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The effects of COVID-19 on the interrelationship among oil prices, stock prices and exchange rates in selected oil exporting economies

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ABSTRACT

This paper re-examines the performances of stock prices, oil prices and exchange rates in twelve oil exporting countries amidst the ravaging consequences of the ongoing worldwide coronavirus pandemic. Consequently, the study adopted a panel Vector Autoregressive (pVAR) model which applied data from the pre- and post-COVID-19 periods. Contrary to the pre-COVID-19 pandemic period, the pVAR Granger causality test indicates that the stock market can as well affect the exchange rate market, though positively. Furthermore, the Impulse response functions (IRFs) shows that a shock to crude oil prices provokes a negative response by exchange rates in the post-COVID-19 pandemic era only. The Forecast Error Variance Decomposition (FEVD) estimates that such innovations to crude oil prices account for the varying fluctuations in exchange rates and stock returns at different periods, but is neither influenced by the stock market activities nor the exchange rate market in the post-COVID-19 pandemic era. This suggests that before COVID-19, the different markets in the selected oil producing economies were only affected by their market fundamentals and dynamics only, but this changed with the plummeting oil prices in the COVID-19 pandemic era. The development of vaccines and the immediate vaccination of the world people will ease the lockdowns and increase the demand for crude oil by the high oil importing countries. With the improved earnings from this, and the associated appreciation of the local currencies against the US dollars, the capital market activities of these net oil exporting countries improve. Policy makers and investors should consider the dynamics in the oil market while making decisions.

1. Introduction

The trilateral interrelations among stock prices, oil prices and exchange rates have generated heated debates among practitioners, policy makers and the academics, worldwide. The stock markets of many oil exporting countries are facing worse times. This is due to the outbreak of the deadly coronavirus pandemic in December 2019, the plummeting price of oil, a traditionally volatile commodity (Fayyad and Daly, 2016) and the depreciating local currencies. Oil is an important source of energy and a necessary input for production in an economy. It is a source of energy for powering automobiles, aircrafts, etc., in the transportation industry, powers electricity generating engines in the energy sectors, and a source of raw material for petrochemical industries (Enitan Odupitan, 2017). Oil is a major source of foreign exchange to oil exporting countries.

To contain the spread of this highly contagious COVID-19 virus which has brought nearly half of the world to a standstill (Ali et al., 2020), the world resorted to physical and social distancing orders, which also includes restrictions and bans on international and local flights, especially as there are yet no vaccines for it. These affected non-essential businesses, the tourism and aviation industries, etc., bringing down global oil demand, especially in the transportation sector, of the United States, the European Union, and Japan where oil is largely consumed (Taghizadeh-Hesary, 2020), as well as China which also faced a decreased demand for oil for electricity and petroleum production (Norouzi et al., 2020). Unfortunately, this coincided with the period of failed negotiations between Russia and the Organization of the Petroleum Exporting Countries (OPEC) to reduce the daily barrel production of oil, (Gharib et al., 2020). The outcome is an excess supply of crude oil in a period of reduced demand, and further plunge in the price in the

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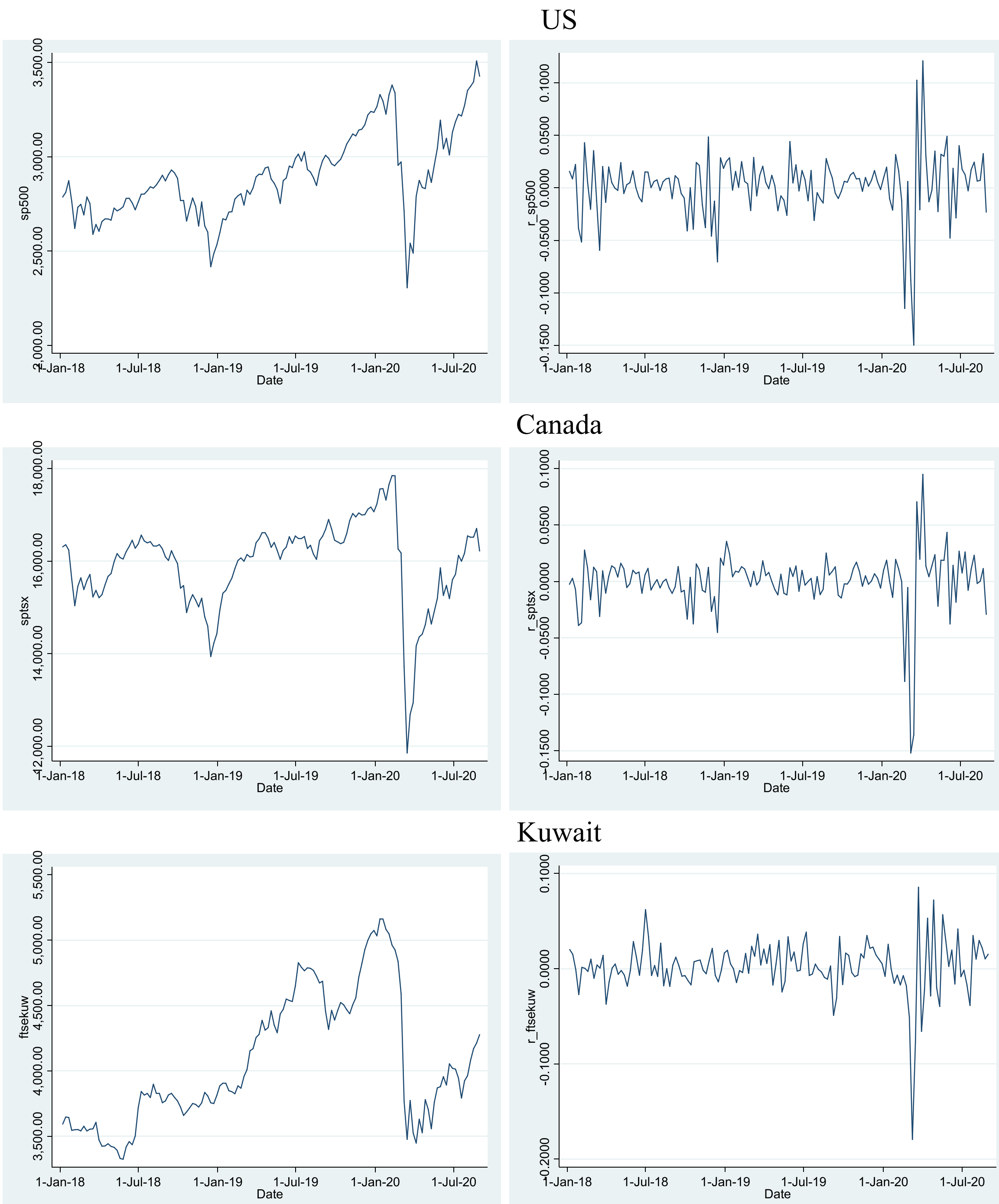
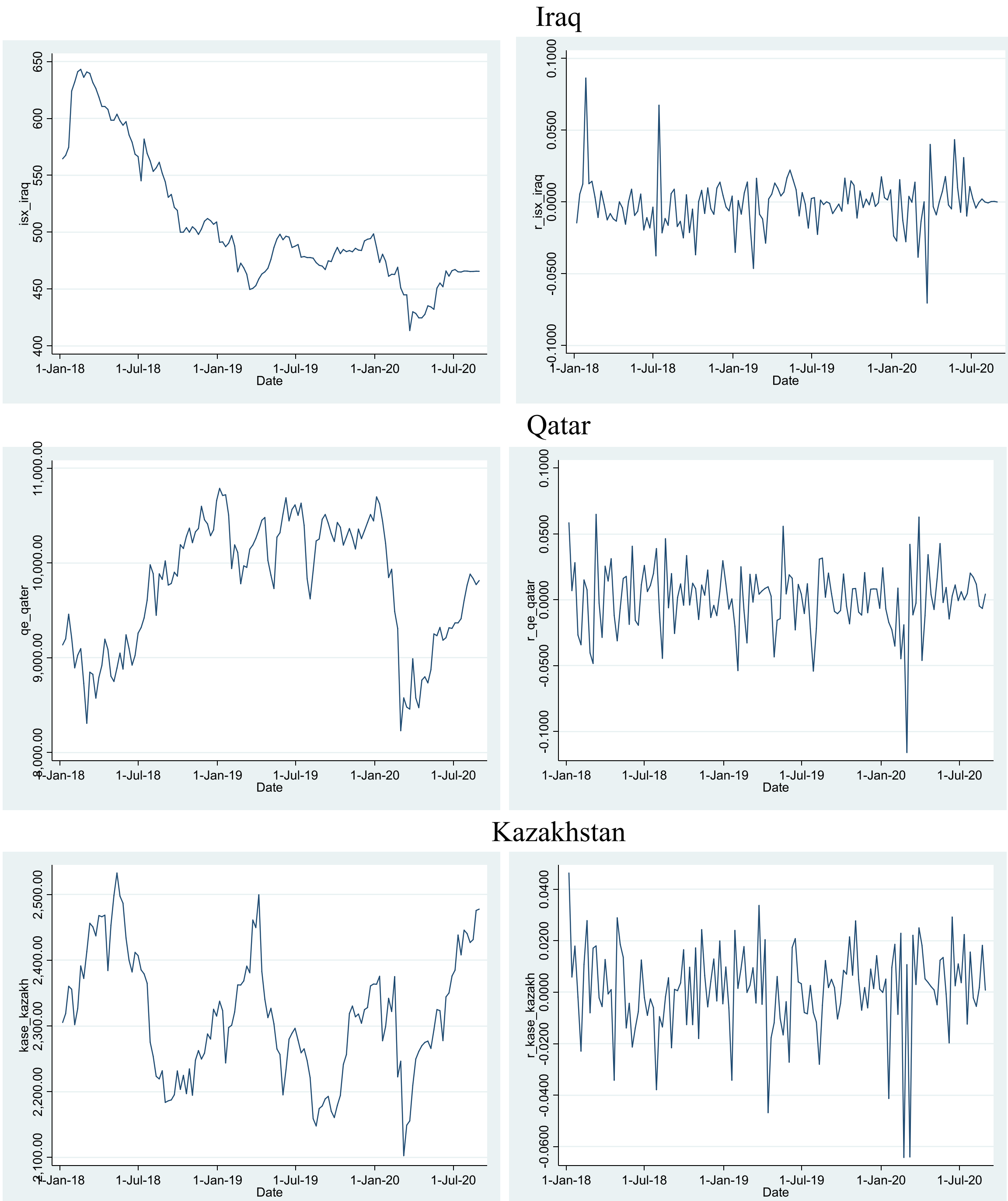


Fig. 1. Major stock and oil indices of selected net-oil producing economies.
Notes: Weekly data from 7 January 2018 to 30 August 2020. Actual (graphs at left) and computed returns (graphs at right).

COVID-19 era. These crises have led to jeopardy in economies all over the world, turning into a disruptive financial contagion and eroding the financial gains of yesterdays in a very short period of time.

Attempts have been made to estimate the magnitude and impacts of this crisis on stock markets. Salisu, Ebuh and Usman (2020) document that between February and March 2020, the US stock prices dropped by 32%, the UK's by 27.9%, the Italy's by 39.3%, the Brazil's by 40.5%, the Russia's by 24.2% while the China's which plummeted by 10.1%, displayed relative calm with lower volatility during both the epidemic and pandemic periods (Ali et al., 2020). Similarly, Zhang et al. (2020) also find that the United States' stock market hit the circuit breaker mechanism, four times in ten days, in March 2020, since it triggered only once, in 1997, the UK's main index, dropped more than 10% on 12 March 2020, in its worst day since 1987, while the stock market in Japan plunged more than 20% from its highest position in December 2019. Mazur, Dang, and Vega (2020) noted that this drastic fall in equity values were observed in the petroleum, real estate, entertainment, and hospitality stocks, while the stocks of natural gas, food, healthcare, and software firms on the universe of S&P 1500 still earn high positive returns. Aruna and Rajesh (2020) report that COVID-19 has a positive



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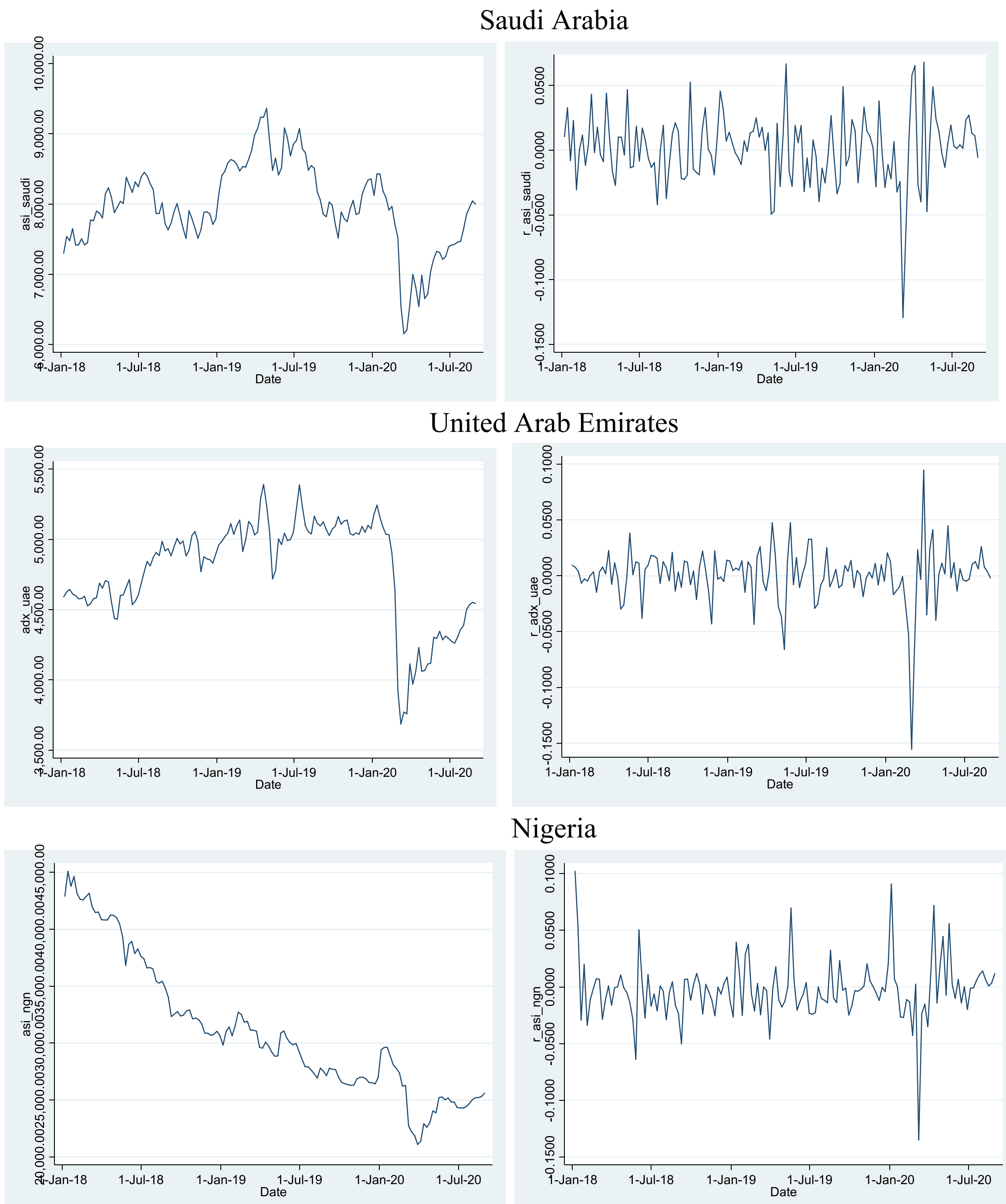
impact on Indian stock market even in the period of plummeting crude oil price.

The above studies represent the stock markets' reactions to the plummeting oil prices among the oil importing countries in the COVID-19 era. This may not be the case for oil exporting countries with dissimilar characteristics. It has been noted that the stock market reactions to oil shocks depend on whether the country imports or export oil, and whether supply or aggregate demand factors motivated the changes in oil price (Wang, Wu and Yang, 2013). For example, Taghizadeh Hesary, Yoshino, Abdoli, and Farzinvash, (2013), opine that a fall (rise) in oil prices is a positive (negative) shock which will motive more (less) purchases from the importing (exporting) countries, but negatively (positively) affects the oil revenue accruable to the exporting countries.

