for Oman. The coefficients of the long-term impacts indicate that the stock markets in Oman and Bahrain are affected in the long run by the shock in oil demand. This indicates for dominance the short-lived effect of positive and negative changes in oil demand shocks on the majority of GCC markets. The higher influence of oil demand shocks on stock markets in Saudi Arabia and Qatar as compared to Oman might be explained by the size of oil exports of the two countries that exceeds the Omani oil exports, where Saudi Arabia is always ranked first in oil production and exports among its GCC neighbors, Qatar is also considered as one of the largest oil and gas exporter in the region and at a global level. The row labelled F-statistics indicates for presence of cointegration among the variables and tests for the null hypothesis of H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ in Equations 4 to 9, it confirms the cointegration among GCC stock markets and oil demand shock, except for Qatar. This might be due to an improvement in the economic diversification of Qatar towards less dependence on oil revenues [59]. The Wald-short and Wald-long rows represent the t-statistics used for testing the short- and long-run asymmetric hypothesis of H_0: $\Omega_2 = \Omega_3$ and $\delta_2 = \delta_3$, respectively, in Equations 4 to 9. The purpose of the Wald test is to check whether the changes in independent variables lead to the same effects on the dependent variables of GCC markets over time. The asymmetric testing using the Wald statistics is believed to be insightful and indicative since it checks for the existence of permanent patterns of responses exhibited by the dependent variables to changes in regressors. The Wald test statistics indicate for asymmetric impact of oil demand shock on GCC markets in both the long and short run, except for the Oman stock markets.

Panel B illustrates the impact of the oil supply shock on GCC indices. The results show that in general, the upward and downward trends in oil supplies do exhibit significant impact on almost all GCC markets, and this is somewhat plausible since the change in level of GCC oil production and supplies can tremendously affect the economic activities in these countries since oil exports has historically been a main growth engine and major supplement for government subsidize and social allowances. However, the only noticeable difference is that Saudi Arabian and UAE stock markets do not seem to have long-term cointegration with oil supplies, where the F-statistic value does not exceed the upper bounds [53]. This might be explained by the fact that Saudi Arabia has always been considered as one of the top ten oil exporters in the world, hence the long-run effect of demand shock can be more pronounced than the supply shock. Moreover, the stock markets in Saudi Arabia and the UAE are the largest markets in the GCC region in terms of market capitalization; hence, the declines in oil supplies would have less impact on the market performance as compared to smaller-sized markets in Bahrain, Oman, and Kuwait. The outcomes for the Wald test in short and long asymmetries indicate that the changes in global oil supply in both ups and downward movements instigate asymmetric responses by the GCC markets. In other words, the decrease in global oil supplies (negative shock) have different, and most probably, more significant impact on the GCC stock indices than the upsurge in oil supplies, and this is somewhat plausible that, unlike the reduction in oil sales, the increase in oil supplies leads in general to more favorable economic and financial outcomes (higher revenues) in these countries. An additional factor that affects the oil prices is the investors' precautions and uncertainty pertinent to the future oil supplies as a result of operational malfunction or due to political and social unrest, or other factors related to the uncertainty about the global oil demand in the near future, which is inextricably related to the global economic condition. These uncertainties might lead to fluctuations in the value of financial derivatives such as oil futures contracts.

The results of Panel C demonstrate the effect of investors' fear and uncertainty about the future oil prices represented by the oil risk shock. The outcomes in panel C reveal that the risk or uncertainty that blankets the oil market can have a significant effect on the GCC stock markets, and this is somewhat plausible since these countries are known for their heavy dependence on oil revenues as a main economic and financial growth engine. Hence, the uncertainty about oil prices would lead to an increase in investors' fear about the financial stability of these economies.

Panel D lists the impact of positive and negative shocks in the S&P500 index on the GCC markets. The S&P500 index was chosen as a representative of the global stock market to check the responsiveness of GCC stock markets to global financial shocks. The results indicate that in the long run, the stock markets in Kuwait, Qatar, Saudi Arabia, and the UAE respond to shocks in the S&P500 index. The outcomes also indicate that the markets in Bahrain and Kuwait seem to be isolated from the positive and negative shocks in the U.S. stock index.

