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# When Oil Moves the Market: Asymmetric Tail Effects of Oil Price Shocks on Stock Returns in Major Oil-Producing Countries

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**ABSTRACT**

This study investigates how oil price shocks influence stock market performance in major oil-producing countries, with a focus on extreme-tail dynamics over the period January 2019 to November 2024. Employing an advanced extension of the Multi-Threshold Nonlinear Autoregressive Distributed Lag (MTNARDL) model, oil price shocks are decomposed into five partial sums based on extreme threshold boundaries, allowing for the identification of distinct impacts stemming from demand, supply, and risk-driven shocks. The results reveal strong asymmetric effects: Extreme negative demand shocks significantly depress stock returns, while extreme positive shocks tend to have weaker or insignificant impacts. Additionally, risk-related oil shocks exert substantial influence across most of the markets examined. These findings demonstrate that stock markets in major oil-producing countries are closely linked to oil price fluctuations, regardless of whether these originate from demand, supply, or risk factors. The results carry important implications for investors and policymakers, underscoring the need for economic diversification, particularly in less developed oil-producing economies, in order to reduce vulnerability to oil-related volatility. By introducing an extreme-tail modeling framework, this paper contributes to the literature on financial market responses to energy price shocks and provides valuable insights for managing oil-driven market risks.

**Keywords:** Oil Price Shocks, Stock Market Performance, Asymmetric Effects, Tail Risk, MTNARDL Model, Major Oil-Producing Countries
**JEL Classifications:** G12, G15, Q43, C32, C58

## 1. INTRODUCTION

Oil production and exports have always been a significant factor in determining the levels of economic growth and a dominant source for government expenditure in oil producing countries. In general, a high level of revenues from oil exports helps stimulating the economic growth, supports the economic diversification efforts, and stabilizes the exchange rates and national balance of payment (Mohammed et al. 2020). The contribution of oil production and export to national GDP varies among the top oil producing countries, that in some countries the oil production and exports constitutes a significant share of the GDP and the oil export revenues have always been a main economic growth engine such as in Saudi Arabia, and Kuwait where the oil rent income contributes by more than 25% of their GDP (According to the World Bank database[1]). Other oil producing countries are categorized by their moderate reliance on oil rent income to support their national income and government spending. For instance, the oil exports in Russia, and Kazakhstan comprises up to 15% of their GDP. On the contrary, the developed economies are, in general, less reliant on oil export income in their economic growth levels such as in USA and Canada where the oil rent % of GDP amount to 0.6%, and 2.8%, respectively, and this can be imputed to the economic development and diversification

1 https://data.worldbank.org/indicator/NY.GDP.PETR.RT.ZS

relative to less developed oil producing nations such as GCC and African countries. In fact, the stock markets in main oil producers, especially developing economies, are not isolated from the oil price movement, the oil price levels often serve as a barometer for economic health in these countries as the high oil prices increase investors' confidence in these markets and lead to higher inflows and capital into equities. On the other hand, a drop in oil prices can trigger market downturns due to fears of economic slowdown or budget deficits. For instance, in Saudi Arabia, the performance of Saudi Aramco (the world's largest oil company) has a vital effect on the Saudi stock market. Likewise, the performance of Gazprom in Russia impacts the performance of the Russian stock index. Based on that, it is believed that a shock in oil market will have noticeable effects on stock markets' performance in main oil producing countries. The theoretical foundation for the nexus among oil price shocks and stock market returns is grounded in several key factors. In a nutshell, the increase in oil prices leads to an escalation of the input costs across various sectors of the economy such as industrial, transportation, manufacturing, and petrochemicals. These higher production costs negatively affect future earnings of the respective companies and lead to a decline in stock prices due to reduced corporate earnings. This, in turn, makes investors more cautious, as it can diminish the value of their portfolios (Salisu and Oloko, 2015). Additionally, heightened volatility and falling stock market returns may cause widespread economic disruptions by reducing household income and further dampening investor confidence.

The empirical attempt of Kilian (2009) that disentangled the supply and demand shocks in the oil market was extended by Kilian and Park (2009) who investigated the effect of different oil demand and supply shocks on the US stock market. Following that, the seminal work of Ready (2018) has identified three main causes of oil price fluctuations. First, the oil demand shock; that arises from a sharp decline in global demand for oil imports and productions. Ready (2018) estimates the three types of oil price shocks as follows; The demand shocks are assessed as the size of returns on the global index of the oil producing companies that are orthogonal to the unanticipated changes of VIX index. The second shock represents fluctuations in the global oil supplies due to sudden halt or disruption of oil extraction and production process, which basically leads to escalation in global oil prices. The oil supply shocks are identified as proportion of variations in oil prices and assumed to be orthogonal to innovation in VIX index along with the demand shocks. The third source of the shock is the risk factor or precautionary shock which reflects the investors' sentiment about oil price stability in the near future and captures, to a large extent, the perceived ambiguity surrounding global oil demand and supply flows. The risk shocks are proxied by the innovation in the VIX index.

In the last few years, the oil price movements have witnessed a significant volatile pattern due to various economic and geopolitical events. That in the wake of COVID-19 pandemic, the oil market faced an extreme demand shock due to prolonged global lockdowns, restricted transportation, and halted production. Unlike this shock in global demand for oil, it has been noticed that political and social unrest can also lead to pronounce shock in global oil supplies, for instance the Ukrainian war which has started in early 2022 has triggered a supply shock and caused a sharp rise in oil prices due to announced sanctions and boycott imposed on the energy sectors of Russia. The aim of this paper is to investigate the effect of extreme of oil shocks on the stock markets in main oil producing countries of USA, Canada, Russia, Nigeria, China, Brazil, UAE, Saudi Arabia, Kuwait, and Kazakhstan, who in total account for more than 70% of the global crude oil production for the time period from 2019 to 2024. For this aim, research in this paper aims to answer the following questions: First; what type of oil price shocks (oil demand, oil supply, or risk shocks) can possess greater influence on the returns of stock indices in major oil producing countries? Second, how does this effect/s change in the wake of extreme oil price movements which have been witnessed during the COVID-19 pandemic in 2020 and the prolonged Ukrainian crisis? Third, do stock market returns in these countries react more (less) strongly when oil prices decrease than to increase? It is believed that these testable questions, if answered, should help policymakers in these countries along with investors to understand who the global oil market shocks can influence the stock market returns, and how do the stock markets react in the presence of extreme oil price shocks. This knowledge is expected to help investors to improve the performance of investment portfolios and their risk-return tradeoffs.

The previous literature who measured the interdependences among oil price movements and stock returns in oil producing countries have provided valuable outcomes and insights such as the ones of Filis et al. (2011), Wang et al. (2013). However, their empirical investigations have utilized datasets up to 2010. There is unanimity among researchers and field experts that the global oil market has witnessed significant shocks and volatility in the last few years such as the one observed during the 2019 pandemic and the ongoing political unrest in Eastern Europe. Consequently, the need for new attempts that utilize more recent datasets has emerged to cover those recent events. Another attempt by Al-Mohamad et al. (2022) has measured effect of COVID-19 pandemic on the nexus between oil price fluctuations and stock markets in oil producing countries. Although the outcomes of the study confirmed the leading role of oil demand shock in influencing stock markets, however the empirical methodology employed in that paper was based on the innovation accounting analysis of the vector autoregressive (VAR) which builds on linear approximation of the relationships among time series variables. A wide range of research scholars and econometricians affirm that random behavior is one of the main characteristics of time series variables, which implies a tendency of such variables to exhibit non-linear and asymmetric responses to independent variables in the system, and this in turn casts some doubts on the accountability and accuracy of the Al-Mohamad et al. (2022) outcomes. Based on the above, this study provides a more recent and advanced empirical attempt to fill this research gap by employing various non-liner econometric techniques to capture the extreme tail effect of oil price shocks on stock indices in major oil importing countries during a time window that covers the most recent shocks in the global oil market.