Oil occupies a central aspect in the economic development, especially in oil exporting economies (Kumar, 2019). Since oil trade is done using exchange rate, oil therefore is a major driver of exchange rates movements via balance of trade (Turhan et al., 2014), in these oil exporting countries whose major earnings are from oil. Imbalances in trade, usually causes oscillations in the exchange rates. In this era of COVID-19 pandemic, it is not surprising that plunges in oil prices is shrinking the government budgets of exporting countries, whose revenue is majorly oil based (Taghizadeh-Hesary, 2020). The stock market is one of those sectors badly affected by this low earnings. With a fall in the price of oil, a crucial input in most firms' production process, the expected cash flows accruable to oil exporting countries also falls, affecting earnings, exchange rate, government budget revenues and expenditures,



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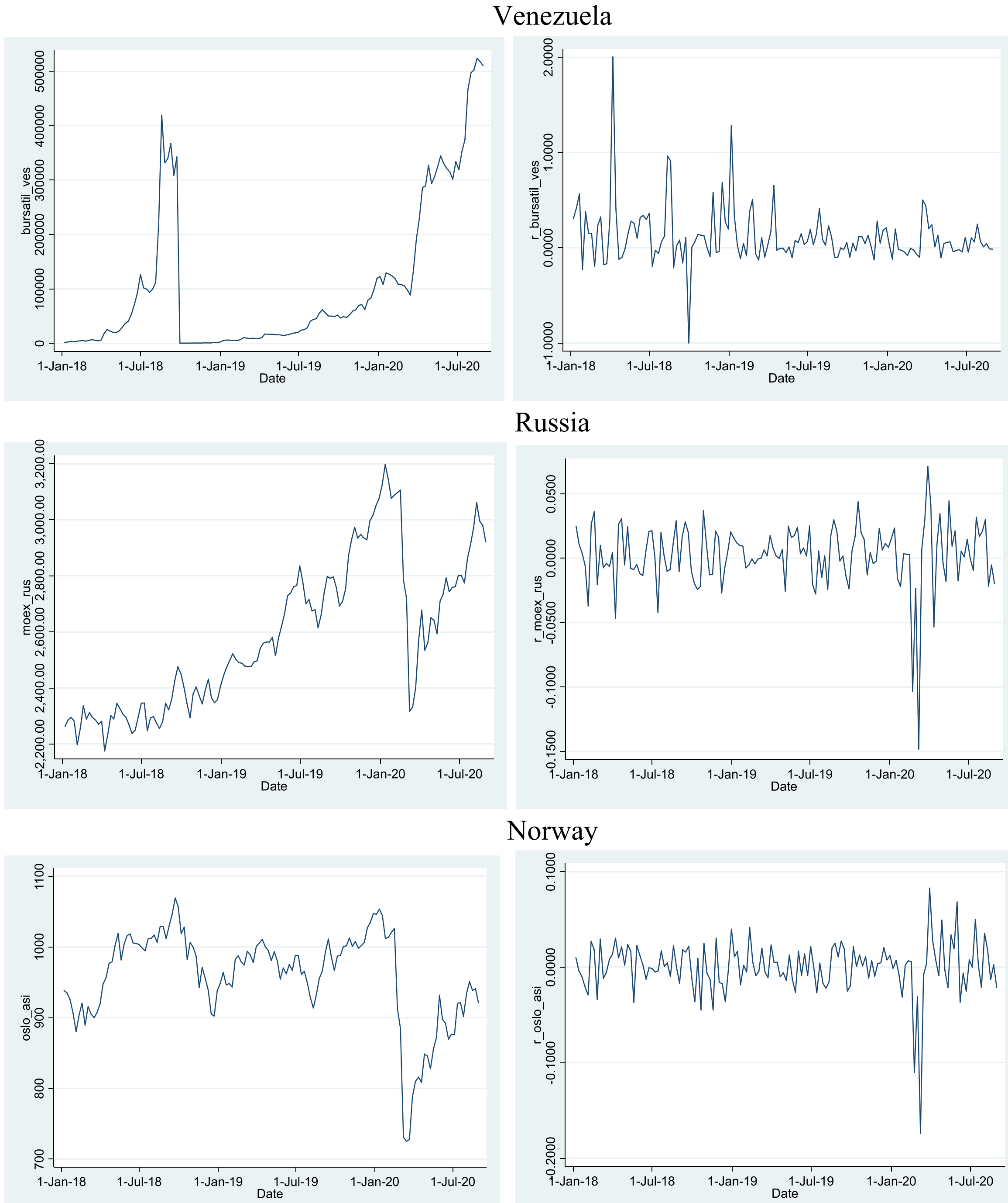
aggregate demand, and thus corporate income and stock prices, the reverse is the case in the oil importing countries (Arouri and Nguyen, 2010; Rafailidis and Katrakilidis, 2014, Arouri et al., 2011). The foregoing shows that these macroeconomic variables further influence the stock and the exchange rate markets (Hamilton, 1983, Amano and van Norden, 1995). It also establishes that the stock markets of oil importing and exporting countries will react differently to the plummeting oil prices given the exchange rates in the different economies, in this COVID-19 era. For example, available data shows that in the pre-COVID-19 period, stock prices, exchange rates and crude oil prices moved most times in different directions, meaning that the fluctuations in each of the markets were not particularly driven by the movements in another market(s). This was not the case in the post-COVID-19 period when the plummeting oil prices caused depreciation in the exchange rates of many of the net oil exporting countries, including Saudi Arabia, Nigeria, Iraq, Iran, Qater, etc. The depreciation in the Venezuelan exchange rate which started before the COVID-19 became wider in the COVID-19 period, while the U.S. currency strengthened against other currencies (see also Fig. 1 and Fig. 2).

This study therefore re-evaluates the linkages between international oil prices, stock prices and exchange rates of major oil producing economies in the COVID-19 era. A number of studies have examined the relationship among these variables, majority investigated only the bivariate relations without considering their trilateral associations given the global pandemic (COVID-19). Again, crude oil prices are stated in the United States dollars which has appreciated greatly against that of



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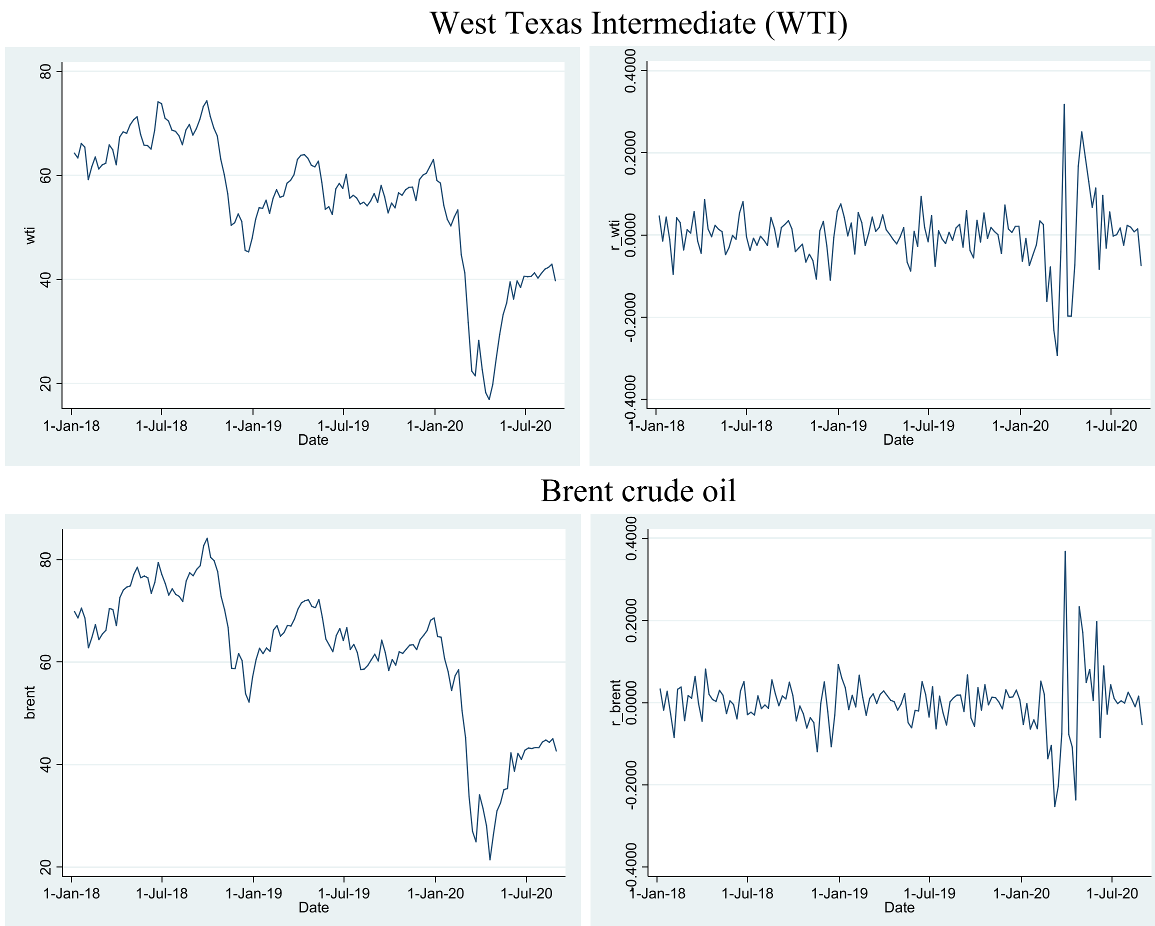
the oil exporting countries in this period of COVID-19, it is therefore important to investigate the impact of the appreciated US dollars (currency of exchange) on both the crude oil price and the stock market activities of the oil exporting countries, which according to Roubaud and Arouri (2018) impacts the price observed by both producers and consumers of crude oil and its by-products. This study fills these lacunas by investigating the trilateral relationships among oil prices, stock prices and exchange rates in the pre – and post – COVID-19 declaration periods. The outcome will provide fresh ideas about how the dynamics of oil prices and exchange rates are transferred to the stock markets and vice versa (Hamilton, 2003), during a disease like pandemic. It will also provide necessary information to effectively predict movements in oil prices, stock markets and currencies, thereby generating gainful investments (Arouri et al., 2011).

A glimpse at the results show that before COVID-19, the different markets in the selected oil producing economies were only affected by their market fundamentals and dynamics, but this changed with the plummeting oil prices in the COVID-19 pandemic era. The pandemic engineered plummeting oil price fluctuations resulted to varying fluctuations in exchange rates and stock returns at different periods that were neither motivated by activities in the stock market nor the exchange rate market in the post-COVID-19 pandemic era.

The rest of the paper is organized as follows: Section two provides the literature review; Section three describes the data and the preliminary analysis on the data; Section four defines and specifies the model. The results of the analysis were discussed in Section five, robustness checks



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were carried out in Section six while Section seven concludes the work.

2. Literature review

In prior literature, there are three strands of debates, which includes one, the relationship between stock markets and oil prices; second, on the association between stock markets and exchange rate, while the third is on the linkage between oil prices and exchange rates. Nevertheless, not many studies have investigated the linkages between the three variables – oil prices, exchange rates and stock prices.

2.1. Stock markets and exchange rates

The stock markets-exchange rates nexus is governed by two basic approaches. They are the stock approach (developed by Frankel, 1983; Branson and Henderson, 1985) and the flow approach (developed by Dornbusch and Fischer, 1980). The stock approach also known as the portfolio balance approach describes a situation where the rise in stock prices results to an immediate increase in wealth of individuals. This circumstance will lead to increase in demand for money and further push the market interest rates upward. These dynamics will draw foreign financiers' interests to domestic assets by investing more in the home market, thereby appreciating the value of the domestic currency (Mollick and Sakaki, 2019; Rai and Garg, 2021). On the other hand, it postulates that the depreciation of domestic currency will favour domestic firms the more and increase their competitive advantage against foreign firms. This will improve local productive activities, resulting to more exports and greater cash flows. Accordingly, increase in exports and cash flows will invariably 'ceteris paribus' increase the value of the firm and further lead to increase in prices of shares (Mollick and Sakaki, 2019; Rai and Garg, 2021).

Some of the studies that examined the stock markets-exchange rates nexus are; Cho et al. (2016) investigated the relationship between stock market index and exchange rates for developed and emerging economies. They proxied global stock market conditions by MSCI world index returns in local currencies. Their report showed that on average, developed markets have higher correlations than emerging markets in the period between 1996 and 2009. Others include Wong (2017) for four Asian and three major currencies, Volkov and Yuhn (2016) for five commodity currencies, Chkili and Nguyen (2014) for BRICS countries, Caporale et al. (2014) for the recent financial crisis period, Andreou et al. (2013) for emerging markets. Examining the degree of exchange rate exposure (at firm level), Chang et al. (2013) found that causality runs from currency to stock returns; Kalra (2011) and Lin (2012) for Asian currencies. Katechos (2011) proposed a very simple approach without commodity factors and suggested that interest rate differentials determine the sign of the link between exchange rates and stock markets. Using a GARCH (1,1) modelling, they found that world equity returns – FTSE index, are the only factor accounting for exchange rates movements. Rehan et al. (2019) examined the interaction between stock market prices and foreign exchange rates, with evidence from south Asian economies. By adopting a co-integration and error correction models (ECM), they find both short-run and long-run association between the variables in the case of Sri Lanka, while no relationship was observed in India and Pakistan.

Recently, studies have been conducted to examine the relationship between stock markets and exchange rates during the coronavirus period. For example, Syahri and Robiyanto (2020) analysed the