Panel E demonstrates the results for the GCC stock market connection with the cryptocurrency markets. In general, it has been noticed that the flourishing and rise of the cryptocurrency market can induce investors to shift their investment capital from stocks to the cryptocurrency market [59]. However, the results in Panel E do not support these findings, where the impact of positive and negative shocks in bitcoin exhibits a negligible impact on GCC stock markets (except Qatar and Saudi Arabia), and the F-statistics for long-run cointegration do not indicate any significant impact of bitcoin movement on GCC stock markets in the long run.

Panel F, finally, tests whether the shocks in precious metals represented by gold lead to significant changes in the GCC markets. The result indicates that stock markets in Oman and Kuwait respond to shocks in gold prices in the short term. However, the Wald tests for long and short confirm the asymmetric effects of gold price shocks on the GCC stock markets, and this supports a reciprocal relationship among stock markets and gold and comes in line with the safe haven characteristics of gold investment.

Table 3. NARDL results

Variables	Regressors	Regressands					
Panel A: Oil Demand Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔD^{-}(-1)	0.0389***	0.0001	-	0.0754***	0.1606***	-
	ΔD^{+}	0.01803**	0.0679***	-	0.0383***	-0.1333***	0.0224**
	ΔD^{+}(-1)	-	0.07135	-	0.0428***	0.1041***	-
Long Run	D^{-}	0.0411***	0.0001	0.0014*	-0.0005	-0.0019	-0.0006
	$D^{-}(-1)$	-	-	-	-	-	-
	D^{+}	0.0406***	0.0002	0.0017*	-0.0006	-0.0018	-0.0005
	$D^{+}(-1)$	-	-	-	-	-	-
	F Statistic	15.67***	6.21***	7.32***	1.89	4.58***	4.00***
	Wald Short	5.95***	10.76***	-	12.29***	5.12***	4.99***
	Wald Long	47.00***	2.40*	23.89***	3.06**	17.23***	12.33***
Panel B: Oil Supply Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔS^{-}	0.0109**	0.0012	-0.1712**	0.0037*	0.0052*	0.1040***
	ΔS^{+}	-0.0149***	-0.1399***	-0.1481**	0.02401**	0.4192***	-0.0003
Long Run	S^{-}	0.0005	0.0365***	0.0243**	0.0773***	-0.0003	0.0252**
	S^{+}	0.0006	0.0364***	0.0250**	0.0753***	0.0005	0.0250**
	F Statistic	5.55***	3.95**	3.02	3.67*	2.74	2.86
	Wald Short	13.26***	8.54***	4.37**	9.60***	3.48**	10.36***
	Wald Long	2.97*	3.63**	4.56**	4.81***	5.99***	2.00
Panel C: Oil Risk Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔR^{-}	0.08479***	0.4511***	0.3055***	-0.2859***	1.1679***	-0.1418***
	$\Delta R^{-}(-1)$	-0.0002	-	0.3447***	-	-	-
	ΔR^{+}	-0.0078***	0.0038*	-0.0090**	-0.3416***	-0.0908**	-0.1262***
Long Run	R^{-}	0.11620***	0.8511***	0.5655***	0.0001	0.8362***	0.0006
	R^{+}	0.11649***	0.8519***	0.5675***	0.0003	0.8376***	0.0009
	F Statistic	8.97***	7.38***	4.78***	1.30	4.19**	2.30
	Wald Short	11.30***	6.88***	1.61	0.381	6.69***	3.79**
	Wald Long	2.93*	7.13***	3.01**	5.18***	5.66***	1.98
Panel D: S&P500		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	$\Delta S\&P^{-}$	-	0.0009	-0.0135***	-0.0217***	-	-0.0042**
	$\Delta S\&P^{+}$	0.0003	0.0002	0.0169***	0.0001	-0.0735***	0.0000
Long Run	$S\&P^{-}$	0.0001	0.0011*	0.0004	0.0011*	0.0017**	0.0009*
	$S\&P^{+}$	0.0001	0.0044*	0.0004	0.0009*	0.0016**	0.0008*
	F Statistic	6.83***	4.85***	2.09	2.88	4.56***	5.87***
	Wald Short	-	3.07**	4.05**	12.83***	-	2.22
	Wald Long	2.75*	18.62***	5.36***	4.46**	5.60***	17.31***
Panel E: Bitcoin		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔB^{-}	-	-	-	-0.0004	0.0006	-
	ΔB^{+}	-	-	-	-	0.0012**	-
Long Run	B^{-}	0.0000	0.0000	0.0000	0.0596***	0.0001	0.0000
	B^{+}	0.0000	0.0000	0.0000	0.0553***	0.0001	0.0000
	F Statistic	2.51	1.34	2.15	2.74	0.85	0.72
	Wald Short	-	-	-	-	3.13**	-
	Wald Long	3.75**	2.48**	3.55**	6.02***	7.12***	0.26
Panel F: Gold		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi. A**	**UAE**
Short Run	ΔG^{-}	0.0003	0.0277***	0.0240***	0.0042**	0.0004	-
	ΔG^{+}	-0.0003	0.0517***	-0.0434***	0.0002	0.0002	0.0003
Long Run	G^{-}	0.0001	0.0003	0.0002	0.0009	0.0008	0.0004
	G^{+}	0.0003	0.0005	0.0014	0.0008	0.0008	0.0005
	F Statistic	4.37**	5.74***	3.15	2.96	2.70	1.78
	Wald Short	6.42***	8.10***	6.11***	4.18**	1.45	-
	Wald Long	2.88*	9.71***	4.57*	5.19***	0.30	6.63***

