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COVID-19 pandemic, oil prices and Saudi stock market: empirical evidence from ARDL modeling and Bayer–Hanck cointegration approach

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Abstract

In 2020, the world experienced several significant events, including the coronavirus (COVID-19) pandemic and the collapse of international crude oil prices. The rapid spread of this pandemic has dramatic impacts on financial markets all over the world, thereby increasing market risk aversion in an unprecedented way since the subprime financial crisis. The decline in stock markets implied volatilities of equity and oil prices, thereby heightening turmoil in global financial markets despite comprehensive and substantial financial reforms. To this end, we investigated the likely effects of this pandemic on the Saudi stock market while controlling for oil prices based on daily data for a period from 1/1/2020 to 19/9/2022. To ascertain the existence of a long-run equilibrium relationship between the variables, we applied autoregressive distributed lag (ARDL) modeling and the error correction model, with this ultimately revealing the existence of strong cointegration in the long run. The ARDL bounds test was found to be robust by combined cointegration tests, thus providing further evidence of a strong relationship in the long run. Granger causality tests also yielded evidence of causality between the variables in both directions. The total COVID-19 confirmed cases and oil prices also caused movements in stock returns in the short run. Our findings have some prominent implications for asset managers and policymakers to improve stock market efficiency and boost global economic activity. Saudi authorities can consequently remove the regulatory and legal obstacles to develop their stock market and better improve the risk management, which will allow to make quick decisions in response to any oil price volatilities. Policymakers should also adopt proactive strategies that can comfort stock investors' anxieties over the increasing oil price volatilities. Finally, the findings should be treated with some cautions because of the limited sample size and the tests' statistical inference. Nevertheless, they do open opportunities for further studies to look in more detail at how the COVID-19 pandemic affected, over the short and long run, monetary and fiscal policy coordination, financial stability, and various other macroeconomic indicators in Saudi Arabia.

Keywords COVID-19 pandemic, Oil prices, Stock returns, ARDL bounds test, Bayer–Hanck cointegration test

JEL Classification C22, G1, G15, Q41

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Introduction

Over the past decade, commodities have become popular assets for portfolio investors, just like bonds and stocks. The process of financialization of commodity markets, resulting from the increasing presence of financial investors in commodity markets, experienced a synchronized boom-bust cycle in 2007–2008 subprime crisis where the price volatility of many commodities spiked. As a result, an extensive literature having discussed the relationship between commodity markets' financialization, financial activity and the real economy emerged [15, 18, 27–30, 40, 48, 54, 71, 82, 83], etc.).

More recently, in 2019, the world was expecting an economic crisis due to the protectionist war between the United States of America and China when the coronavirus pandemic crisis plunged the world economy into an embarrassing economic situation. Initially, the COVID-19 virus was largely ignored as it spread through its epicenter of Wuhan, China. On February 11, 2020, COVID-19 was declared a global pandemic by the World Health Organization (WHO), triggering stress and uncertainty in global markets. Equities plummeted as market volatility spiked around the world. According to the Economic Times Journal, the coronavirus pandemic and the associated restrictions clearly had a discernable effect on financial markets.

In a nutshell, the advent of the COVID-19 pandemic has caused significant disturbances to global financial and oil markets. The global financial markets reacted relatively moderately as the virus spread, first to the Middle East and then to Europe, fueling fears of a global pandemic. Stock markets values then plunged during the crisis. Dow Jones, NASDAQ 100, and S&P 500 share prices declined on average by 0.56%, 0.27% and 0.53%, respectively, between March 11th and March 31st, 2020.

Moreover, the decline in the demand for crude oil, combined with the Saudi–Russian oil price war, had an instant effect on financial and economic activity, with it being exposed to supply and demand shocks simultaneously. The price per a barrel for the West Texas Intermediate (WTI) dropped drastically from $63.05 on December 30th, 2019 to just $21.55 on March 21st, 2020. On April 21st, 2020, WTI price recorded a negative price of $36.98 per barrel, falling from $18.31 per barrel the previous day. Similarly, Brent crude oil price fell by 47.47% in the same period.