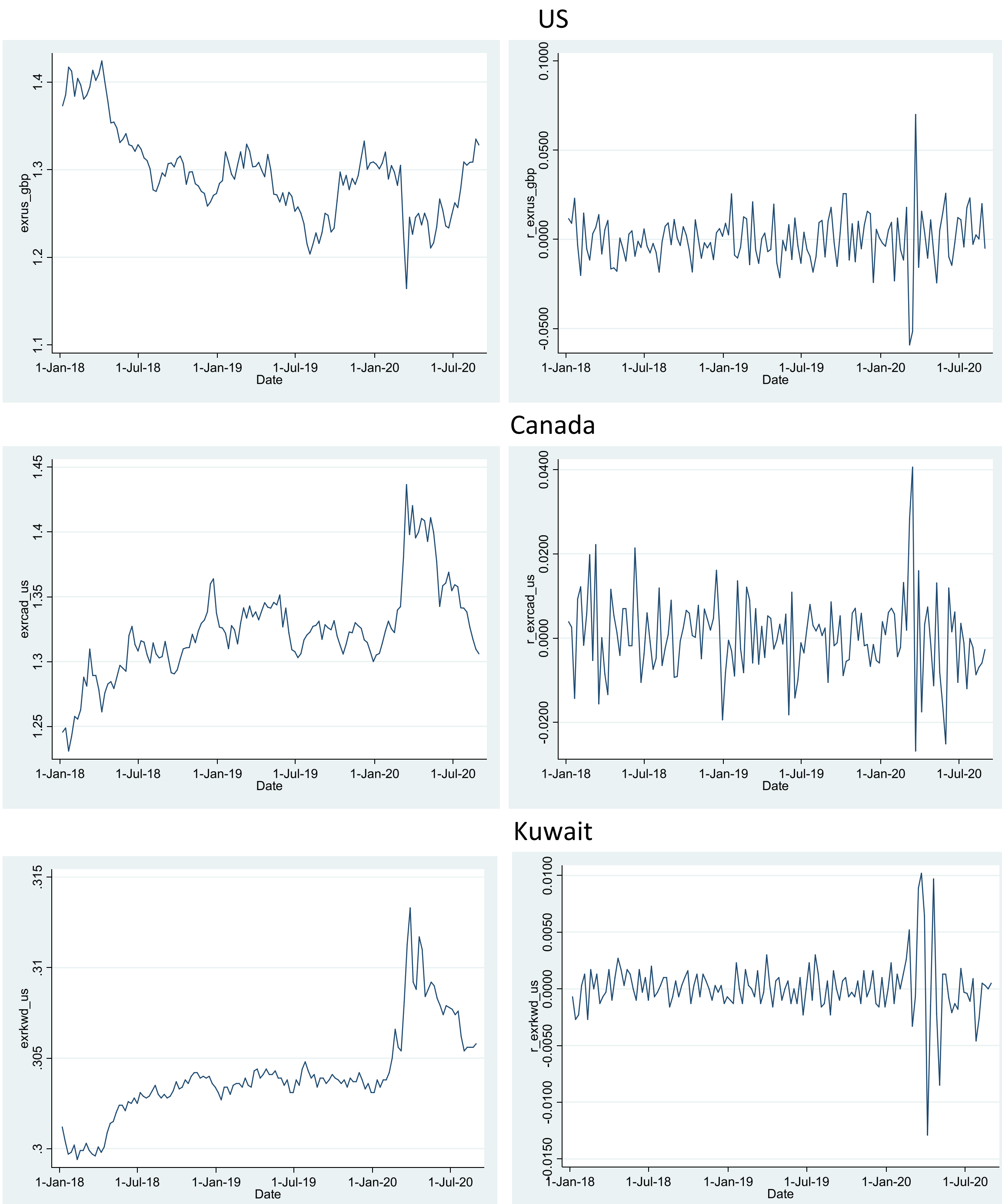
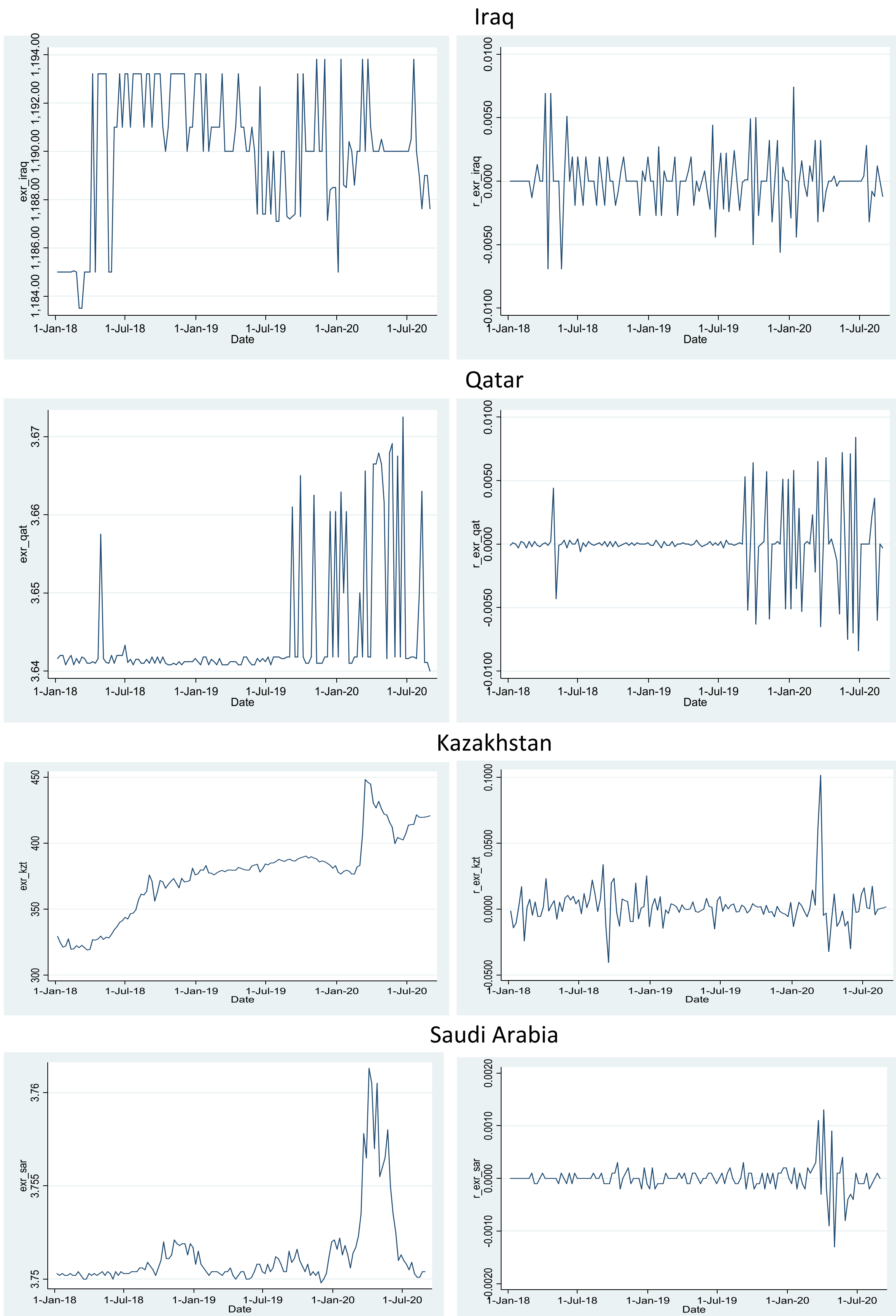


Fig. 2. Exchange rates of selected net-oil producing economies.
Notes: Weekly data from 7 January 2018 to 30 August 2020. Actual (graphs at left) and computed returns (graphs at right).

correlation between exchange rate and stock market returns/volatility in Indonesia Stock Exchange, and find that exchange rate has a negative dynamic impact on the composite stock market index. Aslam et al. (2020) investigated the behaviour of global dominant currencies that are transacted on the international FOREX market during the coronavirus period and observed that the efficient operations of the FOREX market was negatively impact during the period, with different magnitudes in different countries. Camba and Camba (2020) also find a negative effect of COVID-19 on exchange rate and stock exchange market in the Philippines. Prabheesh and Kumar (2021) analysed the dynamics in the foreign exchange rate and stock markets during the COVID-19 period in India and documented that the stock market was negatively impacted.

Hoshikawa and Yoshimi (2021) investigated how COVID-19 influenced the responses of the South Korean Won and stock market price index. By adopting a generalized autoregressive conditional heteroskedasticity and OLS models, they find that volatility in the stock market intensified and the exchange rate depreciated as the health crisis persisted. Konstantakis et al. (2021) also documented that the volatility in the euro to dollar exchange rate intensified during the coronavirus health crisis period. Further, Narayan (2022) find that the total exchange rate volatility spill-overs was more during the COVID-19 period



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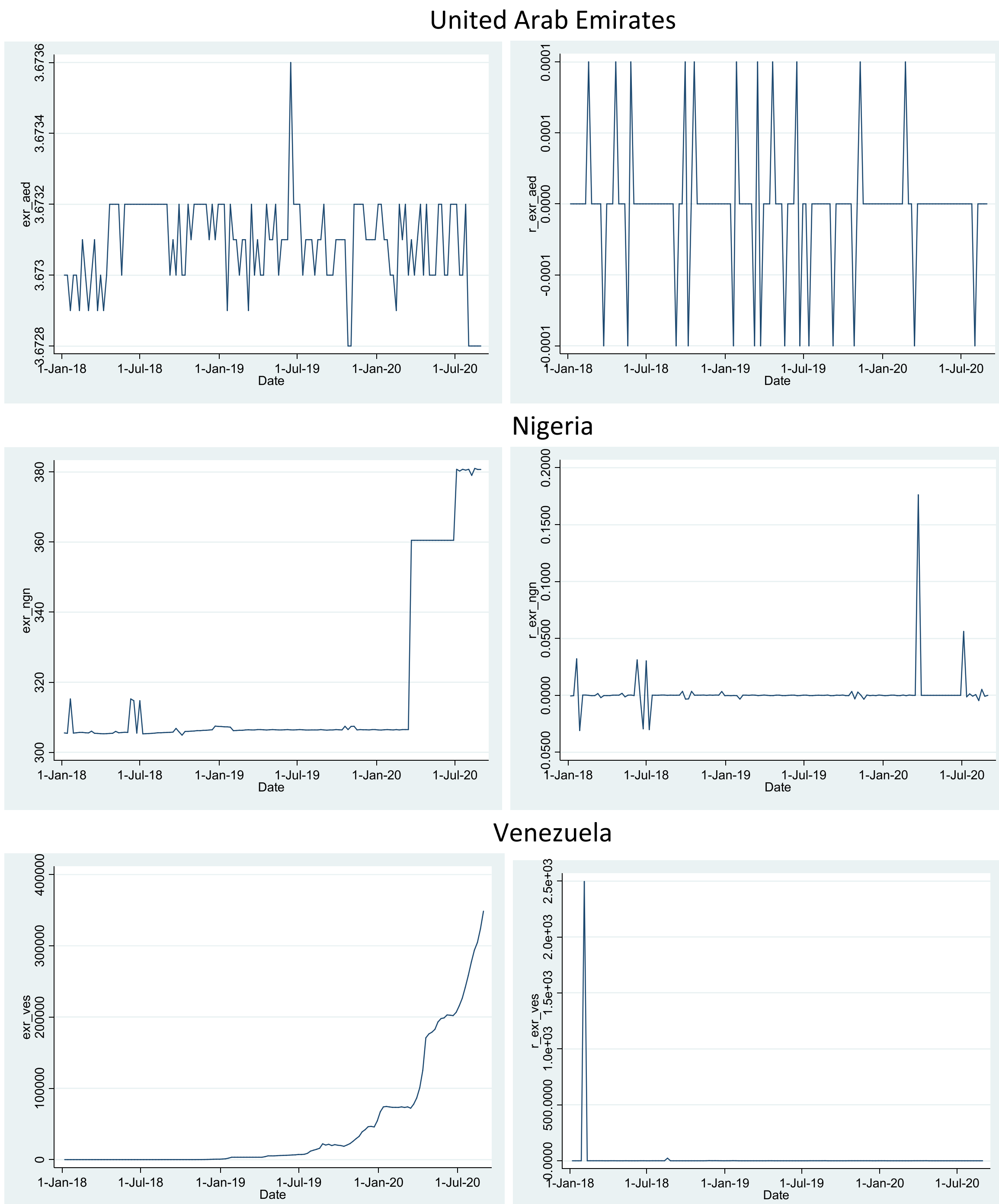

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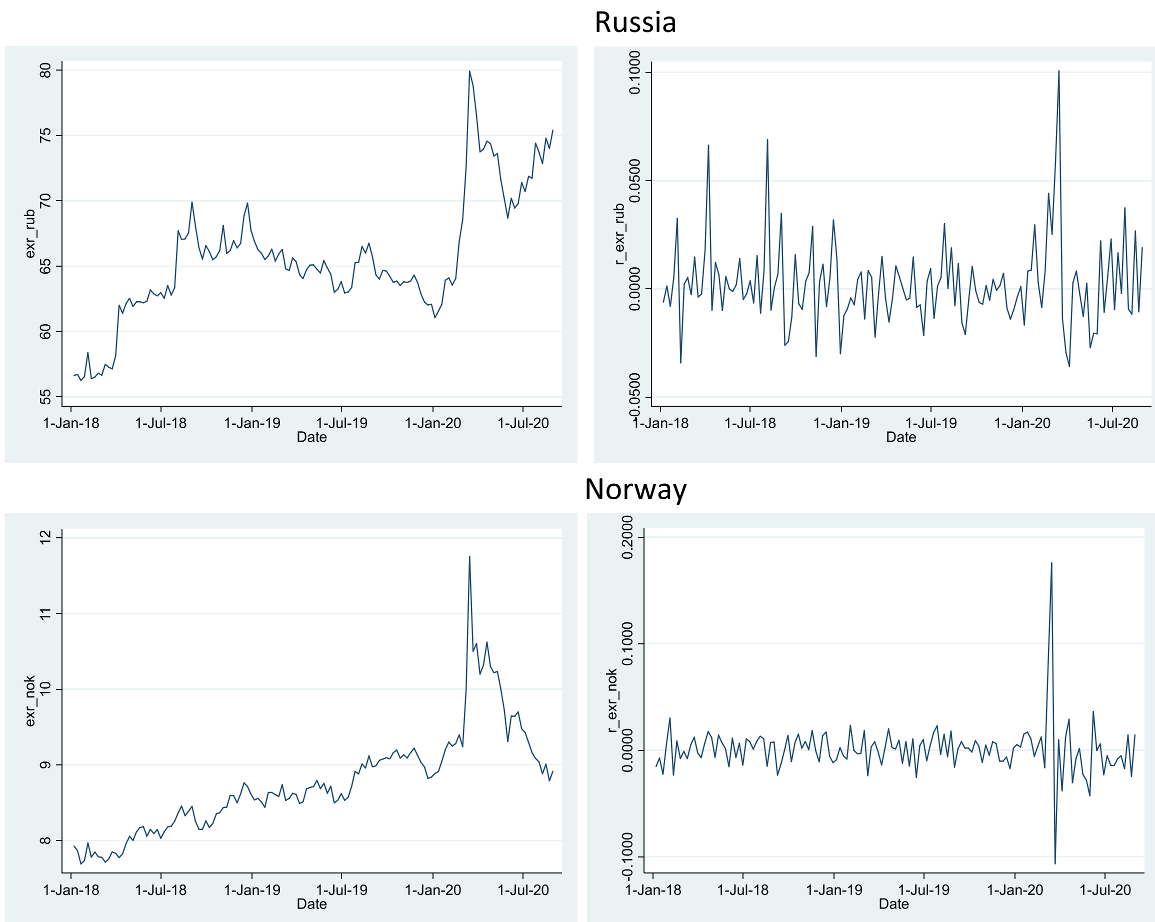
(about 37.7 per cent) than the pre – COVID-19 period (about 26.1 per cent); but the exchange rate own volatility was stronger (about 56–75 per cent). Thorbecke (2021) analysed the French and South Korean exchange rates and stock market returns exposure during the coronavirus period, and documented that Korean firms are more resilient to the pandemic than French firms. This is consistent with the findings documented in Kumeka et al. (2021) for selected African stock markets. Also, the French economy is more vulnerable to exchange rate appreciation than the Korean economy.

Conversely, some studies documented positive association between stock and exchange rate markets. Narayan (2020) examined the response of the Japanese currency to the US dollar and observed that the Yen was more volatile in the pre-coronavirus period than during the health crisis period, suggesting that the Japanese currency was in a transiency phase. Narayan, Devpura and Wang (2020) analysed the impact of the Japanese Yen on its stock market returns, and significant positive relationship was found between the variables. The impact was higher during the pandemic than in the pre-pandemic crisis period. Amewu et al. (2022) examined the correlation between the composite equity stock index in Ghana and exchange rate during the COVID-19 era; they find a strong co-movement between the series, but the relationship is short-lived with short memory. In study for the pre – and during – COVID-19 periods, Asaad (2021) however did not find any significant relationship between exchange rate and stock market prices in the case



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of Iraq. In sum, most studies in recent time documented a negative relationship between stock market and exchange rate during COVID-19 period, or negative effects of COVID-19 on the exchange rate and stock markets.

2.2. Oil prices and exchange rates

The postulations as to why the dynamics in the crude oil market influence the foreign exchange rate markets were put forward by Krugman (1983a and b) and Golub (1983). Owing to these arguments, the extant literature has investigated the exchange rates-oil prices nexus. For example, following the law of one price, Bloomburg and Harris (1995) illustrates the effects of currency movements on oil prices and reported negative correlation between commodity prices, and increase in the US dollars after 1986. Pindyck and Rotemberg (1990) reported that adjustments in currencies affect oil prices. This was later confirmed by Sadorsky (2000). Another set of studies by Ghosh (2011), Benassy--Quere et al. (2007) and Amano and Norden (1998) documented that oil prices have been the overriding cause of consistent shocks in real exchange rates, especially dollar appreciation. Specifically, the US dollar depreciation against other currencies is as a result of rises in crude oil prices (Brayek et al., 2015; Turhan et al., 2013, 2014; Wu et al., 2012; Akram, 2009; Narayan et al., 2008). Contrariwise, Zhang, Fan, Tsai, and Wei (2008) found that global crude oil prices are strongly affected by the US dollar exchange rate in the long run, however, with restricted impact in the short term. Following the outbreak of COVID-19 pandemic, some researches have been conducted on the correlation between crude oil and foreign exchange rate markets (see for example, Devpura, 2020; Salisu et al., 2020; Devpura, 2021; Villarreal-Samaniego, 2021; Prabheesh and Kumar, 2021; Asaad, 2021; Candila et al., 2021; Rai and Garg, 2021; Villarreal-Samaniego, 2021; Ozturk and CAVDAR, 2021; Baek, 2022).

2.3. Stock prices and oil prices

Theoretically, the linkage between stock prices and international oil prices can be accounted for by two main transmission channels – the direct and indirect channels (Mollick and Sakaki, 2019). As documented in Hooker (2002) and Kilian (2009), oil prices directly impact stock prices through future cash flows with its influence on the entire economy. On the other hand, oil prices indirectly affect stock prices by impacting the interest rate used in discounting future cash flows (Mollick and Sakaki, 2019; Ciner, 2013; Basher et al., 2012). The discounted cash flows are mirrored in the economy through income, interest rates, inflation, production costs, consumer attitude and economic growth, and other activities in the macro economy influencing shock in crude oil (Arouri and Nguyen, 2010).