Note 1: Significant at 10% (*), 5% (**), and 1% (***). Note 2: The F-statistic tests for the existence of cointegration through the null hypothesis of H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ (Please refer to Eq.4 to 9.) The Wald Short test assesses the existence of short-term asymmetries through the null hypothesis of H_0: $\Omega_2 = \Omega_3$, while the Wald Long tests for the long-run asymmetric effects through the null hypothesis H_0: $\delta_2 = \delta_3 = 0$. Note 3: In this table, we report the coefficients up to four decimal places. The 0.0000 represents either a zero value for the coefficient, which indicates that the corresponding independent variable exists in the model equation with zero effect, or it might have a negligible value in the fifth or sixth digits; however, the dash (-) indicates that the model has excluded the dependent variable from the regression.

The results of the MTNARDL test are demonstrated in Table 4. Prior to the explanation of its main findings, we need to reaffirm that the main purpose of this paper is to measure the impact of extreme tail movements of oil shocks along with S&P500, bitcoin, and gold on stock markets in the GCC region. Hence, our focus will be on four partial sums for each independent variable. The first two partial sums of each independent variable are from 0% to 2.5% and from 2.5% to 5%. These two partial series are presented by represented by the coefficients $\varphi 1$ and $\varphi 2$ and will depict the sharp (extreme) decrease in the value of independent variables. The third and fourth series represent the values in the independent variable, ranging from 95% to 97.5% and from 97.5% to 100%, represented by the coefficients $\varphi 4$ and $\varphi 5$, respectively, and capture the significant positive values of the independent variables. Thus, in this paper, we are classifying the independent variables changes in extreme tails to distinguish the impact of smaller to larger shocks in oil demand, supply, risk variables, in addition to other explanatory variables, on the stock market indices in GCC countries.