This study contributes to existing literature on different fronts. First, on the methodological front, the main contribution of this paper is that it advances the MTNARDL approach to investigate the asymmetric extreme tail effects by decomposing the independent variables into five partial sums through fixing the threshold at the extreme boundaries of extreme positive and negative values at 2.5th, 5th, 95th, and 97.5th quantiles. This new approach builds on the seminal works of Verheyen (2013) for bi-threshold NARDL model where the independent variables are decomposed into three partial sums using thresholds set at 70th and 30th quantiles, and on MTNARDL with five partial sums of Pal and Mitra (2015; 2016) where regressors are divided up into five sums using thresholds at 80th, 60th, 40th, and 20th quantiles. Second, this paper covers the time period from 2019 until the end of 2024 during which the oil prices have been subject to various cataclysmic shocks starting with the oil demand shock due to the outbreak of COVID-19 pandemic at the end of 2019 and during 2020, the time window of the analysis in this paper also covers a significant oil supply shock that happened as a result of the political instabilities caused by Ukrainian conflict where the cease of oil supplies from one of the main producers (Russia), accounting for 10-12% of global crude oil productions has led to significant escalation in prices. Last, the research in this paper enriches the existing literature on impact of oil price movements on stock markets by highlighting the effects on stock indices of main oil producing countries. The major findings in this paper indicate that the extreme negative shocks in oil demand, supply, and risk shocks can significantly influence most stock markets, while sharp increase in global oil prices does not produce a similar effect.

The reminder of this paper is organized as follows; part two presents the literature review section. Part three demonstrates the data sets and identifies the variables. Part four illustrates the methodology and econometrical approach used in this paper, part five explains the outcomes of the tests, and part six concludes the paper.

## 2. LITERATURE REVIEW

In recent years, the effect of oil price volatilities and fluctuations on stock markets has become increasingly significant, largely due to a series of major economic and geopolitical events, including the COVID-19 pandemic, Ukraine crisis, and current global trade tensions. These developments have thrown uncertainty over the global economic and financial scenes. A new strand of literature has emerged in an attempt to analyze how different types of oil price shocks such as demand, supply, and risk can be related to stock market performance, particularly in major oil producing countries that heavily rely on oil revenues to drive economic growth. Starting with Kilian and Park (2009), the oil price shocks are found to have significant effects on the main oil-importing stock market indices. Filis et al. (2011), confirms these findings and found that the stock indices in oil exporting countries are less responsive to oil price shocks compared to their oil importing counterparts. In a similar study, Wang et al. (2013) measured the impact of oil price shocks on stock market returns in same groups of countries. Their findings suggest that the responses of stock markets to oil price shock are dependent on economic nature and classification of the countries and on whether the shock is generated by supply or demand changes. Recently, Al-Mohamad et al. (2022) evaluated the effect of COVID-19 pandemic on the nexus among oil price fluctuations and stock markets in a group of oil producing countries. The outcomes revealed that during the pandemic period, oil price movements have exerted stronger effects on the stock returns of these countries. Sraieb et al. (2022) measured the effect of oil shocks on stock markets in main oil-importing countries. They found that the stock market returns in main oil importing countries were negatively affected by oil price shocks during the pandemic period. These results came in line with the findings of Ando et al. (2018) who found risk spillover and contagion from oil price fluctuations to stock markets. Mensi et al. (2024), found that during the extreme market movements, the oil price changes seem to have a more significant effect on stock markets. Similarly, Hanif et al. (2024), measured the effect of oil price shocks on major oil-producing nations. The study found that the demand shock plays a major influence on these markets, while the oil risk shock primarily affects stock indices in China, India, and U.S. Sim and Zhou (2015), examined the connectedness among the U.S stock market and oil price fluctuations through different data and regressions quantiles. The study found that during extreme market conditions such as high volatility periods, oil prices exhibit a more pronounced effect on the U.S stock markets compared to stability times. Analogously, Bouri (2021), examined the time-varying spillover among US stock market, oil, and gold prices. The findings indicated for the existence of substantial volatility spillover among these variables with reciprocal volatility spillover among the U.S. market and oil prices. Ji et al. (2020) investigated risk transmission among BRICS stock markets and oil price movements. They found that the oil demand shock is the main driver of risk transmission on BRICS stock markets. In the same line, Naeem et al. (2020) measured the impact of oil and gold price movements on BRICS stock indices in pre and post GFC. The outcomes of the study affirmed that the correlation among BRICS and oil markets has been intensified in post GFC as compared to before.

A main strand of literature has emerged to highlight the nexus among oil price shocks and the stock markets in the gulf cooperation council countries (GCC) as it contains a group of main oil producing countries such as Saudi Arabia, UAE, and Kuwait. Oil production and exports remain the major cornerstone for their economic growth and development. Starting with recent study by Ziadat and McMillan (2022), oil price movements are found to be very crucial in the risk-return trade-offs in these markets. However, the stock market's reaction to positive and negative oil shocks varies significantly. Bashir (2022) studied the effect of oil demand and supply shocks on GCC stock markets. They found that oil demand shock has greater effect than supply shock on GCC markets. Tien and Hung (2022) utilized the wavelet-based DCC model to measure the volatility spillovers from oil index to GCC markets. They found that during periods of extreme price movement, the shock spillover is swiftly transmitted to the regional stock indices. In the same line, Alotaibi and Morales (2022) examined the volatility spillover among oil prices and GCC markets, they found that oil price shocks exhibit significant influences on the risk and return features of GCC indices. Atif et al. (2022) also found evidence for time-varying impact of oil price shocks on GCC stock market indices. Yousuf and Zhai (2022) measured the volatility spillover for potential portfolio hedging between GCC stock markets and global variables including oil prices. The outcomes showed significant shifts in spillover intensity between normal periods and crises, including global financial crisis and the COVID-19 pandemic. Shamsudheen et al. (2022) examined the effect of declining oil prices during the pandemic on GCC markets, and they conclude that GCC markets were positively affected by increased oil prices, however the escalated instability of global oil market leads to negative consequences on these markets. More recently, Bouri et al. (2023) examined the impact of geopolitical risk factors on the stock market returns in the GCC region. The outcomes suggested that geopolitical and social tensions play a significant role in accelerating the shock spillovers from oil to GCC stock markets. Jreisat et al. (2023a) employes the nonlinear ARDL model to investigate the impact of oil price fluctuations on GCC markets before and after the COVID-19 pandemic. The results indicated that both negative and positive oil affect the GCC stock markets in short and long-term periods. The results also found nonlinear trajectories in the long-term except for stock indices in Saudi Arabia and UAE. Ebadi and Razaq (2024) utilized the regime-switching cointegration method to detect the nature of stock markets responses to oil shocks in GCC region. They found that, interestingly, stock market investors tend to react optimistically toward positive oil shocks rather than negative ones.

It can be clearly noticed that the existing literature attempts to measure the impact of oil price shocks on stock markets in different groups of countries, including emerging and developed, oil importing and exporting, using variety of methodologies and econometric models. However, we believe that the micro or extreme tiny shock sign effect has been overlooked so far. Hence, we aim in this study to contribute to existing literature by shedding more light on the extreme tail impact of the three oil price shocks (demand, supply, and risk shocks) on stock markets in main oil producing countries. For this purpose, we utilize a special version of the MTNARDL that is based on the extreme thresholds impositions at 97.5$^{th}$, 95$^{th}$, 5$^{th}$, and 2.5$^{th}$ quantiles to investigate the asymmetric impact (if any) of extreme positive and negative shocks in oil demand, supply, and uncertainty on stock markets in main oil producing countries. The asymmetric analysis through this model is expected to track the influence of extremely negative and positive changes in crude prices on these stock indices and identify the extent to which oil price fluctuations can trigger a significant impact on these indices.