A good number of studies have been carried out in the literature with mixed results. For example, Salisu et al. (2020) analyse the oil prices-stock prices nexus in the period of COVID-19 outbreak using both PVAR and panel logit models. They find that oil and stock markets exhibit contemporaneous and long term effects of own and cross shocks in the post-COVID-19 announcements than in the pre-COVID-19 announcements. Narayan and Gupta (2015) found that decreases in crude oil prices explain the behaviour of US stock returns better then increases in oil prices. Sadorsky (2001) examined stock returns and oil prices in the oil & gas firms and reported co-movements. Conversely, Kilian and Park (2009) report that oil supply shocks do not affect stock prices, but the shocks in oil demand cause stock prices to fall in the U.S. stock prices.

Furthermore, using an SVAR approach which segregated oil price shocks into three components – oil supply, global aggregate demand, and global oil demand, Apergis and Miller (2009) report that stock prices are not strongly and significantly affected by oil market shocks. Several other studies have also examined the correlation between stock markets and oil prices (see, Boldanov et al., 2016; Kang et al., 2015; Narayan and Gupta, 2015; Pradhan et al., 2015; Narayan and Sharma, 2014; Broadstock and Filis, 2014; Broadstock et al., 2012; Arouri and Rault, 2012; Narayan and Sharma, 2011; Hayat and Narayan, 2011; Cifarelli and Paladino, 2010; Jammazi and Aloui, 2010; Chen, 2009; Miller and Ratti, 2009; Park and Ratti, 2008; Boyer and Filion, 2007; Huang et al., 2005; Hammoudeh et al., 2004; Sadorsky, 2001; Jones and Kaul, 1996; Sadorsky, 1999).

Following the advent of COVID-19 pandemic, several studies have emerged to consider the effects of the health crisis to the crude oil/energy and stock markets. For example, Liu et al. (2020) analysed the interrelationship among coronavirus, crude oil and the US stock markets. By implementing the time-varying parameter vector autoregressive model, they documented an adverse link between stock market returns and crude oil returns during the COVID-19 period. Also, Prabheesh, Padhan and Garg (2020b) investigated how COVID-19 influences the association between oil price and stock market in net oil-importing economies in Asia. They find positive correlation between stock market returns and crude oil market returns in the period of the pandemic, which suggests that the decline in crude oil prices deteriorates the stock market returns. Nwosa (2021) find that the outbreak of coronavirus disease has negative impact on crude oil prices, stock market returns and exchange rate movement in Nigeria. Sharif et al. (2020) also corroborated the negative impact of COVID-19 on oil prices and stock market returns in the US. Mzoughi et al. (2020) concluded that COVID-19 induced crisis has adverse but short-term effect on crude oil price. Prabheesh, Garg and Padhan (2020a) argued that there is a positive time-varying reliance between stock market returns and crude oil returns during the pandemic period; suggesting that the fall in crude oil prices cause the stock returns to decline as a result of poor expected returns in the oil industry. Wang et al. (2021) documented that COVID-19 has positive impact on stock prices of Electronic Art firms, while stock price index and crude oil prices are negatively related.

Further, using a SVAR model, Mugaloglu et al. (2021) find that structural fluctuations linked to the international crude oil market were unimportant with little explanatory power, whereas volatilities related to stock market became pronounced as their explanatory power increased during the coronavirus health crisis. Zhang (2021) observed that the COVID-19 enhances stock market returns in China, but faintly intensified the oil stock volatility. In another study for China, Shi and Kong (2021) studied the relationship between oil price and stock market during the pandemic and argued that the volatility spill-over effect between the two markets was stronger during the health crisis. Abuzayed and Al-Fayoumi (2021) analysed the spill-over shocks from the crude oil market to the stock markets in the Gulf Cooperation Council (GCC) for two periods – before and during coronavirus pandemic. By adopting the DCC-GARCH procedure, they concluded that the stock markets in GCC were at risk from the systematic spill-over from the oil risk, and the effects were stronger in the health crisis than prior to the period. Hence, investors need to factor in extreme oil risk in planning a portfolio strategy and/or diversifying their investments. Hung (2020) corroborated significant systematic volatility spill-over from crude oil prices to stock markets in France, Germany, Italy, Spain and the UK, but the effect is strengthened in the pandemic era than in the pre-coronavirus outbreak. Bourghelle et al. (2021) also documented that due to demand and supply shocks in the international crude oil market, oil price volatility intensified as a result of the global pandemic. Chien et al. (2021) confirm the negative impact of COVID-19 on stock market returns and energy prices in the case of USA, Europe and China, and very weak correlation was observed between oil and stock exchange markets and between oil and exchange markets. However, more recently Akram and Haider (2022) documented that globally, crude oil prices and clean energy stocks exhibit poor positive relationship during the COVID-19 period.

Conversely, other studies such as Suripto et al. (2021) find negative relationship between oil exchange rate and stock price returns, but oil prices have positive effect on stock price returns in the case of Indonesia. Also, Akhtaruzzaman et al. (2021) find that volatility in oil market was beneficial to oil supply industries but detrimental to the financial and oil consumer industries. In all, the coronavirus seems to taper-off the exposure levels of financial and nonfinancial firms. Similar evidence was found in Salisu et al. (2021) who documented that gold is a safe haven against the shocks from crude oil market. Zhang, Narayan and Devpura (2021) further confirmed that the explanatory power the crude oil market has on stock market weakened due to the outbreak of the COVID-19 health crisis by around 89.5 per cent. This signifies that following advent of coronavirus; financial markets were disrupted, leading to economic inactivity and thereafter the effect of crude oil market on stock markets weakened.

2.4. Studies on oil prices, stock returns, and exchange rate

In the past one decade, studies have deployed different methodologies to analyse simultaneously the relation among the three financial factors (oil prices, stock returns and exchange rates). Basher, Huag and Sardosky (2012) investigate the dynamic association between oil prices, stock returns and exchange rates, and several other factors under a structural vector autoregressive methodology in emerging markets. For India, Jain and Biswal (2016) quantify the dynamic linkages among oil price, exchange rate, and the stock market as well gold price. Further, in Mexico, Delgado et al. (2018) examine the interactions among stock market returns, exchange rate and oil prices, and report that currency (the Mexican peso) appreciation in Mexico causes the stock market index to move upward. In addition, the Mexican peso appreciates as oil becomes expensive in international market. Using a VAR and a Markov-switching VAR, Roubaud and Arouri (2018) found significant nonlinear interrelations between exchange rate, oil and stock markets, and oil occupies a predominant position in the transmission of price shocks to both the exchange rate and stock markets. The trilateral and time-varying regressions of Bai and Koong (2018) for China and the U.S. from 1991 to 2015 show that while a positive bidirectional relationship exists between oil prices and the stock markets, increases in oil prices lead to falls in currencies. The study applied a SVAR and diagonal BEKK GARCH models.

Recently, Mollick and Sakaki (2019) analyse the relationships among these variables for 8 industrial countries and 6 emerging economies. Employing the standard VAR and GARCH (1, 1) models, they report that positive shocks in oil prices appreciate the local currency against the US dollars in the short-term in both industrial and emerging economies. They also found that innovations in FTSE depreciate local currency against the US dollar in both markets. Investigating the symmetric and asymmetric causal linkages among the variables in India from January 1994 to December 2015, Kumar (2019) reported strong evidence of nonlinear causality running in both directions of oil prices and exchange rates, and oil prices and stock prices; and unidirectional causality running from exchange rates to stock prices. For Chkir et al. (2020) there exists a negative significant link between oil prices and exchange in both oil-exporting and importing economies from January 1990 to March 2017.

These above studies present strong theoretical points indicating the linkages between oil prices and stock prices, exchange rates and stock prices, and oil prices and exchange rates. However, studies have not investigated the dynamic interrelations or trilateral inter-linkages among the variables in the oil exporting markets during the global COVID-19 pandemic. This becomes relevant given the ravaging effects the COVID-19 pandemic has on the whole world economy.

3. Data and preliminary analysis – pre – and post – COVID-19 declaration periods

3.1. Descriptive analysis

The sample is made up of twelve major oil-producing economies in the world (Canada, Iraq, Kazakhstan, Kuwait, Nigeria, Norway, Qatar, Russia, Saudi Arabia, United Arab Emirates, United States and Venezuela). This study is on the relationship between stock market, oil prices and exchange rates, employing the following proxies for the data: stock markets, S&P 500 (Standard and Poor's 500), S&P/TSX Composite (Canada), FTSE (NASDAQ Kuwait 15), ISXMain60 (Iraq), QE General (QSI) (Qatar), KASE (Kazakhstan), Tadawal All Share (Saudi Arabia), ADX General (UAE), NSE All Share (Nigeria), Bursatil (Venezuela), MOEX (Russia) and OSEAX (Norway). For exchange rates, USD (US dollar to British Pounds), CAD (Canadian Dollar), KWD (Kuwaiti Dinar), IQD (Iraqi Dinar), QAR (Qatari Riyal), KZT (Kazakh), SAR (Saudi Riyal), AED (UAE Dirham), NGN (Nigerian Naira), VES (Venezuelan Bolivar), RUB (Russian Ruble) and NOK (Norwegian Krone). The US dollar is chosen as a reference because of its importance as a main international currency. For oil prices, weekly Brent Oil Futures (BX0) was used.[1]

All series in this study were collected on weekly basis and sourced from www.investing.com from 7 January 2018 to 30 August 2020. To account for the effects of COVID-19, the study is partitioned into two periods. That is, the first period ranging from 7 January 2018 to 8 March 2020, marking to the period before the coronavirus was announced a global pandemic by WHO (Pre-COVID-19 declaration) whereas the second period ranges from 15 March 2020 to 30 August 2020 (post-COVID-19 declaration).[2,3] Partitioning the study into two periods provides the opportunity to investigate the interrelations between the chosen variables over the distinction periods –certainty (before COVID-19) and uncertainty (during COVID-19), and the collapse in oil prices. The analysis employed log – returns of the original variables computed as $r_{it} = \ln(p_{it}/p_{it-1})$, where r_{it} denotes weekly returns for stocks, oil and exchange rates of country i at time t, p_{it} is the weekly closing stock indexes, oil prices and exchange rates of country i at time t and p_{it-1} is the lag of closing stock indexes, oil prices and exchange rates for country i.

As shown in Table 1, every set of stock prices, oil prices and exchange rates indicate lower average returns in the period before COVID-19 was declared a pandemic than in the post declaration period in all countries except for Venezuela. This is contrary to the findings in Salisu et al. (2020). In terms of variations, the series appear to be more volatile in the post-COVID-19 declaration than in the pre-COVID-19 declaration in all economies except for Venezuela with very high standard deviation in the period before COVID-19 was announced a global pandemic. Further, as indicated by the skewness, our data in the pre-COVID-19 period appear to show more asymmetry than the post-COVID-19 period. In the pre-pandemic period, stock and oil prices for all the countries are leptokurtic; exchange rate is mesokurtic in Canada and Kuwait, platykurtic in Saudi Arabia and leptokurtic in the other economies.

On the other hand, during the post-pandemic period, stock prices are leptokurtic in the US, Canada, Qatar, Iraq, Venezuela, Nigeria and UAE, platykurtic in Norway, Kazakhstan and Kuwait and mesokurtic in Russia. Exchange rates in the post-COVID-19 period are mesokurtic and platykurtic in Saudi Arabia and Qatar respectively but it is leptokurtic in other series. Nonetheless, considering the value of the US Dollar exchange rates for the economies, Table 2 shows larger average values for every set of exchange rate in the post-COVID-19 pandemic declaration period than in the pre-COVID-19 declaration period. This is not surprising as the US dollar appreciated strongly after the pronouncement of COVID-19 pandemic, after most economies in the world depreciated their currencies against the dollar. Furthermore, panel summary statistics are displayed in Table 3. These results are consistent with those presented in Table 1. Specifically, at level, stock market and exchange rate indices average values and variations are higher during the pandemic period than the period before the pandemic. Also, in terms of the crude oil market, as expected Brent and WTI have higher mean values in the pre – COVID-19 period than during the COVID-19 period, whereas the variations are stronger during than before pandemic. Considering the returns, the results are however, mixed; stock market index has larger mean value during than before with higher variations in the pre-pandemic period, while exchange rate has larger average value in pre – than during – the COVID-19 period. Lastly, in terms of returns, Brent and WTI have negative mean values in the pre – and positive mean values during COVID-19 period, and with higher variations in the pandemic period than the period before the pandemic.

3.2. Graphical analysis

Further, we present all the series in levels, graphs at the left, and the respective computed returns, graphs at the right, in Fig. 1. Fig. 1 contains the series for the stock and oil prices for the full sample. It is seen that stock prices of all sampled economies significantly plummeted and exhibited more volatile behaviour during the post-COVID-19 declaration period than in the pre-COVID-19 declaration period, except for Venezuela that experience increase in stock prices and less volatility during the post-COVID-19 declaration. Next, oil prices as proxied by Brent drastically decreased following the declaration of COVID-19 declaration, however with brisk increase and decrease as the pandemic persists. Similarly, in terms of exchange rates as presented Fig. 2, all countries' currencies strongly depreciated against the US Dollars after the pronouncement of COVID-19. As portrayed in the figures, in returns, except for Venezuela, all countries that depreciated their currency against the dollar encountered high instability during the post-COVID-19 declaration period than in the pre-COVID-19 declaration period. These findings (see also Fig. 1 and below) further gave the impetus to carry out this study.

3.3. Panel unit root tests – pre – COVID-19 and post – COVID-19 periods

To determine whether there exists cross-section dependence and the order of integration of all categories of the series, we performed the Pesaran cross-sectional dependence (CD) (Pesaran, 2004) and the cross-sectionally augmented IPS (CIPS) (Pesaran, 2007) tests. The outcomes of the two tests are exhibited in Table 4 Panels A and B for the pre – COVID-19 declaration and post – COVID-19 declaration periods, respectively.

From Table 4 it shows that there exists cross-sectional dependence in all series, both in the log returns and in the first differences, based on the outcomes of the Pesaran CD test (see Pesaran, 2004). This portends the existence of correlation between the series across economies. This paved way for conducting only the second-generation unit root test, the CIPS test (see Pesaran, 2007). The simple reason for this exercise is as a result of the inconsistency in the first-generation unit root tests in the presence of CD (see Santiago et al., 2019). The results shows that some of the series are either in the neighbourhood of I(0) or I(1). However, in terms of their first differences, stationarity without and with trend in all series was established. This validates the choice of the methodology of panel vector autoregressive model (pVAR).

[1] We also used crude oil WTI (West Texas Intermediate) Futures (TV0) as additional results for robustness.

[2] Our data starts from 7 January 2018 because of the availability of data for all sampled economies.

[3] The Post-COVID-19 period is defined in this manner as it captures when the World Health Organisation (WHO) declared the COVID-19 outbreak a pandemic and the effect of the COVID-19 on macroeconomic fundamentals in the world especially on crude oil and global stock prices is more pronounced.

Table 1
Descriptive statistics for stock and oil prices.