Regardless of whether the economy is oil-importing or exporting, oil price shocks significantly affect stock return and volatility (Kilian and Park [60], Kang et al. 57, Erahman et al. [36], Mugableh [65], [16], Wen [89], [5, 47, 74]. The theoretical underpinning for the relationship between oil prices and stock returns (SR) reflects that the first ones can negatively affect the second either directly or indirectly: directly by impacting future cash flows, and indirectly through an impact on the interest rate used to discount future cash flows [6, 52, 78].

The literature has widely discussed the dully effect the higher oil prices has on stock market indices by lowering economic activity, increasing input prices, reducing firm profits, and increasing inflation rates. Furthermore, higher oil prices along with economic uncertainty and high-risk premium cause the fall of stock prices. Therefore, the conventional intuition is that an increase in oil prices leads to increasing the cost of energy consumption thereby reducing profit margins and negatively affecting stock markets.

Empirically, earlier studies including Cunado and de Gracia [32], Jones and Kaul [52], Huang et al. [49], Sadorsky [77], Wei [86], Aloui et al. [11], Kang et al. [55], Smyth and Narayan [81], Harjoto et al. [44], Tissaoui et al. [84], Yan et al. [90], Raifu [74], and Wei et al. [88] investigated the linkage between oil prices and stock market returns. However, the empirical evidence of these works has generally focused on developed countries (Germany, France, Italy, UK, Canada, Japan, US) and appears, in terms of impact and causality directions, inconclusive failing thereby to reach agreement. They argue that an increase in world oil prices results in a negative response to domestic stock market returns. World oil prices are then considered as more crucial for the stock (financial) markets than the national oil price. Also, the effect on stock returns of oil price changes depends on whether the shocks are supply-side shocks or demand-side ones. In the Saudi Arabian context, empirical evidence on the nexus between COVID-19 pandemic, oil prices and stock returns are very limited and far from to be exhaustive. They include basically and not exclusively Tissaoui et al. [84], Abuzayed and Al-Fayoumi [2], Al-Najjar [9], Wasiuzzaman [85], and Alshaikhmubarek et al. [12].

In this regard, the present paper attempts to fulfill the gap already existing in this literature by establishing whether the total COVID-19 cases influenced Saudi stock returns while controlling for oil prices. To do this, we applied autoregressive distributed lag (ARDL) models which allowed us to establish, for both stationary and non-stationary series, whether the relationships that exist among stock returns, oil prices, and confirmed COVID-19 cases converged toward a long-run equilibrium or not. Several previous literature have proved the capacity of ARDL models in analyzing long- and short-run dynamics. In doing so, this study attempts to fill the gap in the existing literature in many ways. First, we focus on the likely impacts of COVID-19 pandemic on the Saudi stock market considering oil price shocks since the Saudi Arabia is the World's largest oil exporter, thereby playing a crucial role in the global oil market. Moreover, we utilize a battery of econometric tests (the Bayer–Hanck cointegration test and the Granger causality analysis) to investigate the robustness of the ARDL and to establish the direction of causality between the different variables. We assume consequently that total COVID-19 confirmed cases and oil prices caused movements in stock returns in the short and the long run.

The remainder of this paper is structured as follows: Sect. "Literature review" presents a review of the relevant literature. Sect. "Research methodology" describes the study's model and the empirical methodology. Sect. "Results and discussion" presents and discusses the empirical results. Finally, Sect. "Bounds test of cointegration results" discusses the main conclusions of the paper.

Literature review

Starting with Hamilton's [43] seminal study, a vast body of subsequent studies have examined the nexus between oil prices and various economic and/or financial indicators, including but not limited to stock returns thereby receiving a fair share of analysis. Our strand of the literature distinguishes between pre- and post-COVID-19 pandemic while presenting the main works on the connection between oil prices and economic and financial aspects.