## 3. DATA AND VARIABLES IDENTIFICATION

The research in this paper utilizes daily stock prices for a group of main oil producing countries namely, USA, Canada, Russia, Nigeria, China, Brazil, UAE, Saudi Arabia, Kuwait, and Kazakhstan. The list of the top ten oil producers (as per Statista database) basically includes Iran and Iraq, however the stock markets in Nigeria and Kazakhstan were considered in this study to replace their counterparts of Iran and Iraq due to lack of data pertinent to daily stock prices. In fact, Nigeria is classified as the top oil producer in the African continent, hence the inclusion of this market is expected to make the outcomes and results in this study more diversified and comprehensive. Moreover, the stock market in Kazakhstan was chosen to complete the top ten oil producers list as it has the second largest oil reserve in the European continent after Russia (Statista, 2023)[2]. For the oil price shocks, we follow Ready's (2018) approach where we use the World Integrated Oil and Gas Producers Index, the percentage change in the second nearest maturity of New York Mercantile Exchange crude oil futures contracts to proxy for oil prices, and the VIX index. Based on these variables, we construct the demand shock, risk shock, and supply shock as explained in the next section. This study covers the time period from January 2019 to November 2024. The time window covered in this paper has witnessed main global events starting with the outbreak of the COVID-19 pandemic in late 2019 and early 2020. During the pandemic period, the world economy has faced a drastic decline in demands for oil due to cease of global industries and trade. On the other hand, the geopolitical crisis triggered by the Ukraine conflict in early 2022, caused a stop of Russian oil supplies and led to a significant supply shock.

In this study, we follow Ready (2018) in dividing up the oil price shocks into three components: Demand shock, supply shock, and risk shock. The daily oil price movements are decomposed into their underlying drivers. According to this approach, the demand shock is identified as the share of returns from global oil-producing companies that is orthogonal to the Chicago board options exchange (CBOE) volatility index (VIX). The risk shock is then identified based on innovations in the VIX index. The supply shock is calculated as the residual component that remains after accounting for both the demand and risk shocks, following the method outlined oby Li and Guo (2022). To estimate these shocks, we employ an Autoregressive Integrated Moving Average (ARIMA) model with the specification ARIMA(1,1).

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

The $Su_t$, $De_t$, $Ri_t$ are the supply, demand, and risk shocks, respectively. $\Delta p_t$ is the change in oil price, $R_t^{prod}$ represents the return of oil companies, and $\zeta_{VIX,t}$ is the unexpected changes to VIX.

## 4. ECONOMETRIC SPECIFICATIONS

In this paper, we build upon our empirical analysis on the NARDL model proposed by Shin et al. (2014). They introduced the nonlinear ARDL model with a single threshold to divide up the regressors into two partial sums, positive and negative. The positive partial sum captures the escalation in independent variable whereas the negative partial sum reflects the drop of the independent variable. Based on this approach, further developments were introduced such as the bi-threshold NARDL approach by Verheyen (2013) who decomposed the regressor inro three partial sums using the 30$^{th}$ and 70$^{th}$ quantiles. In their Simental work, Pal and Mitra (2015; 2016) have generalized the NARDL model to introduce a multiple threshold NARDL (MTNARDL) that imposed multiple

2 https://www.statista.com/statistics/1295407/oil-production-in-kazakhstan/

thresholds on independent variable on different points such as $20^{th}$, $40^{th}$, $60^{th}$, and $80^{th}$. In this paper, we propose a new approach when applying the MTNARDL based on extreme tails, where thresholds are imposed on the following quantiles of $2.5^{th}$, $5^{th}$, $95^{th}$, and $97.5^{th}$ to capture the potential behavior of outliers of regressors on dependent variables in the system. The extreme tails MTNARDL approach applied in this paper is expected to capture the effect of extreme drops and escalations in oil price shocks (demand, supply, and risk shocks) on stock markets performance of main oil producing countries.

### 4.1. ARDL Model

We start our empirical investigation with the ARDL test proposed by Pesaran et al. (2001). This model enables for capturing the long and short-run co-movements among the variables. The ARDL equation can be presented as:

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{i=0}^{n} \gamma_{2i} \Delta Z_{t-i} + \lambda_1 X_{t-1} + \lambda_2 Z_{t-1} + \varepsilon_t \qquad (1)]$$

Where $X_t$ is stock market returns in oil producing countries (separately) at the time $t$, $Z_t$ shows the oil shock variables of demand, supply, and risk. The short-run co-movement among the variables is measured by the coefficients $\lambda$ of the first differences $\Delta$ of the variables. The ARDL model specifications in this paper are presented as follows:

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{i=0}^{n} \gamma_{2i} \Delta demandshock_{t-i} + \sum_{i=0}^{n} \gamma_{3i} \Delta supplyshock_{t-i} + \sum_{i=0}^{n} \gamma_{4i} \Delta riskshock_{t-i} + \lambda_1 X_{t-1} + \lambda_2 demandshock_{t-1} + \lambda_3 supplyshock_{t-1} + \lambda_4 riskshock_{t-1} + \varepsilon_t \qquad (2)$$

The null hypothesis of no cointegration is $H_0$: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ tested against the alternative hypothesis of $H_1$: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq 0$. If the F- statistic value exceeds the upper bound critical values of Pesaran et al. (2001), the cointegration among the variables will be confirmed, otherwise the null hypothesis of no cointegration will not be rejected. The short-term dependence among the variables is represented through the coefficients $\gamma_2$-$\gamma_4$.

### 4.2. The NARDL Approach

It has been widely argued in the literature that the ARDL model lacks robustness since it relies on the linear impact assumption, where the effect of independent variables changes on independent ones is linear regardless of nature and sign of change or shock in the regressors. However, the time series variables are known by their random behavior and severe fluctuations if exposed to drastic external factors, where they can exhibit non-linear and/or asymmetric effects of the independent variables in the system. For this reason, research in this paper proceeds to apply the non-linear ARDL model proposed by Shin et al. (2014). The advantage of the NARDL model is twofold; first, it tests whether the dependent variables react similarly to positive and negative shocks in regressors. Second, it captures the asymmetric effects of changes in independent variables in both long and short-run horizons. Since oil price shocks can be attributed to various shocks, demand, supply, and precautionary, these shocks might be expected to influence the stock markets performance in different ways. For instance, a shock in oil demand can lead to more significant effects on oil producing countries as compared to changes in oil supplies. To test for that, we begin by decomposing each regressor to two patrial sums as:

$$Z_t = Z_0 + Z_t^+ + Z_t^- \qquad (3)$$

The $X_t^+$ and $X_t^-$ represents the influence of increase and decrease in independent variables of oil price shocks on oil producing stock indices. The $X_t^+$ and $X_t^-$ are expressed as:

$$Z_t^+ = \sum_{i=1}^{t} \Delta Z_i^+ = \sum_{i=1}^{t} \max(\Delta Z_i, 0) \qquad (3a)$$

$$Z_t^- = \sum_{i=1}^{t} \Delta Z_i^- = \sum_{i=1}^{t} \min(\Delta Z_i, 0) \qquad (3b)$$

The NARDL equations of the positive and negative shocks in independent variables are presented as follows:

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \gamma_{2i} \Delta demandshock_{t-i}^+ + \sum_{i=0}^{n2} \gamma_{3i} \Delta demandshock_{t-i}^- + \lambda_1 X_{t-1} + \lambda_2 demandshock_{t-i}^+ + \lambda_3 demandshock_{t-i}^- + \varepsilon_t \qquad (4)$$

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \gamma_{2i} \Delta supplyshock_{t-i}^+ + \sum_{i=0}^{n2} \gamma_{3i} \Delta supplyshock_{t-i}^- + \lambda_1 X_{t-1} + \lambda_2 supplyshock_{t-i}^+ + \lambda_3 supplyshock_{t-i}^- + \varepsilon_t \qquad (5)$$

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{i=0}^{n2} \gamma_{2i} \Delta riskshock_{t-i}^+ + \sum_{i=0}^{n2} \gamma_{3i} \Delta riskshock_{t-i}^- + \lambda_1 X_{t-1} + \lambda_2 riskshock_{t-i}^+ + \lambda_3 riskshock_{t-i}^- + \varepsilon_t \qquad (6)$$

The NARDL in equations (4-6) shows the effect of positive and negative shocks in oil prices on stock markets return in main oil producing countries. For instance, equation (4) depicts the effect of positive and negative values of oil demand shock on the stock markets, equation (5) however tests the impact of shocks in oil supplies on stock market performance in these countries. The same applies for the risk or precautionary shock. The long-run asymmetries in equations 4-6 tested using Wald test null hypothesis of $H_0$: $\lambda_2 = \lambda_3$. The short-run asymmetry in equations 4-6 is measured using the Wald test statistics with the null hypothesis of no asymmetry $H_0$: $\gamma_2 = \gamma_3$. The cointegration among the variables is tested through the null $H_0$: $\lambda_1 = \lambda_2 = \lambda_3 = 0$.