Stock indices and Crude Oil prices														
Before COVID-19 – level														
	USA	Canada	Qatar	Norway	Russia	Kazakhstan	UAE	Nigeria	Saudi Arabia	Venezuela	Kuwait	Iraq	Brent Oil	WTI
Mean	2865.5910	16112.7200	9888.3500	977.5604	2548.8660	2310.2390	4901.1910	32526.6500	8134.3860	56334.7400	4109.7290	518.2224	66.78	59.95
Maximum	3380.1600	17848.3600	10787.7500	1069.1400	3196.8800	2532.6700	5391.8800	45092.8300	9361.9600	419352.4000	5162.3700	643.1100	84.16	74.34
Minimum	2416.6200	13716.3300	8230.4100	730.9900	2175.1600	2102.6800	3685.5600	22734.0700	6552.4900	364.5200	3323.7000	444.9000	33.85	31.73
Std. Dev.	193.3097	765.1515	639.0053	47.8051	269.3735	92.9241	263.0747	5451.5390	487.4931	81974.6300	525.7260	55.5085	7.899	7.526
Skewness	0.6209	−0.4734	−0.7344	−1.3948	0.7129	0.2272	−1.4086	0.7388	0.1934	2.6093	0.3830	0.8953	−0.561	−0.415
Kurtosis	3.2271	3.7242	2.3812	7.7730	2.3707	2.4021	6.8214	2.3896	3.1744	10.0626	1.8460	2.4960	4.732	3.68
Returns														
Mean	0.0002	−0.0013	0.0003	−0.0017	0.0007	−0.0003	−0.0015	−0.0043	−0.0005	0.1236	0.0009	−0.0021	−0.00487	−0.00454
Maximum	0.0485	0.0355	0.0649	0.0414	0.0438	0.0463	0.0474	0.1021	0.0667	2.0028	0.0620	0.0862	0.0931	0.0937
Minimum	−0.1149	−0.1520	−0.1159	−0.1739	−0.1482	−0.0642	−0.1553	−0.1349	−0.1292	−0.9989	−0.1794	−0.0464	−0.2523	−0.2313
Std. Dev.	0.0246	0.0215	0.0258	0.0265	0.0245	0.0179	0.0242	0.0268	0.0258	0.3190	0.0246	0.0173	0.0472	0.0487
Skewness	−1.6382	−3.7403	−0.7130	−3.0026	−2.6307	−0.8789	−2.5431	0.1235	−0.8232	2.2274	−3.3809	1.2331	−1.5590	−1.2082
Kurtosis	7.7533	24.5780	5.7750	18.9384	15.7437	5.1015	16.4211	10.1257	7.3377	14.8207	26.9091	9.7301	8.8510	6.6853
Observations	114	114	114	114	114	114	114	114	114	114	114	114	114	114
Post – COVID-19 Declaration – level														
Mean	3035.398	15145.27	9192.091	867.9092	2742.030	2333.322	4232.831	24070.20	7187.781	339322.2	3849.098	449.5360	37.1484	33.546
Maximum	3508.010	16705.79	9882.930	950.9400	3061.990	2477.770	4552.200	25605.64	8045.090	523875.6	4277.240	467.1600	45.05	42.97
Minimum	2304.920	11851.81	8458.320	725.0600	2331.610	2149.090	3758.350	21094.62	6154.850	88643.18	3447.420	413.5200	21.44	16.94
Std. Dev.	302.5816	1252.708	452.2490	63.05080	182.3257	95.34932	212.0027	1341.737	522.2401	114572.7	232.6400	17.86380	7.3916	8.9091
Skewness	−0.612222	−1.020766	−0.145764	−0.748771	−0.321887	−0.185289	−0.556198	−0.931435	−0.232727	−0.059431	−0.101640	−0.503280	−0.6322	−0.6482
Kurtosis	2.911831	3.536872	1.948518	2.849783	2.711241	2.101988	2.974934	2.587780	2.398879	2.776337	2.162421	1.697162	2.017	1.8168
Returns														
Mean	0.0107	0.0076	0.0056	0.0097	0.0097	0.0066	0.0087	0.0050	0.0085	0.0772	0.0059	0.0020	0.017	0.0182
Maximum	0.1210	0.0949	0.0628	0.0827	0.0713	0.0292	0.0945	0.0719	0.0679	0.5014	0.0856	0.0433	0.3682	0.3175
Minimum	−0.1498	−0.1359	−0.0460	−0.0366	−0.0534	−0.0197	−0.0399	−0.0351	−0.0607	−0.1035	−0.0773	−0.0705	−0.2365	−0.2931
Std. Dev.	0.0502	0.0411	0.0207	0.0301	0.0263	0.0119	0.0260	0.0239	0.0318	0.1506	0.0405	0.0206	0.1295	0.1373
Skewness	−0.7586	−1.3188	0.5040	0.7687	−0.0186	−0.0177	1.2134	1.1325	−0.1038	1.4425	−0.0624	−1.1345	0.6195	−0.0407
Kurtosis	6.1761	7.7042	4.9108	2.9311	3.3545	2.5874	6.3278	4.4159	3.0432	4.6419	2.5735	8.0973	4.0268	3.2422
Obns	25	25	25	25	25	25	25	25	25	25	25	25	25	25

Note: stock indexes of the selected economies – pre - and post – COVID-19 periods.
Source: compiled by authors.

Table 2
Descriptive statistics Exchange rates.

Before COVID-19 – level	USA	Canada	Kuwait	Venezuela	Saudi Arabia	Russia	Qatar	Norway	Nigeria	Kazakhstan	Iraq	UAE
Mean	1.3046	1.3134	0.3031	13079.3100	3.7507	63.9261	3.6429	8.5457	306.5167	366.2482	1190.0560	3.6731
Maximum	1.4241	1.3804	0.3066	74580.4700	3.7523	72.6133	3.6650	9.9981	315.2500	406.7800	1193.8100	3.6736
Minimum	1.2037	1.2311	0.2994	0.0001	3.7498	56.2572	3.6408	7.6906	304.9000	319.0950	1183.5000	3.6728
Std. Dev.	0.0483	0.0255	0.0014	22049.8400	0.0006	3.1812	0.0052	0.4641	1.7116	23.4166	2.9195	0.0001
Skewness	0.5563	−0.7906	−1.1120	1.8829	1.0393	−0.7018	3.1922	0.1031	4.2856	−0.9043	−0.5573	0.0766
Kurtosis	3.1751	4.1804	3.8911	5.2883	2.9660	3.7596	11.6764	2.6130	21.7110	2.3454	2.2296	5.2681
Returns												
Mean	−0.0008	0.0010	0.0001	22.1945	0.0000	0.0023	0.0000	0.0020	0.0000	0.0019	0.0001	0.0000
Maximum	0.0256	0.0283	0.0052	2496.0000	0.0003	0.0689	0.0064	0.0819	0.0321	0.0616	0.0074	0.0001
Minimum	−0.0592	−0.0194	−0.0033	−0.0854	−0.0002	−0.0342	−0.0063	−0.0253	−0.0309	−0.0405	−0.0069	−0.0001
Std. Dev.	0.0126	0.0082	0.0014	233.7536	0.0001	0.0172	0.0020	0.0138	0.0071	0.0111	0.0024	0.0000
Skewness	−0.6779	0.3009	0.3424	10.5347	0.1322	1.2839	0.0324	1.5161	0.2032	1.1467	0.1645	−0.0382
Kurtosis	5.8342	3.7889	3.4969	111.9895	2.7079	6.3514	7.4606	11.4593	18.2319	11.2379	5.0685	4.9550
Obns	114	114	114	114	114	114	114	114	114	114	114	114
Post – COVID-19 Declaration – level												
Mean	1.2581	1.3693	0.3082	202653.5000	3.7540	73.1893	3.6529	9.7538	365.5360	420.1752	1190.0740	3.6730
Maximum	1.3349	1.4365	0.3133	348557.8000	3.7613	79.9236	3.6725	11.7547	381.0000	448.1250	1193.8100	3.6732
Minimum	1.1643	1.3061	0.3054	72169.7400	3.7501	68.6860	3.6400	8.7886	306.5000	399.6550	1187.6200	3.6728
Std. Dev.	0.0398	0.0365	0.0020	73849.2500	0.0037	2.7544	0.0128	0.7143	15.6535	12.9304	1.3651	0.0001
Skewness	0.1373	−0.0288	0.6688	0.0053	0.5469	0.5572	0.2644	0.7783	−1.9675	0.5917	1.2021	−0.3280
Kurtosis	2.9746	1.9656	3.1270	2.5529	1.9890	3.1539	1.1917	3.4511	9.1157	2.9592	5.8352	1.9757
Returns												
Mean	0.0034	−0.0021	0.0001	0.0668	0.0000	0.0019	0.0000	−0.0036	0.0093	0.0016	−0.0002	0.0000
Maximum	0.0700	0.0406	0.0102	0.3623	0.0013	0.1007	0.0084	0.1757	0.1762	0.1016	0.0032	0.0000
Minimum	−0.0517	−0.0268	−0.0129	−0.0246	−0.0013	−0.0358	−0.0084	−0.1066	−0.0046	−0.0322	−0.0032	−0.0001
Std. Dev.	0.0219	0.0141	0.0050	0.0832	0.0006	0.0278	0.0049	0.0467	0.0366	0.0240	0.0014	0.0000
Skewness	0.4805	0.8435	−0.0269	2.2276	0.3162	1.7832	−0.0072	1.9325	4.1147	2.8616	0.0530	−3.0963
Kurtosis	5.7645	4.7613	4.0888	8.0293	3.7955	7.4086	2.2556	10.5563	18.9511	13.4497	4.1785	10.5870
Obns	25	25	25	25	25	25	25	25	25	25	25	25

Note: exchange rates of the selected economies– pre - and post – COVID-19 periods.
Source: compiled by authors.

Table 3
Panel Descriptive statistics and cross-sectional dependence.

Variable Pre – COVID-19	Obs	Mean	Std Dev.	Min.	Max.
Natural logarithms					
lSmi	1368	8.4657	1.2812	5.8986	12.9465
lExr	1368	2.8195	2.9920	−9.2103	11.2196
lBrent	1368	4.1938	0.1265	3.5219	4.4327
lWti	1368	4.0850	0.1324	3.4573	4.3086
Log-differences					
DlSmi	1356	0.0017	0.1994	−6.8459	1.0995
DlExr	1356	0.0156	0.2334	−0.0892	7.8228
DlBrent	1356	−0.0064	0.0495	−0.2907	0.0890
DlWti	1356	−0.0063	0.0505	−0.2631	0.0896
Post – COVID-19					
Natural logarithms					
lSmi	300	8.6277	1.6264	6.0247	13.1690
lExr	300	3.4181	3.6475	−1.1861	12.7616
lBrent	300	3.5934	0.2148	3.0653	3.8078
lWti	300	3.4723	0.2991	2.8297	3.7605
First differences					
DlSmi	288	0.0141	0.0478	−0.1092	0.4064
DlExr	288	0.0049	0.0319	−0.1127	0.3092
DlBrent	288	0.0191	0.1156	−0.2698	0.3135
DlWti	288	0.0239	0.1174	−0.2197	0.2758

Note: smi, exr, brent and wti represent stock market index, exchange rate, Brent crude oil price and West Intermediate Texas. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods.
Source: compiled by authors.

3.4. Correlation and variance inflation factor (VIF)

The correlation matrix and the variance inflation factor statistics were carried out to confirm whether collinearity and multicollinearity do not pose any problem for the estimation. From Table 5, it is obvious that there are very small values of correlation, low VIF and mean VIF values in the two periods. However, in the pre-COVID-19 period, a negative correlation was observed between stock prices and exchange

Table 4
Cross-sectional dependence test and cross-sectionally augmented IPS - unit root test.

Variables	Cross-sectional dependence (CD)			CIPS (Zt – bar)	
Pre –COVID-19					
Natural logarithms					
	CD test	Corr	Abs(corr)	Without trend	With trend
lSmr	12.42***	0.143	0.448	1.896	4.817
lExr	17.84***	0.206	0.388	−5.281***	−3.999***
lBrent	86.74***	1.000	1.000	16.936	16.945
lWti					
First differences					
DlSmr	21.36***	0.247	0.265	−11.223***	−10.306***
DlExr	3.50***	0.040	0.145	- 15.368***	−14.607***
DlBrent	86.36***	1.000	1.000	16.936	16.945
DlWti					
Post – COVID-19					
Variables	**Cross-sectional dependence (CD)**			**CIPS (Zt – bar)**	
Natural logarithms					
	CD test	Corr	Abs(corr)	Without trend	With trend
lSmr	34.96***	0.861	0.861	−2.746***	−0.482
lExr	1.64	0.04	0.482	−1.058	−1.887**
lBrent	40.62***	1.000	1.000	15.642	14.974
First differences					
DlSmr	4.99***	0.125	0.286	−9.147***	−7.521***
DlExr	1.37	0.034	0.276	−5.824***	−4.613***
DlBrent	39.80***	1.000	1.000	15.642	14.974

Note: smi, exr, brent and wti represent stock market index, exchange rate, Brent crude oil price and West Intermediate Texas. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods. ***signifies1% level of statistical significance and ** denotes 5% level of significant.
Source: compiled by authors.

Table 5
Correlation matrices and variance inflation factor statistics.

Variables	lsmr	lexr	lbrent	Variables	Dlsmr	Dlexr	Dlbrent
Pre – COVID-19							
lSmr	1.0000			DlSmr	1.0000		
lExr	−0.0578	1.0000		DlExr	0.0947	1.0000	
lBrent	0.0034	−0.0732	1.0000	DlBrent	0.0490	−0.0332	1.0000
VIF		1.01	1.01	VIF		1.00	1.00
Mean VIF	1.01			Mean VIF	1.00		
Post – COVID-19							
Variables	lsmr	lexr	lbrent	Variables	Dlsmr	Dlexr	Dlbrent
lSmr	1			DlSmr	1		
lExr	0.4029	1		DlExr	0.3447	1	
lBrent	0.0428	0.005	1	DlBrent	0.1105	−0.1702	1
VIF		1	1	VIF		1.03	1.03
Mean VIF	1			Mean VIF	1.03		

Note: smi, exr, brent and wti represent stock market index, exchange rate, Brent crude oil price and West Intermediate Texas. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods.
Source: compiled by authors.

Table 6
Lag order selection criteria.

Pre – COVID-19						
Lag	CD	J	J – P value	MBIC	MAIC	MQIC
1	0.2430443	50.96987	0.0000538	−78.20272	14.96987	−19.97813
2	0.2794986	11.31281	0.2548754	−53.27348	−6.687191	−24.16119
3	0.070414					
Post – COVID-19						
Lag	CD	J	J – P value	MBIC	MAIC	MQIC
1	0.87838	35.7408	0.00762	−62.911	−0.2592	−25.503
2	0.86716	27.8261	0.00102	−21.5	9.82605	−2.7959
3	0.82224					

Note: using the *pvarsoc,* we generated the following – coefficient of determination (CD), the Hansen's J statistic (J), with the corresponding probability value (J-P value) (Hansen, 1982), the Bayesian information criterion (MBIC), the Akaike information criterion (MAIC), and Andrews and Lu (2001)'s Quinn information criterion (MQIC).

rates, with a positive correlation between oil price (Brent) and stock prices. In the post-COVID-19 declaration period, all variables are positively correlated. In terms of variance inflation factor, the post-COVID-19 declaration period has slightly high mean VIF (1.03) than the pre-COVID-19 declaration period (1.00). These confirmed that collinearity and multicollinearity are issues in our estimations.

3.5. Optimal lag length of the panel VAR specification

To proceed with our pVAR estimation, the optimal lag length selection statistics was estimated. Based on the Hansen's J (1982) test for over-identification limits, which chooses any of the modified Bayesian information criteria (MBIC), Akaike information criteria (MAIC) or Hannan-Quinn information criteria (MQIC), with the least information criterion (see Santiago et al., 2019; Babalos and Stavroyiannis, 2020; Abrigo and Love, 2016). The analyses are exhibited in Table 6.

In the pre-COVID-19 period, MAIC and MQIC criteria are most minimized when two lags are considered, whereas the MBIC criterion is least when one lag is selected. From Table 6, notwithstanding the diverse results, the second-order pVAR is favoured based on the MAIC criterion (see Serena and Perron, 2001).[4] On the other hand, the post-COVID-19 declaration period in panel B of Table 6, conditions that the pVAR estimation be based on the one lag. This is because it minimizes all the criteria – MBIC, MAIC and MQIC (see Andrews and Lu, 2001; Serena and Perron, 2001).

4. PVAR model and specification (pVAR)

The model of choice for analysis is the pVAR. Developed by Love and Zicchino (2006), the model accounts for unobserved individual heterogeneity for the whole variables by introducing fixed effects that improve the coherence and the consistency of the measurement. It provides a superior analysis by offering ideas of causality among the series, shocks/innovations and impulse responses, and the forecast error variances of the variables own and cross shocks. This shows how each variable contributes to other variables to attain equilibrium. Another fundamental advantage of the pVAR model is that it has the capability to contain short time measurement estimated by the Generalized Method of Moments (*GMM*) process (Abrigo and Love, 2016).

The pVAR model also corrects for the implementation of forward orthogonal deviations (Head et al., 2016), and fits a multivariate panel regression all endogenous series on their lags and any lags of the independent variables (Abrigo and Love, 2016). Besides, the pVAR model is a superior system to analyse the trilateral linkage because of its numerous practical advantages. One, it is unbiased with regards to any particular theory of finance or development. The model is most concerned with the contemporary movements of variables than on a particular concept of macroeconomics,[5] which, if not corrected, can be distorting (Kireyev, 2000). Next, following the certainty of interrelations, the current pVAR model does not distinguish between dependent and independent series; rather every variable is endogenously considered. Variables in the pVAR model depend on both their individual historical realization and also on

[4] It should be noted that, according to Andrews and Lu (2001), the Modified Akaike Criterion works best in small samples, as in our case.

[5] Notwithstanding the fact that there is no explicit economic theory backing the PVAR model, our variables of interest are based on the cash flow hypothesis.