Panel A of Table 4 demonstrates the outcomes for extremely small to extremely large changes in global oil demand on GCC stock markets. The short-run coefficients for $\varphi 1$ indicate for remarkable effect of extreme negative values in the oil demand shock on all GCC markets; however, the coefficients of $\varphi 2$ only affect the markets in Oman and the UAE. The extreme positive shocks in oil demand are illustrated by the coefficients of $\varphi 4$ and $\varphi 5$ exhibit a significant impact on all GCC markets except for Saudi Arabia (in the case of $\varphi 4$), while the very extreme positive shock in the demand shock is presented by the coefficients of $\varphi 5$ and escalates the oil demands to its highest limits (97.5% and above), it can only influence Saudi Arabia and the UAE markets. These results come in line with Al-Mohamad et al. (2018) [59] and Afşar et al. (2025) [38]. In terms of the long run effects, it can be noticed in panel A that extreme negative and positive shocks are transmitted through to affect all GCC markets except for the one in Bahrain, and this might be explained by the fact that Bahrain is not as much oil rich as other GCC countries, however the economic activities in Bahrain are well diversified compared to its neighbors. The results for long-term cointegration, along with the short and long asymmetries denoted by F statistics, Wald short and Wald long statistics, respectively, confirm the results of the models above, where the demand shock is found to be most significant to stock markets in GCC countries.

Panel B illustrates the effect of extreme tail shocks of oil supplies on the GCC markets. The results show that in the short run, the significant decrease in oil supplies (regime 1, from 0 to 2.5%) has a significant effect on all GCC markets except for Bahrain. However, the positive shock in global oil supplies led to significant and favorable impacts on markets in Saudi Arabia, the UAE, and Qatar, as indicated by the coefficients of $\varphi 4$ and $\varphi 5$. The same applies to stock market responses in GCC countries to long-term supply shocks, except for the UAE, where the country has already passed multiple phases toward economic diversification. Dubai and Abu Dhabi, the two main states in the UAE, are now standing as international financial hubs and channels through which, a significant proportion of the international trade is transferred.

Panel C indicates that the results of risk shock regimes are not parsimonious, where the stock markets in the majority of GCC countries seem to be affected by the precautionary atmospherics in the oil markets, both in the short and long run. Moving to the outcomes pertinent to the potential asymmetric impact of S&P500 shocks on GCC indices.

The outcomes in panel D indicate that the impacts of severe movements of the S&P500 mainly exhibit significant effects on GCC stock markets in the short-term for Qatar and the UAE, and this might be due to the higher degree of financial connection of these two countries with the rest of the world, as compared to other GCC stock markets.

The results in panel E demonstrate a lack of remarkable effects of extreme shocks in bitcoin on the GCC indices, and this supports the outcomes of the NARDL test results presented in Table 3, where the shocks in bitcoin have a negligible effect on GCC stock markets. However, the results in panel E indicate that the extreme change in the bitcoin value can cause an asymmetric effect on the GCC markets in the long term. These outcomes are somewhat plausible since bitcoin has less popularity in developing countries compared to developed countries, where it takes the market participant a longer period of time to react to the radical changes in cryptocurrencies. Finally, panel F presents the results of gold price changes on the GCC markets. It can be noticed that extreme positive and negative changes in gold prices have significant effects on stock markets in Qatar, Saudi Arabia, and the UAE. These results confirm that gold represents an alternative investment for stocks in developing countries where investors swiftly react to gold price changes either to make higher returns or to hedge against the sharp volatility in stock markets, and this is in line with the findings of Khaki et al. (2022) [59].