### 4.3 Multiple Threshold NARDL (MTNARDL) Model Specification for Extreme Tail Measurement

In their seminal work, Pal and Mitra (2015; 2016) introduced an advanced MTNARDL with multiple thresholds imposed on the independent variables at different quantiles. This model is used in literature to highlight the asymmetric impact of the regressors in different quantiles and values on dependent variables. The advantage of this model is that it decomposes the movements and values of independent variables and then measures the effect of each one separately on the dependent time series. In this paper, we propose the extreme tail MTNARDL which allows us to measure the effect of extreme shocks in regressors on dependent variables. More specifically, we are imposing four different thresholds that decompose the independent variable into five patrial sums including four extreme series. These four series are from 0 to 2.5%, and 2.5 to 5% to capture the effect of extreme low values of independent variables, on the other hand from 95% to 97.5% and 97.5% to 100% for extreme high values effects. We believe that this is the first research paper that utilizes the MTNARDL model to measure the extreme tail impact. The four thresholds that decompose the regressors into five partial sums as follows:

$$Z_t = Z_0 + Z_t^{(\Upsilon 1)} + Z_t^{(\Upsilon 2)} + Z_t^{(\Upsilon 3)} + Z_t^{(\Upsilon 4)} + Z_t^{(\Upsilon 5)} \quad (7)$$

Where $Z_t^{(\Upsilon 1)} + Z_t^{(\Upsilon 2)} + Z_t^{(\Upsilon 3)} + Z_t^{(\Upsilon 4)} + Z_t^{(\Upsilon 5)}$ are the five partial sums series of independent variables are generated using the thresholds of $\tau_{2.5}$, $\tau_5$, $\tau_{95}$, $\tau_{97.5}$ at the 2.5th, 5th, 95th, and 97.5th quantiles, respectively. The five partial sums are calculated using the following specifications:

$$Z_t^{(\Upsilon 1)} = \sum_{i=1}^{t} \Delta Z_i^{\Upsilon 1} = \sum_{i=1}^{t} \Delta Z_i^{I} (\Delta Z_i \le \tau_{2.5}) \quad (8a)$$

$$Z_t^{(\Upsilon 2)} = \sum_{i=1}^{t} \Delta Z_i^{\Upsilon 2} = \sum_{i=1}^{t} \Delta Z_i^{I} (\tau_{2.5} < \Delta Z_i \le \tau_5) \quad (8b)$$

$$Z_t^{(\Upsilon 3)} = \sum_{i=1}^{t} \Delta Z_i^{\Upsilon 3} = \sum_{i=1}^{t} \Delta Z_i^{I} (\tau_5 < \Delta Z_i \le \tau_{95}) \quad (8c)$$

$$Z_t^{(\Upsilon 4)} = \sum_{i=1}^{t} \Delta Z_i^{\Upsilon 4} = \sum_{i=1}^{t} \Delta Z_i^{I} (\tau_{95} < \Delta Z_i \le \tau_{97.5}) \quad (8d)$$

$$Z_t^{(\Upsilon 5)} = \sum_{i=1}^{t} \Delta Z_i^{\Upsilon 4} = \sum_{i=1}^{t} \Delta Z_i^{I} (\Delta Z_i > \tau_{97.5}) \quad (8e)$$

Where, $I(.)$ is a dummy variable that equals 1 when the conditions stated within (.) are satisfied, else zero. Based on the specifications above, the MTNARDL at the 2.5, 5, 95, and 97.5 quantiles is denoted as follows:

$$\Delta X_t = \sum_{i=1}^{n1} \gamma_{1i} \Delta X_{t-i} + \sum_{j=1}^{5} \sum_{i=0}^{n2} \gamma_{ki} \Delta Z_{t-i}^{\Upsilon_j} + \lambda_1 X_{t-1} + \sum_{j=1}^{5} \lambda_k Z_{t-1}(\Upsilon_j) + \varepsilon_t \quad (9)$$

The null hypothesis $H_0$: $\lambda_1 = \lambda_2 = \cdots = \lambda_k = 0$ tests for the cointegration, while the alternative hypothesis $H_1$: $\lambda_1 \neq \lambda_2 \neq \cdots \neq \lambda_k \neq 0$of no cointegration. Long-run asymmetries are assessed via the null $H_0$: $\lambda_1 = \lambda_2 = \cdots = \lambda_k = 0$, and the short-run asymmetry is examined by the null hypothesis of $H_0$: $\gamma_2 = \gamma_3 = \cdots = \gamma_k = 0$ In equation 9, the MTNARDL is applied three different times to find the impact of extreme tails of oil demand shock, oil supply shock, and oil risk shock, on stock market in USA, then another three different times to capture the effect of extreme tails of same nine variables on stock index in Canada, and so on so forth.

## 5. RESULTS AND DISCUSSION

The empirical analysis in this paper begins with testing the stationarity of the time series to stand on the order of integration of variables in the system. We use Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests proposed by Dickey and Fuller (1979), and by Phillips and Perron (1988), respectively. Table 1 shows the outcomes of the unit root test for the variables for levels and first differences. The results show that not all variables exhibit the same order of integration in their levels I(0), that according to the outcomes of the ADF and PP tests, the oil price shocks of demand, supply, and risk have significant t statistics at 1% level of confidence, indicating that the null hypothesis of no unit root is rejected. Similarity, the PP outcomes show that stock market in Canada seem to be I(1) in its level. Panel B in Table 1 demonstrates the outcomes of ADF and PP unit root tests for variables in their first difference, it can be noticed that all variables have the same order of integration. Based on the outcomes of the unit root stage, and since the variables exhibit mixed order of integration in their levels, we need to be careful with the cointegration technique we adopt as the majority of the cointegration models such as Johansen and Juselius (1990), and Engle and Granger (1987) are sensitive to the order of the integration and require all variables to share the same order of integration in levels, I(0). Henceforth, we choose to apply the ARDL approach proposed by Pesaran et al. (2001) to measure the short and long-term connectedness among the variables. This approach can be applied regardless of whether the variables are all integrated of same or mixed orders. Also, this model allows testing for the short and long-run co-movements among the variables.

Table 2 demonstrates the results of the ARDL model. The first column in the tables includes the independent variables of three

**Table 1: Unit root results**

| Variables | Augmented Dickey-Fuller | Phillips-Perron |
|---|---|---|
| | t-statistics | t-statistics |
| Panel A: Variables at levels | | |
| USA | −0.6291 | −0.5649 |
| Canada | −2.4315 | −2.6071* |
| Russia | −2.1436 | −1.7259 |
| Nigeria | −0.3702 | −0.5100 |
| China | −1.2784 | −1.1940 |
| Brazil | −1.8397 | −2.0705 |
| UAE | −1.7698 | −1.7944 |
| Saudi Arabia | −1.4734 | −1.5271 |
| Kuwait | −1.9050 | −1.6848 |
| Kazakhstan | 1.1323 | 0.8548 |
| Demand Shock | −13.0935*** | −5.7051*** |
| Supply Shock | −12.1310*** | −4.7558*** |
| Risk Shock | −8.7252*** | −8.8497*** |
| Panel B: Variables at first difference | | |
| USA | −11.6077*** | −42.6060*** |
| Canada | −36.1361*** | −36.1339*** |
| Russia | −9.7144*** | −31.9584*** |
| Nigeria | −43.2726*** | −43.1044*** |
| China | −33.7628*** | −33.6409*** |
| Brazil | −40.1690*** | −40.3062*** |
| UAE | −35.2156*** | −35.1658*** |
| Saudi Arabia | −15.0464*** | −38.8940*** |
| Kuwait | −14.8897*** | −37.7308*** |
| Kazakhstan | −24.0963*** | −38.4496*** |
| Demand Shock | −15.3377*** | −72.6427*** |
| Supply Shock | −24.8639*** | −79.5210*** |
| Risk Shock | −18.4160*** | −53.3902*** |

Significant at 10% (*), 5% (**), and 1% (***)