Table 7
The panel vector autoregressive model results.

Pre – COVID-19			
Response to	Response of		
	Dlsmr	Dlexr	Dlbrent
Dlsmr(t – 1)	0.0163987	−0.019646	0.005465(0
	(0.0169165)	(0.0181897)	.0044392)
Dlsmr(t – 2)	−0.002826	0.0221668	0 .0015955(0
	(0.0182937)	(0.0685116)	.0024323)
Dlexr(t – 1)	0.0135135	−0.000494	0.0049808**
	(0.0125691)	(0.0129578)	(0.0023636)
Dlexr(t – 2)	0.0222488***	−0.0013516	0.0041957**(0
	(0.0079971)	(0.01356)	.0019916)
Dlbrent(t – 1)	−0.1257477(0	0.0090997	−0.0552055(0
	.0807571)	(0.0552392)	.0531102)
Dlbrent(t – 2)	−0.0479011(0	0.0131722	−0.21246***
	.0436,988)	(0.0502154)	(0.0379084)
Post – COVID-19			
Response to	Response of		
	Dlsmr	Dlexr	Dlbrent
Dlsmr(t – 1)	0.187505*	0.159164***	-.0800,525
	(0.0984754)	(0.028713)	(0.2100687)
Dlexr(t – 1)	0.2837313***	0.2539238*	0.4535033*
	(0.1002246)	(0.1381035)	(0.2659007)
Dlbrent(t – 1)	−0.0281485	-.006882	-.2325285***
	(0.020889)	(0.0081892)	(0.066207)

Note: smi, exr and brent represent stock market index, exchange rate, and Brent crude oil price. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods. ***signifies1% level of statistical significance, ** denotes 5% level of significant and * denote 10% level of significant.
Source: compiled by authors.

between stock market, oil prices and exchange rates market in major oil producing economies and to provide practical recommendation.

The proposed panel VAR model used for this study is given by:

$$Z_{it} = \varphi_i + B(L)Z_{it} + \psi_i + \eta_t + \xi_{it} \tag{1}$$

where Z_{it} represents a vector of the stationary variables in our analysis[6] (that is, *SMR, oilp, exr*), and φ_i denotes the vector of country-specific fixed effects. *B(L)* denotes the polynomial matrix in the lag operator with $B(L) = B_1L^1 + B_2L^2 + \dots + B_pL^p$, ψ_i , η_t and ξ_{it} signify the vector that determines the specific effects of the country found in this regression, the dummy variables for the country's specific time and the residual vector respectively. Country and time are denoted by subscripts i and t respectively.

The panel VAR technique specified in Equation (1) can be written in a matrix form in three equations, Equations (2)–(4), thus:

$$\Delta Ln(SMR_{it}) = \varphi_{1i} + \sum_{j=1}^{p} a_{1j}\Delta Ln(SMR_{it-j}) + \sum_{j=1}^{p} b_{1j}\Delta Ln(oilp_{it-j}) + \sum_{j=1}^{p} c_{1j}\Delta Ln(exr_{it-j}) + \psi_{1i} + \eta_{1t} + \xi_{1it} \tag{2}$$

$$\Delta Ln(oilp_{it}) = \varphi_{2i} + \sum_{j=1}^{p} a_{2j}\Delta Ln(SMR_{it-j}) + \sum_{j=1}^{p} b_{2j}\Delta Ln(oilp_{it-j}) + \sum_{j=1}^{p} c_{2j}\Delta Ln(exr_{it-j}) + \psi_{2i} + \eta_{2t} + \xi_{2it} \tag{3}$$

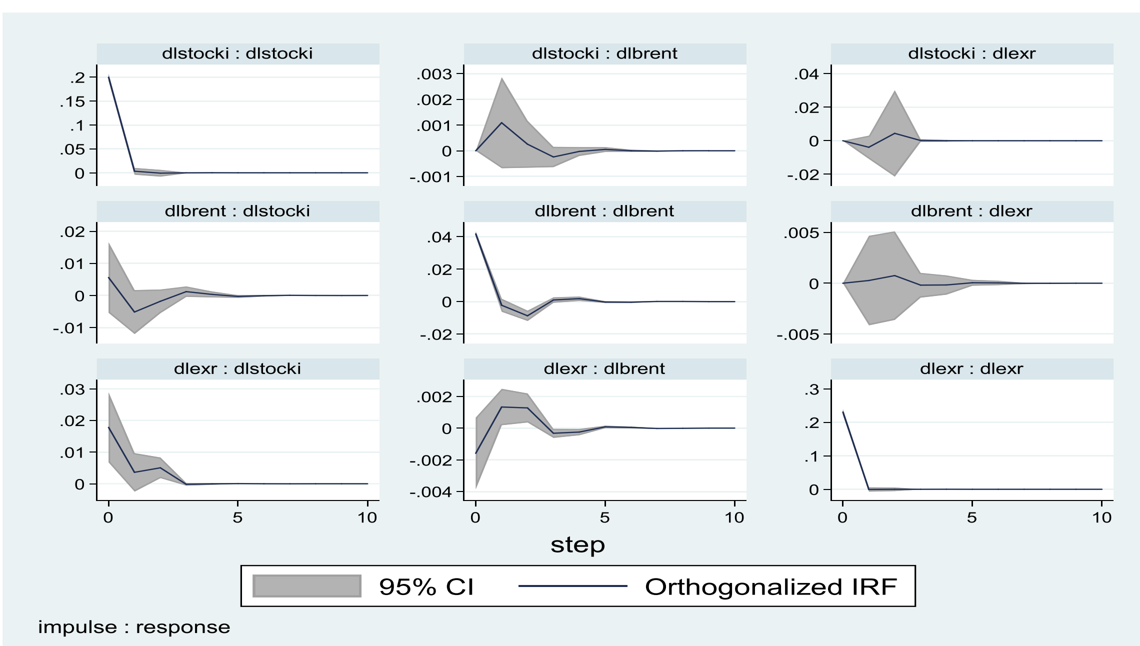


Fig. 3. Impulse response functions. Pre – COVID-19 Declaration.

other variables, which signifies some form of contemporaneousness relationship between the variables. Further, it also offers a model for endogenous and exogenous changes, which are unquestionably the most important sources of macroeconomic dynamics.

Additionally, the pVAR model is comparatively simple for consistent and effective evaluation for either a single country or a panel collection of heterogeneous economies. Lastly, the pVAR model has observable practical value as a useful tool to investigate the joint inter-linkages

[6] Series in this study are converted to the natural logarithm returns for consistency and reliability of our results.

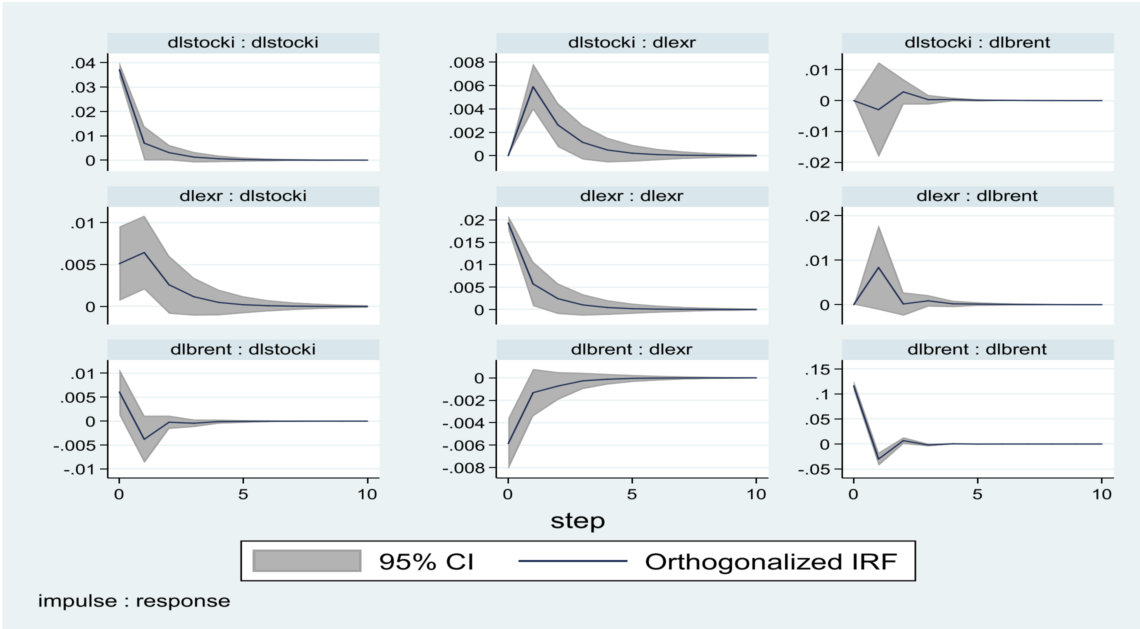


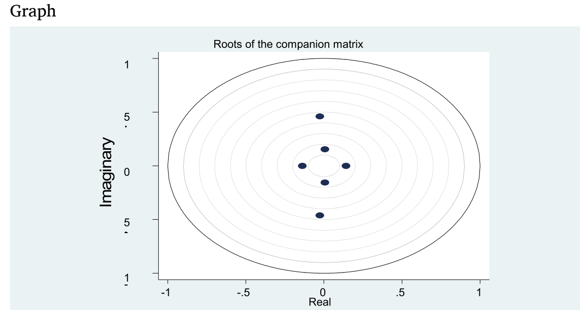
Fig. 4. Impulse response functions. Post – COVID-19 Declaration.

Table 8
Eigenvalue stability condition.

Pre – COVID-19

Eigenvalue Real	Imaginary	Modulus
−0.0268632	−0.460758	0.4615401
−0.0268632	0.4607576	0.4615401
0.0058623	−0.154721	0.1548324
0.0058623	0.1547214	0.1548324
0.1413183	0	0.1413183
0.1386168	0	0.1386168

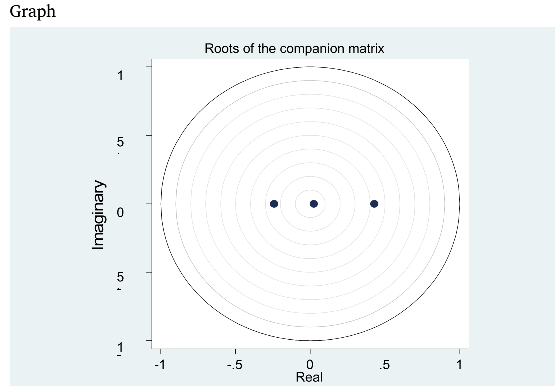
Graph



Post – COVID-19

Eigenvalue Real	Imaginary	Modulus
0.4277893	0	0.4277893
−0.2423531	0	0.2423531
0.0234641	0	0.0234641

Graph



Note: it is obvious from the graph that pVAR satisfies stability condition since All the eigenvalues lie within the unit circle – pre – and post – COVID-19 periods.. Source: Computed by the Authors.

$$\Delta Ln(exr_{it}) = \varphi_{3i} + \sum_{j=1}^{p} a_{3j}\Delta Ln(SMR_{it-j}) + \sum_{j=1}^{p} b_{3j}\Delta Ln(oilp_{it-j}) + \sum_{j=1}^{p} c_{3j}\Delta Ln(exr_{it-j}) + \psi_{3i} + \eta_{3t} + \xi_{3it} \tag{4}$$

In the process of estimating the model, MAIC was opted as a criterion for the optimal lag selection, against MBIC and MQIC j, where $j \in (1, \ldots, p)$. We incorporate fixed effects (denoted as ψ_i) in the pVAR specification to account for individual heterogeneity in the levels of the three variables. The model can also accommodate time effects, represented as φ_i,

Table 9
Panel Granger causality test.

Pre – COVID-19				
Equation/excluded variables		Chi-squared	Df	Prob.
Dlsmr				
	Dlexr**	8.670	2	0.013
	Dlbrent	3.369	2	0.186
	ALL**	12.030	4	0.017
Dlexr				
	Dlsmr	1.323	2	0.516
	Dlbrent	0.088	2	0.957
	ALL	1.474	4	0.831
Dlbrent				
	Dlsmr	1.970	2	0.373
	Dlexr**	8.476	2	0.014
	ALL***	10.993	4	0.027
Post – COVID-19				
Equation/excluded variables		Chi-squared	Df	Prob.
Dlsmr				
	Dlexr***	8.014	1	0.005
	Dlbrent	1.816	1	0.178
	ALL***	14.307	2	0.001
Dlexr				
	Dlsmr***	30.727	1	0
	Dlbrent	0.706	1	0.401
	ALL***	32.082	2	0
Dlbrent				
	Dlsmr	0.145	1	0.703
	Dlexr*	2.909	1	0.088
	ALL	3.075	2	0.215

Note 1: Panel VAR-Granger causality Wald test – pre – and post – COVID-19 periods. Ho: Excluded variable does not Granger-cause Equation variable. Ha: Excluded variable Granger-causes Equation variable. df is degree of freedom. Note 2: ***, **, and * denote 1%. 5% and 10% level of significant respectively.
Source: Computed by the Authors.

which accounts for any unobserved constant time factors at the country level. GMM system was used in the estimation (see Abrigo and Love, 2016 for details).

5. Empirical results and discussion

5.1. Penal VAR estimation results – pre – and post – COVID-19 periods

Table 7 presents the pVAR estimates with two lags and with the robust GMM estimation (*gmmstyle* option) (Holtz-Eakin et al., 1988) – panel A for the pre-COVID-19 declaration period and panel B for the post-COVID-19 declaration period. The robust GMM estimation is capable of replacing missing values with zeroes and has the capacity to produce better effective estimates. However, the coefficients of the estimated pVAR technique carry less messages to the investigator (see Babalos and Stavroyiannis, 2020; Santiago et al., 2019; Galariotis et al., 2016). Rather, the concern of readers is in the effect of independent shocks in every dependent variable on other series in the pVAR method – the forecast error variance decomposition (FEVD) and the related impulse response functions (IRFs). Figs. 3 and 4 displayed the orthogonalised IRFs coupled with the 5 percent error bands produced by the Monte Carlo simulation, while Table 10 exhibited the related forecast error variance decomposition.

Further, the stability of the pVAR was tested, confirmed and validated immediately the eigenvalues lie within the unit circle. Table 8 exhibits the eigenvalue stability condition for the pre- and post-COVID-19 declaration periods. This in addition signifies the stationarity of the series (Lütkepohl, 2005).

5.2. Panel granger causality test

Following the estimation of the two lags and one lag pVAR and confirmation of stability for pre- and post-COVID-19 declaration

Table 10
Forecast error variance decomposition.

Response variable	Forecast Horizon	Dlbrent	Dlexr	Dlsmr
Pre – COVID-19				
Dlbrent				
	1	1	0	0
	2	0.999709	1.36e-06	0.000290
	5	0.999337	0.000013	0.000650
	10	0.999337	0.000013	0.000650
Dlexr				
	1	0.001443	0.998557	0
	2	0.002453	0.996864	0.000682
	5	0.003323	0.995958	0.000719
	10	0.003327	0.995952	0.000721
Dlsmr				
	1	0.007865	0.000777	0.991358
	2	0.008178	0.001434	0.990388
	5	0.008803	0.001553	0.989645
	10	0.008803	0.001555	0.989643
Post – COVID-19				
Response variable	Forecast Horizon	Dlbrent	Dlexr	Dlsmr
Dlbrent				
	1	1	0	0
	2	0.994594	0.004798	0.000608
	5	0.994005	0.004832	0.001162
	10	0.994003	0.004834	0.001163
Dlexr				
	1	0.08421	0.915791	0
	2	0.075616	0.851121	0.073263
	5	0.074404	0.837616	0.08798
	10	0.074395	0.837535	0.088069
Dlsmr				
	1	0.025611	0.018127	0.956263
	2	0.033212	0.043717	0.923071
	5	0.032959	0.048486	0.918555
	10	0.032959	0.048517	0.918523

Note: smi, exr, and brent represent stock market index, exchange rate, and Brent crude oil price. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods.
Source: Computed by the Authors.

respectively, the Granger causality test based on Wald test (Abrigo and Love, 2016) was conducted. The test is made up of two hypotheses: H0: Excluded variable does not Granger-cause Equation. Ha: Excluded variable Granger-causes Equation. Table 9 presents these results. Overall, the result fails to confirm the existence of endogeneity as indicated by the blocks of exogeneity analysis (ALL).