Oil prices and economic aspects in pre-COVID-19 pandemic

Hamilton's [43] seminal work established that the oil market influences the real economy. This relationship can be theoretically modeled through various means, such as output, fiscal and monetary policies, stock markets, and uncertainty. It is generally accepted that the COVID-19 pandemic affected the real economy in addition to the financial sector through production levels and stock valuations.

Moreover, this crisis affected the mobility of workers, trade, and transportation, triggering an overall collapse in both demand and supply and creating a period of global economic instability. Among others, Bernanke [21], Rodrik [76], and Marcus [63] found that it is important to analyze the impact of oil prices on economic instability since it has implications for the overall economy. Jones and Kaul [52] also posited that oil prices influence the wider economy by affecting factors like inflation, productivity, and unemployment.

Several researchers [14, 19, 42, 59, 62] have demonstrated that supply-side oil shocks have milder macroeconomic consequences than demand-side oil shocks. In addition, Kang and Ratti [56] and Antonakakis et al. [13] also studied the connection between unstable economic policy and global shocks in oil prices. They found that changes in oil prices due to overall global production and shocks that are particular to the oil sector do indeed have long-term implications for economic policy uncertainty (EPU), although supply-side oil shocks do not significantly affect EPU in the United States.

In the context of Japan, Abhyankar et al. [1] studied the connexion between oil prices and stock market. Using a structural vector autoregressive (SVAR) model, the authors find positive correlation between oil price shocks and stock returns. Moreover, the results showed negative reaction of Japanese stock market to an increase in oil prices related to oil market specific demand shocks. Finally, demand and supply shocks in the global crude oil market affect Japanese stock returns through changes of expected real cash flows rather than of expected returns, contradicting thereby the results found with US stock market data.

Aloui et al. [11] analyzed the effect of volatility on the returns of crude oil based on a copula method. By creating multivariate distributions of time series data, this aided in measuring the dependency structure between the variables independently of the residual distributions. In addition, this study applied a rolling-window approach to account for equity and economic policy volatility's time-varying impact of on oil returns. The findings suggested that greater volatility in terms of stock indices and economic policy instability (EPI) increases crude oil returns substantially only over certain periods of time. The authors indicated a strong dependency before and during the financial crash and the Great Recession, while the copula calculations over the entire study period point to stock and economic indices having a negative relationship with crude oil returns.

Using SVAR model to explore the complex impact of oil output shocks, both within and outside the US, on EPU, Kang et al. [55] found that EPI varies according to whether the production shocks occurred in the US or outside the US. More specifically, the response is positive and statistically significant when dealing with disruptions in US oil supply but negative and statistically insignificant when dealing with shocks to oil supply from outside the US.

Degiannakis et al. [33] explored how the relationship between financial instability and shocks in oil prices varied over time between January 1994 and March 2015. Based on six parameters representing economic and financial uncertainty, the impulse reactions to endogenous shocks in the oil price indicated that oil supply shocks had no major effect on the volatility of stock indices. In addition, the aggregate market shocks led to less volatility. Ultimately, based on the SVAR tests, the authors could not argue that shocks specific to oil demand increased uncertainty. The findings of the Time-Varying Parameter VAR (TVP-VAR) test indicated that the uncertainty indices' responses to the three shocks in oil prices varied over time, so static strategies may fail to have the desired effect. Indeed, the time-sensitive impulsive responses indicated that the indices for instability exhibited heterogeneous reactions to all three forms of stimuli over various periods of time.

Oil prices and economic aspects in post-COVID-19 pandemic

Albulescu [8] also investigated how figures for COVID-19 cases affected foreign oil prices based on an ARDL approach. The study highlighted the substantial disruptive influence of the coronavirus outbreak, although this was comparatively weak compared to the effect of financial instability and confusing economic policies on the price of oil. Indeed, the effect of COVID-19 on the price of oil price appears to have manifested indirectly through the stability of the financial markets.