**Table 2: ARDL results**

| Variables | Regressors | Regressands | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | USA | Canada | Russia | Nigeria | China | Brazil | UAE | Saudi | Kuwait | Kazakhstan |
| Panel A: Oil Demand Shock | | | | | | | | | | | |
| Short run | $\Delta D$ | 4.1206*** | 2.9056** | 4.8675*** | 3.6936*** | 5.1981*** | 4.1295*** | −6.4028*** | 20.6320*** | 4.6352*** | 3.9981*** |
| | $\Delta D$ (−1) | 7.9716*** | 2.2245 | 6.4774*** | 12.5039*** | 0.1549 | 4.0600*** | 13.3285*** | −4.5487*** | 8.2541*** | 5.2549*** |
| Long run | $D$ | - | 0.5263 | 14.0314*** | 15.4607*** | 6.7636*** | 4.5236*** | 13.1376*** | −14.7897*** | 3.0212*** | 0.9214* |
| | $D$ (−1) | 13.1230*** | 2.3219** | 13.5862*** | 0.0007 | 0.0325 | 19.4625*** | 5.6227*** | 7.4300*** | 2.2145** | 3.2599*** |
| Panel B: Oil supply shock | | | | | | | | | | | |
| Short run | $\Delta S$ | 8.8347*** | - | 0.8546 | 0.0000 | 0.0000 | 0.9592 | 0.0000 | 0.0025 | 0.0001 | 0.0000 |
| | $\Delta S$ (−1) | 4.5659*** | −0.9402 | 0.1127 | 0.0000 | 0.0000 | 0.0992 | 0.0000 | 0.1457 | 0.0000 | 0.0022 |
| Long run | $S$ | 0.0624 | 0.7546 | 0.1996 | 0.0000 | 0.0696 | 0.1452 | 0.4930 | 7.8883*** | 0.0365 | - |
| | $S$ (−1) | 0.6254 | 2.7446** | 0.3648 | 0.7193 | 0.0258 | 0.0000 | 0.0455 | 4.3254*** | 0.02148 | 0.2254 |
| Panel C: Oil risk shock | | | | | | | | | | | |
| Short run | $\Delta R$ | 19.0786 | −1.6077 | −0.1461 | 0.0000 | 0.0000 | −0.7824 | 0.2673 | 0.9889 | - | 0.0001 |
| | $\Delta R$ (−1) | 48.9880 | −0.1943 | - | 0.0000 | 0.0000 | 0.0756 | 0.3366 | 0.3524 | 0.0000 | 0.0003 |
| Long run | $R$ | 2.6336 | 278.293 | 0.0146 | 0.0052 | 0.0042 | 0.0002 | 0.5248 | 5.2545*** | 1.0587* | 0.0052 |
| | $R$ (−1) | 0.8575 | 0.9526 | 0.1275 | 0.4639 | −0.5560 | −0.1349 | 0.1124 | 2.3668*** | 2.3651** | 2.8895** |
| | F Statistics | 5.82*** | 5.35*** | 5.09*** | 0.86 | 0.43 | 0.35 | 12.63*** | 8.23*** | 7.52*** | 6.32*** |

Significant at 10% (*), 5% (**), and 1% (***). F-statistics in the last row tests null hypothesis of no cointegration of $H_0: \lambda_1=\lambda_2=\lambda_3=\lambda_4=0$ tested against the alternative hypothesis of $H_1: \lambda_1\neq\lambda_2\neq\lambda_3\neq\lambda_4\neq 0$

oil shocks in long and short-term horizons. The stock markets in the oil producing countries are regressed independently against the group of independent variables. The F-Statistic in the last row of the table tests for the existence of long-run co-movement among each one of these stock markets and the oil price shocks through testing for potential rejection of the null hypothesis of no cointegration is $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ tested against the alternative hypothesis of $H_1: \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq 0$. Starting with the F-Statistics outcomes, the results indicate for long-run linear association among oil demand, supply, and risk shocks and all stock markets in the system, however the null hypotheses of no cointegration cannot be rejected for stock markets in Nigeria, China, and Brazil. These results, on one hand, support the findings of Filis et al. (2011), Wang et al. (2013), and Al-Mohamad et al. (2022) which affirmed the co-movement among oil price fluctuations and stock markets in main oil exporting countries, also with. The F-Statistics results also indicate for long-run effect of oil shocks on stock markets in UAE, Kuwait, and Saudi Arabis, and this comes in line with the findings of Ziadat and McMillan (2022), Bashir (2022), Alotaibi and Morales (2022), and Atif et al. (2022) that provided evidence of significant impact of oil price shocks on stock markets in GCC countries. One the other hand, the outcomes indicating for the segmentation of stock markets in Nigeria, China, and Brazil from the changes in oil prices might be explained by the fact that the oil rent contribution to GDP in these three countries is negligible as compared to other oil producers. According to the World Bank Database, the oil exporting contribution to GDP in these three countries is <10%, ranging between 0.6% in China and 6.5% in Nigeria, however the contribution of oil exports to GDP in other countries is considered significant. For instance, the oil rent inflows contribute by 20% to GDP in UAE, up to 25% in Russia, 25% in Saudi Arabia. And almost 30% in Kuwait. The results in panes A, B and C, illustrate the short and long-run effects of oil price demand, supply, and risk shocks on the stock markets, respectively. It can be clearly noticed that the demand shock exhibits the most significant effect on these stock markets in both horizons. However, the supply and risk shocks can only influence the markets in USA, Canada, and Saudi Arabia in panel B, and stock indices in Saudia Arabia, Kuwait and Kazakhstan in panel C for risk shock. Also, we notice that the stock market in Saudi Arabia is the only market who receives the shock effects from all types of oil price shocks and this represents the large contribution of oil export proceeds in Saudi Arabian GDP (25%) and supports the findings of Almohamad et al. (2018; 2022), and Jreisat (2023b).

The results of the ARDL approach in Table 2 shed light on the long-run connectedness among the variables, however this approach does not enable splitting the independent variables into sub-series to investigate whether negative (and or) positive variations of oil price shocks transmit large impacts on the oil exporting stock markets. For this purpose, we proceed to apply the nonlinear ARDL model to inspect the asymmetric effects of oil price shocks on stock market indices in main oil producing countries. Table 3 displays the outcomes of the NARDL test, where each oil shock is divided into positive and negative sums. The results in panel A demonstrate that the oil demand shock continues to exhibit significant effect on the stock markets' performance. The increase and decrease (positive and negative) in the global demand for oil