5.2.1. Pre – COVID-19

The Granger causality test results for the pre-COVID-19 declaration period in panel A Table 9 reveal that there is a unidirectional negative causality running from exchange rates returns to stock returns. This shows that changes in exchange rates in these net-oil producing economies appear to negatively affect their stock markets, i.e., exchange rates appear to deteriorate stock markets performances in this economies. The result is consistent with the findings of Basher et al. (2012), Kumar (2019), Narayan (2020), Syahri and Robiyanto (2020), Aslam et al. (2020), Prabheesh and Kumar (2021). For example, Narayan (2020) found a significant effect of the uncertainty caused by COVID-19 on the Japanese Yen and argued that the currency market was non-stationary in the pre-COVID-19, but become stationary during the COVID-19 period. Syahri and Robiyanto (2020) also, confirmed negative dynamic impact of exchange rate on stock returns. The results however, contradict the findings in Narayan et al. (2020) and Amewu et al. (2022) who documented positive significant co-movement between stock returns and exchange rates.

Further, the result also shows a unidirectional causality running from exchange rates returns to oil price returns, with a positive signal. This indicates that before COVID-19, exchanges rates improve oil price returns. This finding supports studies such as Hiemstra and Jones (1994); Kumar (2019); Sadorsky (2000); Zhang and Wei (2010); Reboredo (2012); Salisu et al. (2020); Devpura (2021); Prabheesh and Kumar (2021); Candila et al. (2021). For example, Salisu et al. (2020) claimed that oil price is a good predictor of exchange rate returns in BRICS (Brazil, Russia, India, China and South Africa) economies. Also, Devpura (2021) argued that oil price has partial influence on the Eoru/USDollar exchange rate, but the connection disappeared with the control of coronavirus proxy. Our result opposes the findings in Villarreal-Samaniego (2021); Benhmad (2012); Chen and Chen (2007); Lizardo and Mollick (2010); Tiwari et al. (2013). For example, Villarreal-Samaniego (2021) documented a significant negative impact of oil price on the currency exchanges of five emerging countries. Moreover, Devpura (2020) did not find any substantial effect of oil prices on the Japanese Yen exchange rate.

5.2.2. Post – COVID-19

In the post-COVID-19 declaration period, the Granger causality test results found: bidirectional causality between stock prices returns and exchange rates returns, with a highly significant positive signal in both directions. Nevertheless, the causality appears to be stronger from stock markets to exchange rates. What these results portend is that not only can fluctuations in exchange rates of our selected economies affect stock markets, but also, exchange rates can be influenced by the stock markets performances. Specifically, a rise in stock returns appears to result to depreciation in the exchange rates, whereas exchange rates appreciation appears to increase stock returns. The result also found a positive unidirectional causality from exchange rates returns to oil price returns. This result agrees with the theoretical association between oil prices and exchange rates (Bai and Koong, 2018). It shows that a rise or fall in oil prices does not affect the exchange rates in the selected economies. The positive sign signifies the capability of exchange rates to positively affect oil prices. These findings support studies such as Bloomburg and Harris (1995); Amano and Norden (1998); Pindyck and Rotemberg (1990); Sadorsky (2000); Zhang et al. (2008); Bai and Koong (2018); Rai and Garg (2021); Ozturk and CAVDAR (2021); Zhang et al. (2021); Baek (2022). For example, Rai and Garg (2021) documented a substantial adverse dynamic co-movement and volatility spill-overs between exchange rate and stock market returns in BRIICS countries. Zhang et al. (2021) opined that as a result of the coronavirus health crisis, oil prices influence on stock market returns have dropped by about 89.5 percentage points. Also, most recently, Baek (2022) find a significant asymmetric relationship between oil prices and the South Korean won to the US dollar.

5.3. Impulse response functions (IRFs) discussion

Love and Zicchino (2006) developed the impulse response functions in panel VAR technique, which are based on the Cholesky decomposition of the variance-covariance matrix residues and ensures that innovations are orthogonalised (Sims, 1980).[7] The IRFs disclose the reaction of one variable when affected with a shock or innovation in another variable (s). It also has the capacity of indicating the period in which the series needs to converge to a steady state after the event of the shock or innovation. In our current study, we employed 200 Monte Carlo simulations of a Gaussian approximation to estimate the IRFs confidence intervals following Cholesky decomposition (see Abrigo and Love, 2016).

In theory, there are several directions stock prices are affected by oil prices, which centres on the cash flow hypothesis. In financial theory, a company's share price equals expected present value of discounted future cash flows. Crude oil prices can affect stock prices of firms directly by influencing expected cash flows. The fundamental inkling is based on the fact that oil is an essential input in the production of firms and an increase in oil prices raises the cost and reduces income for businesses, and eventually transferred to consumers in the form of higher prices (see Salisu et al., 2020; Kumar, 2019; Smyth and Narayan, 2018; Salisu and Isah, 2017 Bai and Koong, 2018). Based on the recommendation by Abrigo and Love (2016) and the above economic theoretical underpinning in addition to prior studies, for example, Salisu et al. (2020), the IRFs and FEVD are computed in the following order: oil price, exchange rates and stock returns comes last. The exchange rate served as a moderating variable between oil and stock prices relationship.

5.3.1. Pre-COVID-19 declaration period

The IRFs results in Fig. 3 shows that following an innovation, all series appear to converge to their steady state confirming their stationarity. The IRFs indicate crude oil price returns has a nonlinear effect on stock returns; it has contemporaneous positive impact in the first period, whereas in the second period, it becomes significantly negative before converging to equilibrium in about the third period. A shock to exchange rates returns has a simultaneous positive effect on stock returns, continues on that note in the second period and then fizzles out at about the third period. Further, shocks to stock returns do not have a significant impact on crude oil price and exchange rates, since the confidence intervals include the zero line.

In terms of exchange rates and crude oil prices, exchange rate has a nonlinear effect on crude oil prices. A shock to exchange rates causes a contemporaneous negative response by crude oil prices in period one, whereas in periods two and three, it turns positive and converges to equilibrium in period four. The IRFs results further suggest that crude oil prices do not have fundamental impact on exchange rates. These outcomes corroborate our results from the pVAR model and the Granger causality test results above. Further, we confirmed autoregression of the major part of the variables by the magnitudes of their own shocks.

5.3.2. Post-COVID-19 declaration period

As indicated in Fig. 4 and similar to the Pre-COVID-19 declaration period, stationarity was established since all variables appear to converge to equilibrium. A shock to crude oil prices has a nonlinear impact on stock returns; it causes a positive response by stock returns in period one, while in period two it turns negative and then converges to equilibrium in period three. In the same vein, shocks to exchange rates appear to trigger a positive reaction by stock returns and the effect fizzles out at around the fourth period. A shock to stock returns seem not to have a simultaneous impact on exchange rates but becomes significantly positive in the second period, while a stock to stock returns seem to have no effect at all to crude oil prices. However, shock to crude oil prices appears to prompt a significant negative response by exchange rates. In addition, it is observed that the series own shocks appear to be those with the highest values, thus validating the fact that the main component of the series is autoregressive.

An added truth about our results is that exchange rates seems to persevere the more, therefore, any shock or innovation to this variable generates enduring impact on stock returns and oil prices. Following the Granger causality test results, it is worthy to mention the reaction of stock returns to exchange rates impulse, of stock returns to oil prices impulse, of exchange rates to stock returns impulse, of exchange rates to oil prices impulse. Even though the series reactions appear to be consistent with the results of the Granger causality test, the long term of these innovations effects and joined magnitude show that these are comparatively significant and this explains the relevant causal associations between these series. See the FEVD analysis next.

5.4. Forecast error variance decomposition (FEVD) analysis

It is of a fact that the IRFs produce information with regards to the effect of innovations in one variable on the other variables, but lacks the

[7] See Sims (1980) and Holtz-Eakin et al. (1988) for details on the recommended ordering of variables in pVAR IRFs and FEVD analyses.

ability to provide the scale and magnitude of these impacts. Therefore, it is recommended to conduct variance decomposition to resolve the issue (see Abrigo and Love, 2016). The results of the FEVD gives inference about the forecast error variance percentages in the endogenous variables that are attributable to both own shocks and cross shocks. It also provides the period required for a series to attain equilibrium following the occurrence of a shock or innovation. Following Abrigo and Love (2016), the FEVD Cholesky decomposition was computed using 200 Monte Carlo simulations for 10 weeks.

5.4.1. Pre-COVID-19 declarations period

Table 10 Panel A presents the results of the FEVD achieved from the orthogonalised impulse response parameter matrixes. Starting with stock returns, the result indicates that the variance decomposition is for the most part explained by own shocks. That is, 99.1% in the first week, 99.0% in the second week 98.96% in the fifth and tenth periods. However, in terms of cross shocks, the innovations to oil prices was able to explain about 0.79% and 0.82% of the variations in stock returns in periods one and two, respectively, while around 0.88% of the variations in stock returns was explained in the fifth and tenth periods. Similarly, the FEVD also reveals that exchange rate explains approximately 0.08% and 0.14% in periods one and two, respectively and about 0.16% of the fluctuations in stock returns in periods 5 and 10.

Similarly, FEVD of oil prices begins with primarily self-explanatory, with own shocks accounting approximately 99.97% in period two and 99.93% in periods 5 and 10, of the variance decomposition. This shows that the variable did not indicate signs of endogeneity, as shocks to stock returns and exchange rates seem to have very negligible effects on the explanation of the variations in oil prices. Stock returns explain around 0.03% of the fluctuations in oil prices in period two and 0.06% of the variations in periods 5 and 10. In the same way, exchange rates do not appear to be a dependent variable, since the major explanation of its forecast error variance is more or less restricted to own shocks or innovations. Oil price explained around 0.14% of the fluctuations in exchange rates in week one, 0.25% in the second week and 0.33% in weeks 5 and 10. The explanatory power of shocks to stock returns on exchange rates is very minimal.

Table 11
The panel vector autoregressive model results – robustness check with WTI.

Response to	Response of		
Pre – COVID-19			
	Dlsmr	Dlexr	Dlwti
Dlsmr(t – 1)	0.0175789	-.0169,004	0 .0062,204(0
	(0.0172532)	(0.0172903)	.0040,955)
Dlsmr(t – 2)	-.0072,798	0.0141039	0.0054534**
	(0.0192473)	(0.0688357)	(0.0022597)
Dlexr(t – 1)	0.0131132	-.0009538(0	0.0054676***
	(0.0131028)	.013,067)	(0.0015386)
Dlexr(t – 2)	0.0217297***	-.0015,992	0 .0019,493(0
	(0.0079768)	(0.0131305)	.0014,266)
Dlwti(t – 1)	-.0662,182(0	0.0350784	-.0554,642(0
	.0667,161)	(0.0482355)	.0470,319)
Dlwti(t – 2)	-.0552,151(0	0 .0135,306	-.112,988***(0
	.0484,785)	(0.0475864	.0293,655)
Post – COVID-19			
Response to	**Response of**		
	Dlsmr	Dlexr	Dlwti
Dlsmr(t – 1)	0.1181979	0.1723752***	-.6212422***
	(0.0833038)	(0.02807)	(0.2129577)
Dlexr(t – 1)	0.3608631***	0.2304811*	1.152677***
	(0.0878448)	(0.1237999)	(0.2914007)
Dlwti(t – 1)	0.0173514	-.0199,774**	0.3003203***
	(0.017006)	(0.00831)	(0.0685552)

Note: smi, exr, and wti represent stock market index, exchange rate, and West Intermediate Texas crude oil prices. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods. ***signifies1% level of statistical significance, ** denotes 5% level of significant and * denote 10% level of significant.
Source: compiled by authors.

5.4.2. Post-COVID-19 declaration period

The FEVD results for the post-COVID-19 declaration period are reported in Table 10 Panel B. A cursory glance at the table reveals a little form of interactions among the variables. This corroborates our results from the Granger causality test and the impulse response functions for the period after the COVID-19 outbreak was declared a global pandemic by WHO.

The results reveal that stock markets' own shocks are mainly prominent in the variance decomposition (approximately 95.63% and 92.31% in the first and second weeks and 91.86% in week 5 and 91.85% in week 10). In addition, innovations to oil prices explains about 2.56% of the forecast error variance in the 1st week and approximately 3.32% of the variations in stock returns in the 2nd week and 3.30% in 5th and 10th weeks respectively. Exchange rates explain approximately 1.81%, 4.37%, 4.85% and 4.90% of the changes in stock returns in weeks one, two, five and ten, respectively. These underline the financial hypothesis that crude oil prices and exchange rates have both direct and indirect impacts on the stock markets (Mollick and Sakaki, 2019).

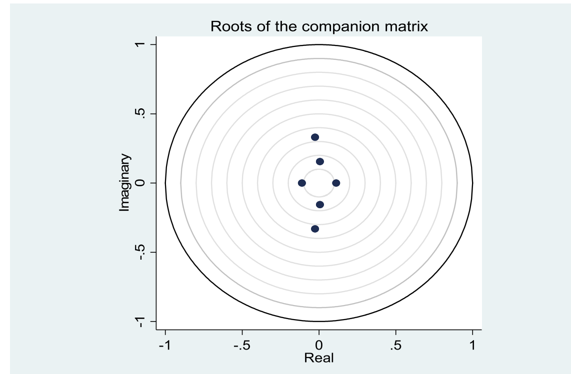
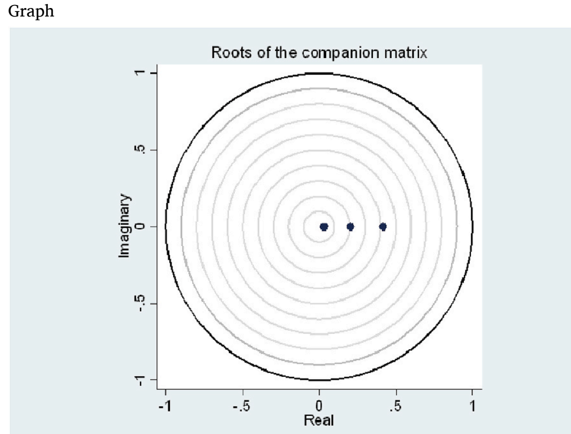
For crude oil prices, the results show that oil prices do not exhibit indications of being an endogenous variable, given that its variations is being mainly accounted for by itself (i.e. 99.46% in the 2nd week and 99.40% in weeks five and ten respectively). This result confirms that both stock markets and exchange rates do not affect the crude oil market. In the case of exchange rates, the innovation to oil price explains approximately 8.42% and, 7.56% of the fluctuations in exchange rates in periods one and two, and 7.44 per cent of the variations in exchange rates in the 5th and 10th weeks, respectively. This indicates that crude oil prices to a certain extent contribute to the performance of the foreign exchange markets of these economies. Shocks to stock returns on the other hand, explain about 7.33% of the variations in exchange rates in the 2nd period and 8.8% in periods five and ten, respectively. This shows that stock markets activities influence the foreign exchange markets. Following these results, it can be inferred from a causality test that runs from exchange rates to stock returns and vice versa at a 1% significant level.

In sum, the FEVD results show that in both the pre- and post-COVID-19 periods, fluctuations in the crude oil and foreign exchange markets contribute more to the volatility in stock market, on the one hand, whereas changes in stock market do not contribute much to explaining the shocks in the crude oil and exchange rate markets, on the other hand. Moreover, in the post-COVID-19 period, shocks to stock and crude oil markets appear to contribute more to the fluctuations in foreign exchange market (between 7 and 9% approximately), than the contributions of crude oil (3%) and foreign exchange (5%) markets to the variations in stock market.

These results portend that the cross shocks between these markets become intensified during the pandemic period than before the pandemic; and the shocks spill-over effects were more from the crude oil and stock markets to the foreign exchange market than from the foreign exchange and crude oil markets to the stock market. Lastly, the shocks spill-over from the foreign exchange and stock markets to the crude oil market appear to be very weak.

Our results are consistent with the findings documented in Thorbecke (2021), Narayan et al. (2020), Camba and Camba (2020), Aslam et al. (2020), Syahri and Robiyanto (2020), Hoshikawa and Yoshimi (2021), Prabheesh and Kumar (2021), Amewu et al. (2022), Narayan (2022). For example, Syahri and Robiyanto (2020) found significant relationship between exchange rate and composite stock price index during the coronavirus era; Aslam et al. (2020) confirmed that the efficiency of the foreign exchange market for six major global currencies declined during the earlier part of the COVID-19 pandemic; Narayan et al. (2020) recorded significant dynamic correlation between the Japanese Yen and the stock market returns, as the Yen depreciated

Table 12
Eigenvalue stability condition – robustness check with WTI.