Table 4. MTNARDL results

Variables	Regressors	Regressands					
Panel A: Oil Demand Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**	**UAE**
Short Run	$\Delta D(\varphi 1)$	0.02264***	0.16753***	0.06859***	0.124887	0.13316***	0.06215***
	$\Delta D(\varphi 1)(-1)$	0.00655**	0.09431***	-	0.063398	0.06907***	0.00575**
	$\Delta D(\varphi 2)$	-	-	0.02521***	-	-	0.03647***
	$\Delta D(\varphi 3)$	0.00469***	0.04498***	0.01730***	0.05352***	0.09837***	0.00710***
	$\Delta D(\varphi 3)(-1)$	-0.00168*	-	-	0.03192***	-0.02396**	0.00087
	$\Delta D(\varphi 4)$	0.00404***	0.05093***	0.05602***	0.08950***	0.09083***	-
	$\Delta D(\varphi 4)(-1)$	-0.00742***		-	0.02990***	-	-
	$\Delta D(\varphi 5)$	-0.00000	-0.00014	-	0.000435	0.00418***	0.00098**
Long Run	$\Delta D(\varphi 5)(-1)$	-0.00091*	-0.00125**	-	-0.00225*	-	0.00005
	$D(\varphi 1)\ (-1)$	0.00012	-0.00085*	-0.00010	-0.00140**	-0.00275**	-0.00051
	$D(\varphi 2)(-1)$	-0.00005	0.00275***	-0.00154**	0.00234**	0.01031***	0.00124*
	$D(\varphi 3)\ (-1)$	0.00026	0.00264***	0.00227***	0.00353**	-0.00102*	-0.00055
	$D(\varphi 4)(-1)$	0.00051	0.00072	-0.00071*	-0.00153**	0.00512***	0.00023
	$D(\varphi 5)\ (-1)$	0.00092*	0.00216***	-0.00019	0.00389**	0.01084***	0.00200***
	F Statistic	3.37*	3.56*	1.65	4.05***	16.22***	4.65***
	Wald Short	1.67	2.32*	2.75**	4.55***	22.72***	4.02***
	Wald Long	20.66***	40.03***	13.70***	19.44***	10.00***	12.00***
Panel B: Oil Supply Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**	**UAE**
Short Run	$\Delta S(\varphi 1)$	-	-0.00356**	0.13632***	0.12488***	0.13316***	0.06215***
	$\Delta S(\varphi 1)(-1)$	-	0.03602***	0.06311***	0.06339****	0.06907***	0.00575*
	$\Delta S(\varphi 2)$	0.13187***	0.63405***	0.46525***	-	-	0.03647
	$\Delta S(\varphi 2)(-1)$	-0.07820***	-	-	-	-	-
	$\Delta S(\varphi 3)$	-	0.00000	0.00000	0.05352***	0.09837***	0.00710**
	$\Delta S(\varphi 3)(-1)$	-	0.00000	0.00000	0.03192***	-0.02396**	0.00087*
	$\Delta S(\varphi 4)$	-0.00796***	0.00000	0.00000	0.08950***	0.09083***	-
	$\Delta S(\varphi 4)(-1)$	-0.04099***	-	-	0.00299	-	-