**Table 3: NARDL results**

| Variables | Regressors | Regressands | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | USA | Canada | Russia | Nigeria | China | Brazil | UAE | Saudi | Kuwait | Kazakhstan |
| Panel A: Oil demand shock | | | | | | | | | | | |
| Short run | $\Delta D^{-}$ | 0.9168 | 33.0748*** | 6.660** | - | 12.1611*** | 43.1615*** | 24.0592*** | 1.2962* | 44.6077*** | −29.3067*** |
| | $\Delta D^{+}$ | 23.3453*** | −18.9799*** | −20.4089*** | 13.4849*** | 19.6835*** | −43.1911*** | −2.7545** | −10.5353*** | −12.9897*** | −23.1918*** |
| Long run | $D^{-}$ | 10.9233*** | 12.0436*** | 12.0269*** | 0.7524 | 5.8147*** | 10.1747*** | 12.1246*** | 44.0253*** | 16.8190*** | 26.5770*** |
| | $D^{+}$ | 10.0546*** | 12.0433*** | 13.7985*** | 0.7462 | 5.7223*** | 19.8992*** | 12.1970*** | 46.2284*** | 1.9095*** | 27.3915*** |
| | F Statistic | 3.35*** | 10.36*** | 5.93*** | 0.65 | 8.33*** | 5.16*** | 4.64*** | 5.85*** | 7.86*** | 7.33*** |
| | Wald Short | 7.42*** | 13.53*** | 2.21 | - | 10.26*** | 32.84*** | 19.45*** | 14.81*** | 10.32*** | 5.47*** |
| | Wald Long | 12.09*** | 26.05*** | 15.61*** | 1.20 | 6.50*** | 3.43** | 3.04** | 8.71*** | 54.70*** | 7.87*** |
| Panel B: Oil supply shock | | | | | | | | | | | |
| Short run | $\Delta S^{-}$ | −0.4324 | −0.5885** | 0.0660 | - | - | −0.1148 | −0.3426 | −0.730 | 0.4958 | - |
| | $\Delta S^{+}$ | 5.2580*** | −3.7627*** | −4.5052*** | - | 5.6229*** | −5.7091*** | −9.0961*** | −6.1436*** | −4.7767*** | −1.7671* |
| Long run | $S^{-}$ | −0.1842 | 3.4745*** | 2.1046** | −0.8189 | −0.0816 | 9.6227** | 0.1432 | 14.1683*** | 1.1219* | −3.7251*** |
| | $S^{+}$ | −0.1683 | 3.4862*** | 2.1013** | −0.8303 | −0.1099 | 9.5577** | 0.1857 | 14.2659*** | 1.1703* | −3.4180*** |
| | F Statistic | 2.23 | 2.51 | 0.69 | 0.79 | 1.36 | 4.24** | 2.71 | 2.75 | 1.60 | 4.19*** |
| | Wald Short | 17.77*** | 10.83*** | 4.13** | - | - | 3.82** | 5.96*** | 5.62*** | 11.33*** | - |
| | Wald Long | 12.12*** | 32.52*** | 11.48*** | 0.47 | 6.07*** | 3.37** | 6.57*** | 5.85*** | 18.58*** | 8.58*** |
| Panel C: Oil risk shock | | | | | | | | | | | |
| Short run | $\Delta R^{-}$ | - | 1.5489* | - | - | - | 6.4100** | - | 2.4250** | - | 21.6825* |
| | $\Delta R^{+}$ | 8.6829*** | - | - | - | - | −4.1422*** | - | −3.8621*** | - | - |
| Long run | $R^{-}$ | −0.2957 | −0.2837 | −4.2488*** | 0.5874 | −0.4044 | 3.1816*** | 2.6430** | 1.0107* | 2.9498*** | −1.7000* |
| | $R^{+}$ | −0.2975 | −0.2825 | −4.2831*** | 0.5352 | −0.4180 | 3.1557*** | 2.6557** | 1.0131* | 2.9662*** | −1.6358* |
| | F Statistic | 3.16* | 2.61 | 1.36 | 0.88 | 1.53 | 2.91 | 2.36 | 2.45 | 1.63 | 6.12*** |
| | Wald Short | - | - | - | - | - | 6.04*** | - | 1.92 | - | - |
| | Wald Long | 3.70** | 3.41* | 9.69*** | - | 5.61*** | 3.47** | 4.63*** | 5.99*** | 0.91 | 7.85*** |

Significant at 10% (*), 5% (**), and 1% (***). The long-run Wald test null hypothesis is $H_0$: $\lambda_2=\lambda_3$. The short-run Wald test null hypothesis is $H_0$: $\gamma_2=\gamma_3$. The cointegration among the variables is tested through the null $H_0$: $\lambda_1=\lambda_2=\lambda_3=0$

leads to significant influence on these markets, with an exception for stock market in Nigeria. These results are somewhat plausible since the changes in demand for oil will consequently lead to a change in production levels to meet the changing demands. Also, the results of panel A support the outcomes of the ARDL test that show a dominating influence of demand shock on stock markets as compared to supply and risk shocks. Also, panel A indicates that the oil demand shocks have asymmetric impacts on the stock indices in main oil producing countries in short and long terms, and this indicates dissimilar effects exerted by demand shocks on these markets. In other words, the stock indices in these countries will react differently (different from their own previous ones) to demand shocks based on whether the shock was positive or negative and this provides clear evidence for an asymmetric effects of oil price changes on stock markets in main oil producers and comes in line with the findings of Jreisat (2023b), and Ebadi and Razaq (2024). Panel B in Table 3 demonstrates the outcomes of positive and negative shocks in oil supplies on the stock market indices. It can be noticed that the decomposition of supply shocks into positive and negative sums provides more robust outcomes compared to panel B of Table 2 for ARDL results. In NARDL outcomes show that the positive shock in oil supplies leads to noticeable negative effects on these stock markets in short-run, this can be explained by the fact that for a given increase in oil supplies, for instance due to new advancement of oil technological and production capabilities, the global oil price is expected to decrease as a result, and this will adversely influence the oil exporting cash flows in these countries. Panel C in the table displays the outcomes of oil risk shock. The risk or precautionary shock can be caused by investors sentiment and beliefs about the future oil supplies and prices. According to Ready (2018), this shock is generated by an unexpected increase in oil prices due to heightened concerns about the potential disruption in oil supplies. The outcomes in panel C indicate that the stock markets in developing or emerging oil producers such as Saudi Arabia, Kuwait, UAE, and Russia are highly affected by the fear and uncertainty pertinent to future oil supplies and prices. Moreover, the significance of coefficients of the long-run impacts seems to be high, and this might be due partial inefficiencies of stock markets in these countries where the markets take longer period of time to adjust to new events. Overall, the results of the NARDL test in Table 3 have shed more light on the nature of effect of oil price shocks on these stock markets, where it can be clearly noticed that the oil demand shock plays dominant role in influencing the stock markets and this comes in line with the findings of Jreisat et al. (2023a), and Bashir (2022) who found that oil demand shock has greater effect than supply shock on stock markets in a major group of oil producing countries (GCC nations). Nevertheless, a further empirical investigation is required to discover if the extreme shocks in oil prices can lead to sharp reaction by these stock markets. For this purpose, we proceed to apply the MTNARDL method to investigate the extreme tail effects. This paper provides a newly developed version of the MTNARDL that allows for extreme quantile investigation through an exogenous determination 2.5%, 5%, 95%, and 97.5% thresholds.

Table 4 demonstrates the outcomes of the MTNARDL for extreme trail effects of oil price shocks on stock markets in main oil

**Table 4: MTNARDL results**

| Variables | Regressors | Regressands | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | USA | Canada | Russia | Nigeria | China | Brazil | UAE | Saudi | Kuwait | Kazakhstan |
| Panel A: Oil demand shock | | | | | | | | | | | |
| Short run | $\Delta D(Y1)$ | 0.6980*** | 0.0620*** | 0.1033*** | 0.0124** | 0.0444*** | 0.1074*** | 0.0618*** | 0.1331*** | 0.1675*** | 0.0853*** |
| | $\Delta D(Y1)(-1)$ | −0.3526*** | −0.0042 | 0.0296** | 0.0226*** | - | −0.0385*** | - | 0.0690*** | 0.0943*** | 0.1333*** |
| | $\Delta D(Y2)$ | 0.4331*** | 0.0239** | 0.1145*** | - | - | 0.0397*** | 0.0492*** | - | - | 0.2306*** |
| | $\Delta D(Y2)(-1)$ | −0.3135*** | 0.0026 | 0.1001*** | 0.0000 | - | - | - | - | - | 0.2062*** |
| | $\Delta D(Y3)$ | 0.3882*** | 0.0358*** | 0.1149*** | 0.0000 | 0.0237*** | 0.0594*** | 0.0408*** | 0.0983*** | 0.0449*** | 0.0881*** |
| | $\Delta D(Y3)(-1)$ | −0.0041 | 0.0086* | 0.0538** | 0.0000 | - | −0.0213*** | - | −0.0239*** | - | 0.1601*** |
| | $\Delta D(Y4)$ | 0.3589*** | 0.0200*** | 0.0008 | 0.0000 | - | 0.0548*** | 0.0206*** | 0.0908*** | 0.0509*** | - |
| | $\Delta D(Y4)(-1)$ | −0.4384*** | - | −0.1172*** | 0.0000 | - | - | −0.0400*** | - | - | - |
| | $\Delta D(Y5)$ | 0.0043 | - | 0.0024 | - | - | 0.0008 | 0.0007 | 0.0041 | −0.0001 | - |
| | $\Delta D(Y5)(-1)$ | 0.0054 | - | 0.0045 | - | - | 0.0005 | 0.0003 | - | −0.0012 | - |
| Long run | $D(Y1)(-1)$ | 0.0020 | −0.0001 | 0.0007 | −0.0005 | −0.0005 | 0.0008 | 0.0006 | −0.00275 | −0.0008 | 0.0031 |
| | $D(Y2)(-1)$ | −0.0083* | −0.0010 | −0.0145** | −0.0010 | −0.0035 | −0.0022 | −0.0018 | 0.0103** | 0.0027 | −0.0002 |
| | $D(Y3)(-1)$ | −0.0314*** | −0.0024 | −0.0080* | 0.0015 | −0.0026 | −0.0024 | 0.0001 | −0.0010 | 0.0026 | −0.0259*** |
| | $D(Y4)(-1)$ | 0.0123** | −0.0005 | −0.0167** | −0.0027 | −0.0050 | −0.0013 | 0.0004 | 0.0051 | 0.0007 | 0.0203*** |
| | $D(Y5)(-1)$ | 0.0060 | 0.0010 | −0.0028 | −0.0003 | 0.0002 | 0.0014 | 0.0015 | 0.0108** | 0.0021 | −0.0007 |
| | F Statistic | 4.29*** | 9.87*** | 3.57** | 1.88 | 3.69** | 5.18*** | 4.55*** | 16.22*** | 3.56** | 5.38*** |
| | Wald Short | 5.66*** | 16.08*** | 2.78** | - | - | 7.90*** | 4.10*** | 22.72*** | 5.18*** | 3.46** |
| | Wald Long | 28.36*** | 32.56*** | 13.41*** | 4.40*** | 11.59*** | 37.07*** | 16.88*** | 10.00*** | 40.03*** | 6.97*** |
| Panel B: Oil supply shock | | | | | | | | | | | |
| Short run | $\Delta S(Y1)$ | - | −0.0679*** | −0.2376*** | 0.0054 | 0.0000 | −0.0503*** | 0.0000 | 0.0063 | 0.0052 | 0.0057 |