Pre – COVID-19			
Eigenvalue			Graph
Real	Imaginary	Modulus	
-.025,795	-.3310094	0.332013	
-.025,795	-.3310094	0.332013	
0.0061339	0.1554432	0.1555642	
0.0061339	−0.1554432	0.1555642	
0.1116468	0	0.1116468	
−0.1111638	0	0.1111638	
Post – COVID-19			
Eigenvalue			Graph
Real	Imaginary	Modulus	
0.414454	0	0.414454	
0.203298	0	0.203298	
0.031247	0	0.031247	

Note: it is obvious from the graph that pVAR satisfies stability condition since All the eigenvalues lie within the unit circle – pre – and post – COVID-19 periods..
Source: Computed by the Authors.

against the US dollar, the returns on stock market improved in Japan. Hoshikawa and Yoshimi (2021) concluded that the coronavirus infection intensified the volatility in stock prices and caused the South Korean won to depreciate in value. Amewu et al. (2022) recently established the dynamic correlation between exchange rate and stock index, even though the intensity tends to fizzle within the medium term. Narayan (2022) documented that in the period of the COVID-19 pandemic, total fluctuation in exchange rate spill-over accounted for about 37.7% of the variations in foreign exchange market, whereas 26.1% of the variations was accounted for in the period prior to the disease outbreak. Further, Prabheesh and Kumar (2021) documented that the uncertainty occasioned the COVID-19 pandemic deteriorated the activities in the stock and crude oil markets, and because of investors' risk aversion, the co-movement between crude oil and stock markets was distorted at the first phase of the health crisis.

6. Additional results – robustness tests with different oil indicator

To corroborate the strength of the results discussed above, we also performed panel vector autoregressive model (Table 11) and the stability tests in Table 12, with panel Granger causality test (Table 13), the forecast error variance decomposition (presented in Table 14) and the impulse response functions (Figs. 5 and 6) for the trivariate, using West Texas Intermediate (WTI) as a proxy for oil price in the place of Brent. This investigation was also done for the two periods. Following all necessary procedures, these are the conclusions: in the case of pre-COVID-19 period, the results do not present any significant qualitative differences when compared to the results above. This indicates that before COVID-19 was declared a global pandemic, the use of Brent or WTI as the international oil price have insignificant influence on the results. Bai and Koong (2018) found similar results.

Contrary to the pre-COVID-19 period, the post-COVID-19 period result finds a strong significant bidirectional causality between stock returns and exchange rates returns on the one hand and between oil prices and exchange rates returns on the other hand, with positive signals in both directions of stock returns and exchange rates; but with negative signal running from oil prices to exchange rates and positive signal running from exchange rates to oil prices. Nevertheless, in the case of oil prices – exchange rates nexus, the causality appears to be stronger from exchange rates to oil prices. Further, we found strong negative unidirectional causality running from stock returns to oil prices, which means the variations in stock returns in these countries, appears to influence the oil market. Moreover, the negative signal observed in this association reveals that improvements in stock returns can possibly deteriorate crude oil prices.

The IRFs results, reveal that shocks to stock returns lead to a significant negative response by oil prices, and shocks in exchange rates leads to a strong positive response by oil prices. All other results remain the same as the ones reported under the pre-COVID-19 declaration period and are in line with the Granger causality test results. Considering the FEVD, the results indicate that for all the series in the pre-COVID-19 period, their forecast error variances are majorly explained by their own shocks. It should be mentioned that at the 10th week,

Table 13
Panel Granger causality test – robustness check with WTI.

Equation/excluded variables		Chi-squared	Df	Prob.
Pre – COVID-19				
Dlsmr				
	Dlexr**	8.212	2	0.016
	Dlwti	1.552	2	0.460
	ALL**	10.220	4	0.037
Dlexr				
	Dlsmr	1.036	2	0.596
	Dlwti	0.542	2	0.763
	ALL	1.322	4	0.858
Dlwti				
	Dlsmr**	8.292	2	0.016
	Dlexr***	13.788	2	0.001
	ALL***	23.544	4	0.000
Post – COVID-19				
Dlsmr				
	Dlexr***	16.875	1	0.000
	Dlwti	1.041	1	0.308
	ALL***	16.967	2	0.000
Dlexr				
	Dlsmr***	37.698	1	0.000
	Dlwti**	5.776	1	0.016
	ALL***	38.186	2	0.000
Dlwti				
	Dlsmr***	8.51	1	0.004
	Dlexr***	15.647	1	0.000
	ALL***	17.287	2	0.000

Note 1: Panel VAR-Granger causality Wald test – pre – and post – COVID-19 periods. Ho: Excluded variable does not Granger-cause Equation variable. Ha: Excluded variable Granger-causes Equation variable. Note 2: ***, **, and * denote 1%. 5% and 10% level of significant respectively.
Source: Computed by the Authors.

Table 14
Forecast error variance decomposition – robustness checks with wti.

Response variable	Forecast Horizon	Dlwti	Dlexr	Dlsmr
Pre – COVID-19				
Dlwti				
	1	1	0	0
	2	0.9997451	0.0000406	0.0002142
	5	0.9995882	0.0000494	0.0003624
	10	0.9995881	0.0000495	0.0003624
Dlexr				
	1	0.0021242	0.9978758	0
	2	0.0032139	0.9960179	0.0007681
	5	0.0034382	0.9952672	0.0012946
	10	0.0034384	0.9952666	0.001295
Dlsmr				
	1	0.0079994	0.000823	0.9911776
	2	0.0082928	0.0010249	0.9906822
	5	0.0088939	0.0011719	0.9899342
	10	0.0088939	0.001172	0.9899341
Post – COVID-19				
Response variable	Forecast Horizon	Dlwti	Dlexr	Dlsmr
Dlwti				
	1	1	0	0
	2	0.94123	0.024684	0.034087
	5	0.937353	0.028348	0.034299
	10	0.937329	0.02836	0.034311
Dlexr				
	1	0.018324	0.981676	0
	2	0.027505	0.881353	0.091142
	5	0.028574	0.864593	0.106833
	10	0.028578	0.86452	0.106902
Dlsmr				
	1	0.009034	0.011834	0.979132
	2	0.010106	0.048322	0.941572
	5	0.010043	0.055167	0.93479
	10	0.010046	0.055197	0.934758

Note: smi, exr, and wt represent stock market index, exchange rate, and West Intermediate Texas crude oil price. Variables in their natural logarithms and first differences – pre - and post – COVID-19 periods.
Source: Computed by the Authors.

shocks to exchange rates and oil prices account for approximately 5.52% and 1.00%, respectively, of the variations in stock returns. Meaning that changes in exchange rates have stronger effects than oil prices on stock returns in the post-COVID-19 declaration period. Further, shocks to stock returns and oil prices explain around 10.69% and 2.86%, respectively, of the changes in exchange rates in the 10th period. Lastly, innovations in exchange rates and stock returns explain about 2.84% and 3.43%, respectively, of the fluctuations in the crude oil market. These results confirm the interconnections between the FEVD and the Granger causality test results; however, the two are not the same. Nevertheless, it should be noted that variables may Granger cause each other without indicating major effect on the adjustment of the "caused" variable.

7. Conclusion

The motivation to carry out this study is hinged on the observations that stock prices of almost all the sampled oil exporting countries significantly plummeted and exhibited more volatile behaviour amidst this COVID-19 pandemic. This was further heightened by the observed differences in the pre- and post-COVID-19 performances of stock prices, oil prices and exchange rates of the countries. This paper presents a pVAR study of the relationship between stock markets, oil prices and exchange rates of twelve major oil-producing economies in the world (Canada, Iraq, Kazakhstan, Kuwait, Nigeria, Norway, Qatar, Russia, Saudi Arabia, United Arab Emirates, United States and Venezuela) in these two periods. The choice of the pVAR is predicated on the existence of cross-sectional dependence in all series or the correlation between the series across economies, both in the log returns and in the first differences (Pesaran, 2004). Some of the series are also diagnosed to be either in the neighbourhood of I(0) or I(1). This is in addition to establishment of stationarity without and with trend in all series, confirmed by the eigenvalue stability condition of the series in both the pre- and post-COVID-19 periods.

The pVAR Granger causality test for the pre-COVID-19 shows a negative unidirectional causality running from exchange rate returns to stock returns. This evidences that changes in exchange rates have negative effects on the performances of the stock markets in these net-oil producing economies. In the post-COVID-19 pandemic era, a highly significant positive bidirectional relationship exists between stock prices returns and exchange rates returns. The relationship between exchange rate returns and oil prices are the same in both periods. The result shows a positive unidirectional causality from exchange rates returns to oil price returns. The positive sign epitomises that exchange rate has the capability to positively affect oil prices. This is corroborated by the IRFs results which confirmed that a shock to exchange rates has positive impacts on stock returns in both periods in the economies sampled. The IRFs also indicate that crude oil price returns have nonlinear effects on stock returns in all periods, but shocks to stock returns do not have any significant impact on crude oil prices and exchange rates in both periods. However, a shock to crude oil prices appears to prompt a significant negative response by exchange rates in the post-COVID-19 pandemic era. This shows that the post-COVID-19 pandemic period, which has seen crude oil prices plummet, is instrumental to the depreciation of the currencies of these selected oil producing economies.

The FEVD estimates that such innovations to crude oil prices account for different magnitudes of fluctuations in exchange rates at different periods, without a corresponding influence of exchange rate on crude oil price. This indicates that crude oil prices to a certain extent affect the performance of the foreign exchange markets of these economies. The result also confirms that innovations to crude oil prices also explain certain degrees of the variations in stock returns in the different weeks. However, the crude oil prices are neither influenced by the stock market activities nor the exchange rate market. With the depreciations in

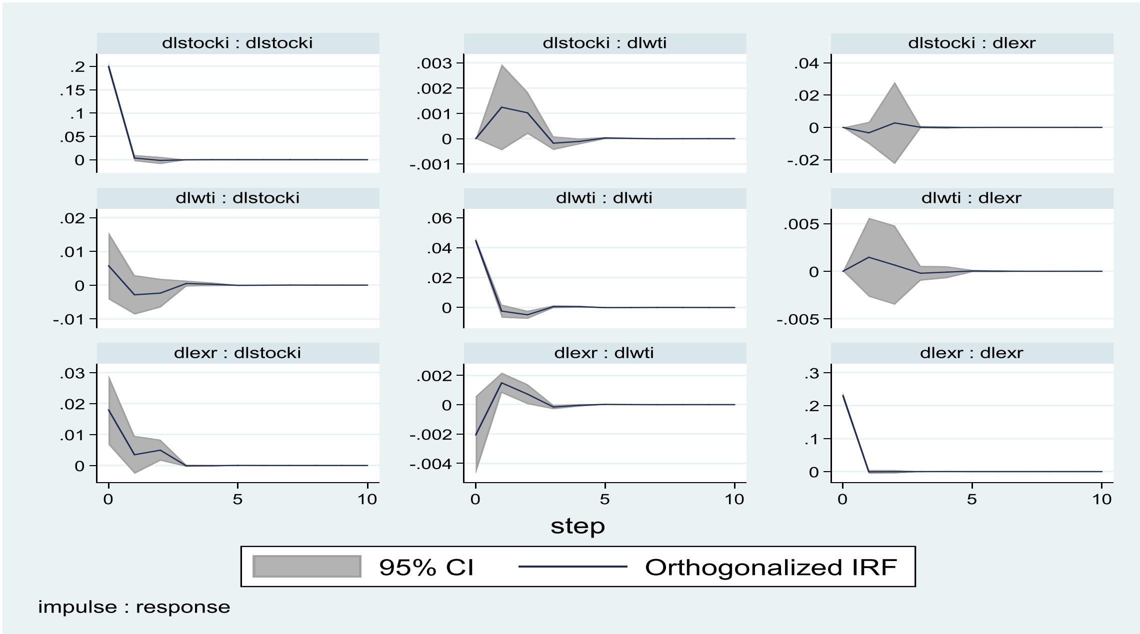


Fig. 5. Impulse response functions. Pre – COVID-19 Declaration – robustness test with WTI.

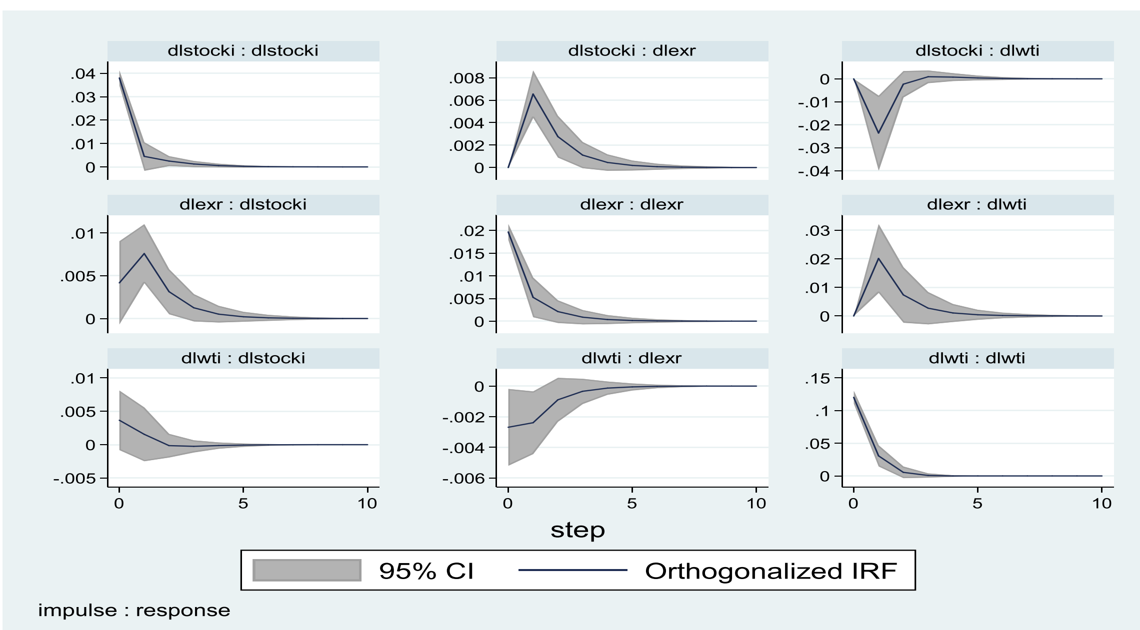


Fig. 6. Impulse response functions. Post – COVID-19 Declaration – robustness test with WTI.

exchange rates, stock returns also increased marginally from the first week. Correspondingly, stock markets activities also influence the foreign exchange markets of these selected oil producing economies in the post-COVID-19 pandemic era at different levels and different weeks. This confirms the existence of a bidirectional relationship between stock price returns and exchange rates in the post-COVID-19 pandemic era Granger causality test result.

This results run contrary to findings in the pre-COVID-19 pandemic era, where the FEVD estimates show that the variance decomposition for the three variables are for the most part explained by own shocks. It is therefore right to conclude that COVID-19, its declaration as a global pandemic and the plummeting crude oil prices which have led to the depreciation in the exchange rates have also negatively affected the stock market activities of the oil producing countries. The major oil importing countries, the US, UK, France, Germany, Canada, China, etc., have faced persistent deceleration in the major sectors of their economies in the COVID-19 era. Drastic reduction in their production activities have led to a fall in the demand for crude oil, thereby further amplifying the stock markets uncertainties. In addition, the US dollars, the reference currency has significantly appreciated amidst the declaration of COVID-19 as a pandemic; this explains the significant causality running from exchange rates to stock markets. The solution to these problems lies in the speedy development of vaccines and the vaccination of people globally. This will encourage the easing of the lockdowns and the rejuvenation of the productive sectors, especially in the high oil importing countries that will increase the demand for crude oil. With the improved earnings from this, the local currencies of these net oil exporting countries will improve against the US dollars, and as such their capital market activities. Furthermore, policy implication from our results shows that crude oil is still very relevant in the world business and that the price of crude oil to a large extent is very important in the determination of prices in other markets. Hence, investors in the exchange rate and stock markets should use the movement of crude oil price as a compass for investment in times of crisis that has affected crude oil market.

Further studies can be carried out to look at the co-movement between these variables at the different waves of the coronavirus.

Authors' statement

Terver Theophilus Kumeka: Conceptualization; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Roles/Writing - original draft; Writing - review & editing.

Damain Chidozie Uzoma-Nwosu: Validation; Visualization; Roles/Writing - original draft; Writing - review & editing.

Maria Onyinye David-Wayas: Resources; Data curation; Writing - review & editing.

Conflicts of interest

None.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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