Al-Awadhi et al [7] attempted to understand how contagious infectious diseases influence financial markets by using panel data techniques to check COVID-19's impact on the stock market in China. The results indicate that frequent increases in both the total reported cases and mortalities had a major detrimental effect on firms' stock returns.

In the context of US economy, Sharif et al. [79] analyzed the nexus between the COVID-19, crude oil prices and stock market, when considering geopolitical risk and EPU. The coherence wavelet method and the wavelet-based Granger causality tests are applied to US daily data. The main results showed a substantially higher effect of the COVID-19 on the geopolitical risk than on the EPU. The COVID-19 impacts are perceived differently over the short or the long run.

Albulescu [8] investigated how official announcements of fresh COVID-19 cases and deaths affected the financial market volatility index (FMVI). The author also contrasted the influence of COVID-19 data published in China with that published outside China. The results indicated that (i) even new cases announced beyond China positively affected the FMVI; (ii) for all models, the death ratio had a significant and positive impact on FMVI, although this effect was stronger outside China; and (iii) the spread of the coronavirus amplified financial uncertainty. COVID-19's longevity could therefor spark a future episode of financial tension.

Using daily data from 23 developed and 53 emerging markets between January and August 2020, Harjoto et al. [44] found strong evidence of an adverse relationship between confirmed cases (mortality rates) and stock returns. In contrast, stock volatility and trading volumes were positively affected by mortality rates and confirmed cases. The authors also indicated that results differed between emerging and developed countries. More specifically, while daily returns, trading volumes, and volatility were affected by daily cases and death rates in emerging countries, they were only affected by the daily cases in developed countries. Finally, the findings support the overreaction hypothesis, which posits that stock markets tend to overreact during periods of rising infections.

Yan et al. [90] investigated the volatility spillovers between global oil-stock markets over the period spanning from January 1, 2019, to March 31, 2021. The authors used wavelet Granger causality methods and find that WTI and Brent oil prices have negative mean returns before COVID-19, but positive mean returns during the pandemic spread. Moreover, the results show positive, significantly lowest, and highest frequency during the COVID-19 outbreak for all selected countries (Canada, China, Kuwait, Russian, and the USA). However, oil price shocks had a more significant impact on the stock markets of the Canada and United States than on the stock markets of other countries.

The study of Khalfaoui et al. [58] is interested by examining the time-varying causal effects of the COVID-19 pandemic on oil prices, stock market volatilities and economic uncertainty in major oil-importing and oil-exporting countries using the wavelet coherence and network analysis. The main findings recognized the great effect the COVID-19 pandemic has on oil prices, stock market indices, and economic uncertainty. Moreover, COVID-19 and oil price changes in oil-exporting countries mirror those in oil-importing ones and vice versa. Finally, the COVID-19 pandemic has a deep immediate time–frequency effects on Canadian, Indian Japanese, South Korean and US economic uncertainties.

Otherwise, Raifu [74] examined the time-varying causality (TVC) between oil returns (OR) and stock returns (SR) in Norway. He finds that the causality direction between OR and SR is determined by the frequency of data. In the case of daily data, a bidirectional causality exists between oil and stock returns. However, in weekly and monthly data a unidirectional causality runs from stock to oil returns. The author established also a TVC between the two variables.

Phoong et al. [70] revisited the stock market–oil prices nexus by considering the impact of macroeconomic shocks in the post-global financial crisis. The Markov switching regression results showed that oil prices and Standard & Poor's 500 market index show that COVID-19 pandemic is the most significant contributor to market volatilities. Moreover, while the relationship between oil prices and stock market is regime-dependent, stock market return is significantly affected by oil price shocks in a volatile regime.