*(Contd...)*

**Table 4:** ***(Continued)***

| | Regressors | Regressands | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | USA | Canada | Russia | Nigeria | China | Brazil | UAE | Saudi | Kuwait | Kazakhstan |
| | ΔS(ϒ1)(−1) | - | −0.0426*** | −0.2814*** | 0.0003 | 0.0000 | −0.1385*** | 0.0000 | −0.0011 | 0.0007 | 0.0000 |
| | ΔS(ϒ2) | −2.2779*** | −0.3294*** | - | 0.0000 | 0.0000 | −0.4346*** | −3.3669*** | −0.0088* | 0.0003 | 0.0015 |
| | ΔS(ϒ2)(−1) | - | - | - | 0.0000 | 0.0000 | - | 0.0048 | −0.0085* | 0.0000 | −0.0081* |
| | ΔS(ϒ3) | 0.8325*** | 0.0696*** | 0.2686*** | 0.0000 | 0.0000 | 0.0000 | 1.5863*** | 0.0020 | 0.0000 | 3.92073*** |
| | ΔS(ϒ3)(−1) | - | 0.0000 | 0.3649*** | 0.0000 | 0.0000 | 0.0000 | 0.0000 | −0.0002 | 0.0000 | 0.0000 |
| | ΔS(ϒ4) | −2.4489*** | 0.0000 | −0.2850*** | 0.0000 | −0.3384*** | 0.0000 | 0.0000 | 0.0008 | −0.0009 | 0.0008 |
| | ΔS(ϒ4)(−1) | 1.7709*** | 0.0000 | 0.5974*** | 0.0000 | −0.1294*** | 0.0000 | - | −0.0055 | 0.0006 | 0.0000 |
| | ΔS(ϒ5) | −0.0336*** | 0.0000 | −0.0087* | 0.0000 | - | 0.0000 | −0.1947*** | 0.0623* | −0.7295*** | −0.0756** |
| | ΔS(ϒ5)(−1) | −0.0055 | 0.0000 | −0.0123** | 0.0000 | - | 0.0000 | - | 0.3369*** | −0.3036*** | 0.0003 |
| Long run | S(ϒ1)(−1) | 0.0178** | −0.0009 | −0.0050 | −0.0032 | −0.0002 | 0.0043 | −0.1257*** | −0.0011 | −0.0099* | −0.0086* |
| | S(ϒ2)(−1) | −0.5767*** | −0.0372*** | −0.0681*** | 0.0004 | −0.0004 | −0.0278*** | −1.6933*** | −0.0085* | 0.0064 | 0.0029 |
| | S(ϒ3)(−1) | −0.3191*** | −0.0245*** | −0.1206*** | −0.0033 | −0.0004 | −0.0025 | 0.9459*** | −0.9359*** | −0.0041 | 0.0011 |
| | S(ϒ4)(−1) | −0.4556*** | −0.0378*** | −0.1145*** | −0.0002 | −0.0004 | −0.0260*** | −1.4458*** | −0.8313*** | −2.2489*** | 0.0066 |
| | S(ϒ5)(−1) | −0.0543*** | 0.0007 | −0.0106** | 0.0009 | 0.0008 | 0.0016 | 0.0532*** | 3.4154*** | −1.1650*** | −2.8047*** |
| | F Statistic | 3.99** | 3.98** | 1.60 | 1.05 | 1.47 | 2.32 | 2.19 | 3.33* | 3.66** | 3.62** |
| | Wald Short | 2.66** | 9.99*** | 3.17** | - | - | - | 6.66*** | 3.51*** | 1.50 | 2.85** |
| | Wald Long | 5.19*** | 6.87*** | 6.16*** | 1.64 | 1.02 | 2.83** | 2.00* | 5.14*** | 3.95*** | 5.95*** |
| Panel C: Oil risk shock | | | | | | | | | | | |
| Short run | ΔR(ϒ1) | −0.3925*** | 0.0183** | 0.0000 | −0.1131*** | 0.1240*** | 0.0194*** | 0.0000 | 6.6238*** | −0.0009 | 0.0007 |
| | ΔR(ϒ1)(−1) | 2.1005*** | 0.1234*** | 0.0000 | 0.0916*** | 0.0533*** | −0.0614*** | 0.0000 | 5.2307*** | 0.0007 | 0..0092* |
| | ΔR(ϒ2) | −2.9642*** | −0.1963*** | 0.0000 | - | −0.0058 | −0.0026 | 0.0000 | 0.0000 | −0.0005 | 0.0000 |
| | ΔR(ϒ2)(−1) | 3.9760*** | 0.1310*** | 0.0000 | - | 0.0329*** | 0.0015 | 0.0000 | 0.0000 | 0.7260*** | 0.0003 |
| | ΔR(ϒ3) | 0.0000 | 0.0000 | - | 0.0010 | 0.0000 | 0.0005 | - | −8.8794*** | −0.0029 | 0.0005 |
| | ΔR(ϒ3)(−1) | −2.9600*** | 0.0000 | - | 0.0008 | 0.0000 | −0.0092* | - | 0.0000 | −0.0000 | 0.0000 |
| | ΔR(ϒ4) | 3.9760*** | −0.0005 | −0.8145*** | 0.0006 | 0.0000 | - | 0.0002 | 2.5922*** | 5.6385*** | - |
| | ΔR(ϒ4)(−1) | −2.9642*** | 0.0006 | 0.0059 | 0.0007 | −0.1893*** | - | 0.0063 | 0.0000 | 14.5449*** | - |
| | ΔR(ϒ5) | 0.0693** | −0.0010 | −0.1352*** | - | −0.0912*** | −0.0045 | −0.0299*** | −0.4861*** | 0.0000 | - |
| | ΔR(ϒ5)(−1) | 0.0089* | 0.0005 | −0.0058 | 0.0000 | 0.4544*** | 0.0058 | −0.0844*** | 0.0000 | 0.0000 | - |
| Long run | R(ϒ1)(−1) | 0.1086*** | 0.0030 | 0.0922*** | −0.0070 | −0.0063 | −0.0058 | 0.0012 | −0.6442*** | −0.0003 | −0.0008 |
| | R(ϒ2)(−1) | −0.8092*** | −0.0427** | −0.2988*** | 0.0206** | −0.0237** | −0.0516 | 0.0000* | 3.6959*** | 0.0040 | −0.0006 |
| | R(ϒ3)(−1) | 0.0014 | −0.0048 | −0.0040 | 0.0009 | −0.0072 | −0.0342*** | 0.0000 | 1.6224*** | 0.0027 | 0.0015 |
| | R(ϒ4)(−1) | −0.0153** | −0.0026 | −0.1772*** | 0.0008 | −0.0574*** | −0.0218*** | 1.0017*** | 2.7721*** | 0.0012 | −0.0006 |
| | R(ϒ5)(−1) | −0.0061 | −0.0108** | −0.0023 | −0.0007 | −0.0009 | −0.0270*** | 0.0084* | 0.0039*** | 0.0032 | 2.4518*** |
| | F Statistic | 3.20* | 2.84 | 1.71 | 1.25 | 3.85** | 3.40** | 1.95 | 1.88 | 2.04 | 3.71*** |
| | Wald Short | 2.54** | 0.12 | 2.93** | - | 4.85*** | 2.89** | 5.46*** | 4.76*** | 2.00 | |
| | Wald Long | 9.13*** | 3.96*** | 5.80*** | 1.58 | 3.50*** | 1.91* | 3.10*** | 2.84** | 5.05*** | 5.08*** |