	$\Delta S(\varphi 5)$	-0.000757	-	-0.00572***	0.00043	0.00418**	0.00098*
	$\Delta S(\varphi 5)(-1)$	-0.00050	-	-0.00477***	-0.00225*	-	0.00005
Long Run	$S(\varphi 1)(-1)$	0.00330**	0.00167**	0.00035	-0.00140	-0.00275**	-0.00051
	$S(\varphi 2)(-1)$	-0.01310***	-0.04181***	-0.02307**	0.00234**	0.01031*	0.00124
	$S(\varphi 3)(-1)$	-0.01040**	-0.03537***	-0.04436***	0.00353***	-0.00102	-0.00055
	$S(\varphi 4)(-1)$	-0.00298*	-0.03724***	-0.00297**	-0.00153*	0.00512**	0.00023
	$S(\varphi 5)(-1)$	0.00000	-0.00356**	0.00455**	0.00389***	0.01084***	0.00200
	F Statistic	3.84**	1.96	2.14	4.05**	16.22***	4.65***
	Wald Short	3.17**	-	3.38**	4.55***	22.72***	3.98***
	Wald Long	7.12***	5.77***	4.01***	19.44***	10.00***	15.36***
Panel C: Oil Risk Shock		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**	**UAE**
Short Run	$\Delta R(\varphi 1)$	-0.00943***	0.012095**	0.00000	-	0.12263***	0.01626**
	$\Delta R(\varphi 1)(-1)$	-0.00115**	-0.00789***	0.00000	-	0.04386***	-0.05997***
	$\Delta R(\varphi 2)$	-0.08558***	-0.49994***	-	0.26790***	0.23384***	0.17704***
	$\Delta R(\varphi 2)(-1)$	-0.01913***	0.28399***	-	0.00489**	0.41225***	-0.10784***
	$\Delta R(\varphi 3)$	-0.02933***	-0.24763***	-	-	-	0.20643***
	$\Delta R(\varphi 3)\ (-1)$	-	-	-	-	-	-
	$\Delta R(\varphi 4)$	-0.15777***	-0.86983***	-0.59532***	-1.25762***	-1.43316***	-0.19473***
	$\Delta R(\varphi 4)(-1)$	-	-	0.17106***	0.173966***	-0.06385***	-
	$\Delta R(\Omega 5)$	0.00168**	0.01297**	-	-0.001710**	-	-
	$\Delta R(\Omega 5)(-1)$	-	-	-	-	-	-
Long Run	$R(\varphi 1)\ (-1)$	0.00396**	-0.00619**	-0.00438***	-0.01539**	-0.00627*	-0.00115
	$R(\varphi 2)\ (-1)$	0.00391**	0.07785***	0.13142***	0.10494***	0.01011**	0.00034
	$R(\varphi 3)\ (-1)$	0.02074***	0.09487***	0.07973***	0.09837***	0.09189***	0.03498**
	$R(\varphi 4)(-1)$	0.01531**	0.05665***	0.15390***	0.05068***	-0.00592*	-0.00587*
	$R(\varphi 5)(-1)$	0.00526***	0.03119***	0.00323**	-0.00789***	0.01693**	-0.00216*
	F Statistic	5.75***	4.01**	4.14**	1.80	2.81*	1.85
	Wald Short	2.03*	3.36***	-	-	2.02	4.66***
	Wald Long	3.42***	2.05*	4.73***	2.70**	4.15***	5.22***