The study of Al-Shboul and Maghyereh [12] highlights the effects of US real economic uncertainty (REU) on the risk connectedness in the oil-stock nexus during the COVID-19 pandemic. Using multiple and partial wavelet coherence methods on daily data from January 2018 to

December 2020, the main findings support the existence of a strong impact of REU indices on risk connectedness, with time-varying and frequency-sensitive patterns. Also, higher coherencies between equity and oil volatilities exist at lower frequencies during the COVID-19 pandemic period.

More recently, Olayungbo et al. [67] explored the correlations between oil price movements and stock markets and their spillover effects during the COVID-19 pandemic and the Russian-Ukraine geopolitical crisis in oil-exporting and European countries. The results obtained from the estimation of a dynamic Markov switching model with daily closing data show a positive and significant response of stock returns to oil price returns in Germany, Italy, and the US during the Covid-19 period while the response is significantly positive only for US in the Russia-Ukraine war period. Finally, significant spillover effects are found from oil prices to stock market in Saudi Arabia; however bidirectional volatility spillover effects exist for Germany, Italy and the US, during the COVID-19 period.

On the other hand, the works realized on the context of Gulf Cooperation Council (GCC) countries, more particularly on Saudi Arabia are very limited. Tissaoui et al. [84] analyzed the relationship between liquidity and volatility in the Saudi stock market (Tadawul) over the COVID-19 outbreak period. Using ARDL modeling, the main results show significant long- and short-run relationship between market illiquidity and volatility in contemporaneous and lagged manner. However, the wavelet coherence analysis confirms that of ARDL analysis. Indeed, the wavelet coherency between realized volatility and illiquidity ratio appears highly pronounced over all time horizons during the COVID-19 outbreak period. Finally, there exist a strong effect of the explanatory power of both COVID-19 cases and market volatility on the movement of the liquidity market, especially in the short term.

Abuzayed and Al-Fayoumi [2] examined the oil price extreme tail risk spillover to individual Gulf Cooperation Council (GCC) stock markets and quantified this spillover's shift before and during the COVID-19 pandemic. Using DCC-GARCH models on daily data from 2017:01 until 2020:05, the authors find that all GCC stock markets received significant systemic oil risk spillover in Phase 2 of COVID-19. Moreover, the United Arab Emirates and Saudi Arabia are more vulnerable to oil extreme risk than the other countries. Accordingly, investors should carefully consider the extreme oil risk effects on GCC stock markets when designing optimal portfolio strategies.

Al-Najjar [9]'s study assessed the effects of COVID-19 and oil prices on the Saudi stock market (SSM) for the period from 01/01/220 to 12/02/2020. Linear regressions and neural network models are used. The main findings are twofold. First, neural networks can achieve the best results when using all independent variables. Second, oil prices have the most substantial effect on the changes in Tadawul All Share Index (TASI) as compared to the COVID-19 indicators. The TASI seems to rapidly follows the changes in oil prices.

In the same context of Saudi Arabia, Wasiuzzaman [85] investigated the effects of the COVID-19 pandemic on the performance of the SSM from December 2019 to the end of July 2020. The results show that the pandemic has positive but mostly insignificant impacts on the mean returns of all indices except for the Real Estate sector Investment Trusts (REITS). Moreover, the TASI itself experienced lower volatility during the pandemic period. Finally, only 9 sectors among 21 experienced significant impacts on volatility, and out of the 9 sectors, only 5 (4) experienced significantly increased (lower) volatility.

Finally, Alshaikhmubarek et al. [12] studied the eventual impacts of the COVID-19 on all Saudi listed stocks. More specifically, the authors considered the consequences of this pandemic on the global stock returns, sectoral stock returns, and the stock returns of specific firm characteristics. On weekly data spanning from 03/03/2020 to 05/25/2021, panel regressions and Wald tests outputs showed the existence of negative impacts of COVID-19 on all market capitalization stocks with some worst on medium stocks. Also, less profitable stocks were more vulnerable to COVID-19 than other profitability groups.