Significant at 10% (*), 5% (**), and 1% (***). The F Statistics tests for the null hypothesis of no cointegration $H_0$: $\lambda_1=\lambda_2=\cdots=\lambda_k=0$ against the alternative hypothesis $H_1$: $\lambda_1\neq\lambda_2\neq\cdots\neq\lambda_k=0$. Long-run asymmetries are assessed via the null $H_0$: $\lambda_1=\lambda_2=\cdots=\lambda_k=0$, and the short-run asymmetry is examined by the null hypothesis of $H_0$: $\gamma_1=\gamma_2=\cdots=\gamma_k=0$

producing countries. Each independent variable (oil price shocks) is divided up into five sums. The first and second series represent the extremely low values of the independent variable i.e. from 0 to 2.5%, and 2.5 to 5%, the last two sums represent the sharp increase in the regressor value, from 95% to 9735%, and from 97.5% to 100%. Panel A illustrates the effect of extreme demand shock values on the stock markets. Where the coefficients of $\Delta D(\Upsilon 1)$ and $\Delta D(\Upsilon 2)$ show the short-term effect of extreme low values of demand shock on the stock markets whereas the $\Delta D(\Upsilon 4)$ and $\Delta D(\Upsilon 5)$ represent the short-run influences at very high quantiles. On the other hand, the coefficient of $\Delta D(\Upsilon 1)$- $\Delta D(\Upsilon 5)$ presents the long-term effects of extreme demand shocks on the stock indices. The outcomes in panel A indicate that the extreme negative shocks in demand for oil represented by $\Delta D(\Upsilon 1)$ and $\Delta D(\Upsilon 2)$ affect all stock markets in producing countries, with no exceptions, either in its lag or original values. These outcomes support the findings of Hanif et al. (2024) who found that the demand shock plays a major influence on stock indices in major oil producers. On the contrary, the extreme positive shock in demand for oil (sharp increase in global oil demands) fails to cause the same effect where the coefficients of $\Delta D(\Upsilon 4)$ are not significant for Nigeria, Russia, and Kazakhstan. However, we can notice that the very high values of demand shock $\Delta D(\Upsilon 5)$, from 975% to 100%, do not have any significant effect of the stock markets. These outcomes seem to be surprising and unexpected, and they indicate that the oil producing countries can benefit from high demand for oil to a certain extent after which no significant benefits can be gained.

In the long run, the results show that the stock market in China is the most affected by extreme movements in oil demands, and this might be explained by the strong manufacturing fundamentals. It can be noticed from panel A that the stock indices in the top oil producing countries are fragile to extreme demand shocks in the short run mainly, and more to negative shocks specifically. Panel B demonstrates the effects of extreme oil supplies on these markets. It can be noticed that the sharp decrease in supplies represented by the coefficients of $\Delta S(\Upsilon 1)$ and $\Delta S(\Upsilon 2)$, cause a negative response by these markets except for markets in Nigeria, Russia, and Kuwait, and this is somewhat implausible given the high reliance of these countries, especially Russia and Kuwait, on oil exporting revenues in their economic fundamentals and growth. One the other side, the extreme positive shock in oil supplies $\Delta S(\Upsilon 4)$ and $\Delta S(\Upsilon 5)$ seem to have positive influence on majority of the stock indices except for Canada, Brazil, and Nigeria, and this might be due to economic diversity especially in Canada and Brazil. In the long run, the extreme shock in oil supplies exhibit significant effect on most of the stock markets except for Nigeria, which seems to be highly segmented from extreme oil shocks, and for China. Panel C in Table 4 demonstrates the outcomes for the precautionary or risk shock effects. It can be noticed that, in general, the risk and uncertainty about the future oil prices can exhibit significant effects on these markets, and this provides more comprehensive and indicative outcomes about risk shock effect compared to the NARDL outcomes in Table 3 above. The outcomes in panel C show that all stock markets in these countries are influenced by high and low uncertainties about oil prices, and this comes in line with empirical literature that affirms on the role of risk and uncertainty in forming the investors' decisions and markets transmissions from bullish to bearish and vice versa. Overall, the MTNARDL results in Table 4 based on extreme quantile investigation affirm on the importance of considering the extreme tail effects of oil shocks in measuring the nexus among stock markets performance and oil price fluctuations, where the extreme positive and negative shocks proved to have asymmetric effects on the stock markets in main oil producing countries. These results support the findings of Mensi et al. (2024), who concluded that the oil price changes seem to have a more significant effect on stock markets during the extreme market conditions.

## 6. CONCLUSION AND POLICY IMPLICATIONS

The oil price movements have witnessed a several shocks in the last few years due to economic and geopolitical factors such as the COVID-19 pandemic, Ukrainian war, and the emerging trade war. These updates have created fear and uncertainty around the globe, especially for the main oil producing countries as they rely on oil exports income to stimulate their economic growth and stabilize other macroeconomic and financial variables. This paper aims at providing further and more detailed evidence on the effect of oil price shocks on stock markets performance in the major oil producing countries of USA, Canada, Russia, Nigeria, China, Brazil, UAE, Saudi Arabia, Kuwait, and Kazakhstan between 2019 and 2024. The countries in this paper account for more than 70% of the total global oil production. The main contribution of this paper is that utilizes an advanced version of the MTNARDL model that allows to investigate the extreme tail effects of oil demand, supply, and risk shocks by decomposing the independent variables into five partial sums through fixing the threshold at the extreme boundaries of extreme positive and negative values at 2.5$^{th}$, 5$^{th}$, 95$^{th}$, and 97.5$^{th}$ quantiles.

The outcomes of the NARDL test show that positive and negative shocks in oil demands exhibit noticeable effect on the stock markets' performance, however these influences can be described as asymmetric due to variation of the size and sign of the shock effect between short and long-term horizons. Also, the NARDL results reveal that a positive shock in oil supplies can cause negative effects on the stock markets in the short run, however the effects of risk shock on the stock market indices seem to be negligible. The outcomes of the NARDL test support the findings of Bashir (2022), Jreisat et al. (2023a), and Hanif et al. (2024), who found evidence for oil shock influences on stock markets in oil producing, and developing, indices, with clear evidence on high influence of the demand shock. The research in this paper proceeds to apply MTNARDL model with extreme tail characteristics. The outcomes of MTNARDL reveal that the extreme negative shocks in demand for oil can influence the majority of stock markets whereas the extremely positive shock in demand for oil (sharp increase in global oil demands) fails to cause the same effect, and this affirms the findings of Mensi et al. (2024) who claimed that oil price changes seem to have a more significant effect on stock markets during the extreme market conditions. Also, the results indicate that the sharp decrease supplies trigger a negative response by these markets except for Nigeria, Russia, and Kuwait, whereas the extreme positive shock in oil supplies affects the markets positively. Finally, the risk shock is found to have significant effects on the dependent variables, where all stock markets in this study are influenced by high and low uncertainties about future oil price movements.

The outcomes in this paper carry important implications to investors and policy makers alike, as it can be noticed clearly that the stock markets in major oil producers are not isolated from the changes in oil prices regardless of whether these changes are triggered by demand, supply, or risk shocks. Hence, the policy makers and stock market authorities need to dedicate more efforts toward economic diversification especially in the less developed countries, also the outcomes in this paper shed more light on the importance of advancing the portfolio diversification efforts when it comes to stock market investment since they are still fragile to fluctuations in the global energy market.

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