Panel D: S&P500		Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
Short Run	$\Delta SP(\varphi 1)$	-	-	-	-0.02110***	0.01511*	0.00619*
	$\Delta SP(\varphi 1)(-1)$	0.00000	-	-	0.02555***	0.00010	0.02124***
	$\Delta SP(\varphi 2)$	0.00000	-0.01669**	0.00000	-0.04425***	-	-0.01297***
	$\Delta SP(\varphi 2)(-1)$	0.00000	0.03122***	0.00000	0.05348***	-	0.02254***
	$\Delta SP(\varphi 3)$	0.00000	-	0.00000	-0.02237***	-	-0.00689***
	$\Delta SP(\varphi 3)(-1)$	0.00000	-	0.00000	0.02236***	-	0.01507***
	$\Delta SP(\varphi 4)$	0.00352*	0.01006**	0.00000	-	0.07221***	-0.00445*
	$\Delta SP(\varphi 4)(-1)$	0.00322	0.04879***	-	-	-	0.01606***
	$\Delta SP(\varphi 5)$	-0.00002	-0.00017	-0.00024	0.00065*	-0.00089*	-0.00000
	$\Delta SP(\varphi 5)(-1)$	0.00005	-	0.00024	0.00107***	-	-
Long Run	$SP(\varphi 1)\ (-1)$	0.00066	0.00184*	0.00068*	0.00077	0.00153*	0.00068
	$SP(\varphi 2)\ (-1)$	-0.00104	-0.00509**	-0.00199	-0.00493*	-0.00211***	-0.00154*
	$SP(\varphi 3)\ (-1)$	0.00017	0.00067	0.00035	0.00031	0.00164*	0.00057
	$SP(\varphi 4)\ (-1)$	0.00046	-0.00169*	-0.00024	-0.00413**	-0.00012	-0.00068
	$SP(\varphi 5)\ (-1)$	-0.00015	-0.00115	-0.00053*	-0.00131*	-0.00211***	-0.00097
	F Statistic	7.24***	5.09***	2.30*	2.97**	3.75**	4.40***
	Wald Short	-	7.81***	-	3.75***	8.06***	3.77***
	Wald Long	9.01***	4.35***	2.71**	4.29***	4.13***	4.26***
Panel E: Bitcoin		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**	**UAE**
Short Run	$\Delta B(\varphi 1)$	0.00010	-	-	-0.00018	-0.00156*	-0.00044*
	$\Delta B(\varphi 1)(-1)$	0.00002	0.00000	-	-0.00104**	-0.00068	-0.00019
	$\Delta B(\varphi 2)$	0.00004	0.00000	-	-	-	-0.00073
	$\Delta B(\varphi 2)(-1)$	-	-	-	-	-	-
	$\Delta B(\varphi 3)$	-	-	0.00050*	-	-0.00091*	-0.00070
	$\Delta B(\varphi 3)(-1)$	0.00000	0.00002	-	-	-0.00161*	-
	$\Delta B(\varphi 4)$	0.00002	0.00001	0.00107*	-	-	-0.00051
	$\Delta B(\varphi 4)(-1)$	0.00000	0.00001	-0.00033	-	-	0.00047
	$\Delta B(\varphi 5)$	-	-	-	0.00007	0.00003	0.00001
	$\Delta B(\varphi 5)(-1)$	-	-	-	-0.00002	0.00005	0.00001
Long Run	$B(\varphi 1)\ (-1)$	0.00001	0.00004	-0.00004	0.00006	0.00006	0.00004
	$B(\varphi 2)\ (-1)$	0.00002	-0.00005	0.00002	-0.00007	0.00003	-0.00003
	$B(\varphi 3)\ (-1)$	0.00001	0.00010	0.00010	0.00012	0.00006	0.00003
	$B(\varphi 4)\ (-1)$	0.00001	0.00003	0.00003	0.00001	0.00013	0.00003
	$B(\varphi 5)\ (-1)$	0.00001	-0.00004	-0.00005	0.00003	0.00004	0.00001
	F Statistic	2.35*	1.58	2.07	3.18**	1.28	1.44
	Wald Short	-	-	-	-	3.68*	3.97***
	Wald Long	3.25***	1.19	4.02***	4.86***	4.06***	2.80*
Panel F: Gold		**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi Arabia**	**UAE**
Short Run	$\Delta G(\varphi 1)$	-	0.02502***	-	0.07054***	0.06251***	0.12453***
	$\Delta G(\varphi 1)(-1)$	-	0.04554***	-	-	-	-
	$\Delta G(\varphi 2)$	0.00000	-	-	0.06221***	0.06287***	0.05400***
	$\Delta G(\varphi 2)(-1)$	0.00000	-	-	-0.00520**		
	$\Delta G(\varphi 3)$	0.00000	0.05939***	0.00444*	0.05293***	0.00026	0.00041
	$\Delta G(\varphi 3)(-1)$	0.00000	-	0.03422***	0.03390***	-	-
	$\Delta G(\varphi 4)$	-	-	-	-	0.00101	0.00021
	$\Delta G(\varphi 4)(-1)$	-	-	-	-	-	-
	$\Delta G(\varphi 5)$	-	-	0.00026	-	0.00642**	0.07541***
	$\Delta G(\varphi 5)(-1)$	-	-	-	-	-	-
Long Run	$G(\varphi 1)\ (-1)$	0.00104*	0.00262*	0.00179*	0.00215**	0.00357**	0.00125**
	$G(\varphi 2)\ (-1)$	-0.00175	-0.01342*	-0.00904**	-0.01144***	0.07469***	0.03685***
	$G(\varphi 3)\ (-1)$	0.00062	0.00095	0.00109*	0.00218*	0.0003	0.001987*
	$G(\varphi 4)\ (-1)$	0.00064*	-0.00802	-0.00532**	-0.00895**	0.00552**	0.03625***
	$G(\varphi 5)\ (-1)$	0.00004	-0.00128*	-0.00045	-0.00182**	0.00622**	0.08586***
	F Statistic	2.73*	1.92	1.56	2.29*	4.50***	6.22***
	Wald Short	-	-	-	3.87***	3.95***	4.33***
	Wald Long	2.58**	2.99**	2.31**	3.75***	3.82***	4.25***

Note 1: Significant at 10% (*), 5% (**), and 1% (***). Note 2: The F-statistic tests for the existence of cointegration through the null hypothesis of H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$ (Please refer to Equation 9). The Wald Short test assesses the existence of short-term asymmetries through the null hypothesis of H_0: $\Omega_2 = \Omega_3 = \Omega_4 = \Omega_5 = \Omega_6 = 0$, while the Wald Long tests for the long-run asymmetric effect through the null hypothesis H_0: $\delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$. Note 3: In this table, we report the coefficients up to four decimal places. The 0.0000 represents either a zero value for the coefficient, which indicates that the corresponding independent variable exists in the model equation with zero effect, or it might have a negligible value in the fifth or sixth digits; however, the dash (-) indicates that the model has excluded the dependent variable from the regression.

6- Conclusion

In this research, the effects of oil price shocks, international stock markets, cryptocurrencies, and precious metals on the stock markets in the Gulf Cooperation Council (GCC) countries will be examined. The complex nature of oil price fluctuations is well acknowledged in this research; hence, these fluctuations have been categorized into demand, supply, and risk shocks to accurately identify which type of shocks affect GCC stock markets in a significant manner. Using a dataset covering 2019-2024, in this research, an NARDL test incorporating multiple thresholds is employed to identify any possible asymmetric outcomes for these markets. The strategy adopted in the research enables identification of the tail domains by establishing critical levels (2.5%, 5%, 95%, and 97.5%) for the independent factors. The outcomes obtained from the research make it clear that the asymmetric effect on GCC stock markets is more apparent in the case of demand shocks in particular. Conversely, positive as well as negative shocks associated with the S&P 500 Index, Bitcoin, and Gold help to understand the short-term versus long-term in these markets in any significant manner. MTNARDL's capability to identify outcomes in the tail domains makes it explicitly clear that in the GCC stock markets, negative demand, supply, and risk shocks in their tail domains exercise a considerably strong influence, with their positive counterparts also carrying a similar weightage in these markets' aspect. At the same time, in these markets, tail domains in the S&P500 signify a notable level, thereby confirming that these markets, in principle being dominated by oil prices, do acknowledge any interference from international financial turmoil triggered by fluctuations in global markets.

Despite being useful for understanding nonlinear relationships and thresholds, the MTNARDL model is also subject to certain limitations. Getting rid of these limitations is quite an important criterion for continuous improvement in the research work. Some significant limitations associated with the MTNARDL model could be closely associated with the phenomenon of endogeneity bias in terms of the simultaneous relation between the independent variables and the dependent variable series. Though MTNARDL is useful for handling asymmetric patterns and drastic market fluctuations, it has limitations in handling reverse causality concerns in financial and economic time series phenomena, which is an essential area for continuous improvement in the research work. Another significant issue concerning the MTNARDL is that the choice for threshold values, even in a systematic manner, appears quite arbitrary at times, which is subject to the number of samples used for testing the research phenomenon. Despite these limitations, the results obtained in the research work could have significant implications for the concerned authorities in the GCC region, including institutional and individual investors in the region. Thus, it is recommended that the concerned authorities in the region would necessarily have to make efforts for the development of other industries excluding petroleum, such as technology, manufacturing, tourism, and renewable energy sources for an appropriate diversified economy in the region for generation to come with stabilized economies for enhanced prosperity in the region, removing concerns for drastic fluctuations in the petroleum market in an appropriate manner for the betterment of all concerned in the region.

7- Declarations

7-1- Author Contributions

Conceptualization, S.M., I.C., A.J., and N.K.; methodology, S.M.; software, S.A.; validation, A.J., A.H., and I.C.; formal analysis, S.A.; investigation, N.K.; resources, A.J. and S.A.; data curation, S.A.; writing—original draft preparation, S.A. and I.C.; writing—review and editing, S.A., I,C., A.H., and N.K.; visualization, I.C.; supervision, A.J.; project administration, S.A. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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