Despite the abundant literature examining the nexus between oil prices and stock markets mainly during the post-COVID-19 pandemic, most of them are rather limited to the context of developed economies. The studies on the stock markets—oil prices nexus in GCC countries are very scarce. Henceforth, our study aims to fill this gap and contribute to the existing literature by focusing on the likely impacts of COVID-19 pandemic on the Saudi stock market considering oil price shocks since Saudi Arabia is the widely regarded as the world's most important oil exporter. Also, we use the famous Bayer-Hack cointegration test to study cointegration, investigating thereby the robustness of the ARDL modeling.

Research methodology

Model specification

Based on the above literature, the nexus between COVID-19 confirmed cases (Covid), oil market prices (Oil), and stock market returns (SR) will be investigated using the following model:

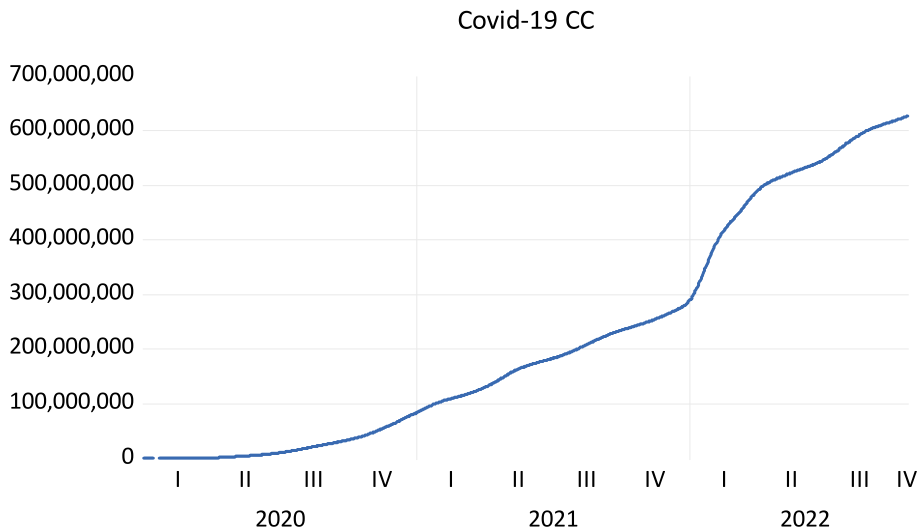

Fig. 1 COVID-19 total confirmed cases

$$SR_t = \alpha_t + \beta_1 Covid_t + \beta_2 Oil_t + \varepsilon_t \quad (1)$$

where *SR* denotes the daily return of the Saudi stock market, *Oil* represents the Brent oil price, *Covid* the daily total confirmed cases, ε_t is the white noise error term and ε_t is the error term for residual effect of the returns.

Data description and summary statistics

In this paper, it is hypothesized that COVID-19 pandemic and world oil prices influence Saudi stock market in the short and the long run. Data from the World Health Organization (WHO) showed that COVID-19 cases around the world rapidly increased from the end of February, so we surmised that this increase had drastic effects on both the oil and financial markets. We extracted daily data for the total confirmed COVID-19 cases (COVID19_CC) from the situation reports of the WHO. Our sample covers a period from January 1, 2020 to October 19, 2022. Saudi stock market returns were represented as the percentage of daily log-price differences: $SR_t = (lnP_t - lnP_{t-1}) * 100$. Finally, crude oil prices were represented by the daily Europe Brent Spot Price FOB index in dollars per barrel, with data being sourced from the US Energy Information Administration (EIA). The stock prices are converted to first difference form, from its natural logarithm to compute stock returns. Besides, the rationale for converting the confirmed COVID-19 cases into natural logarithm form is that it helps in explaining the spread of COVID-19.

Figures 1, 2 and 3 present the dynamics of the different indicators. We can observe how stock returns declined

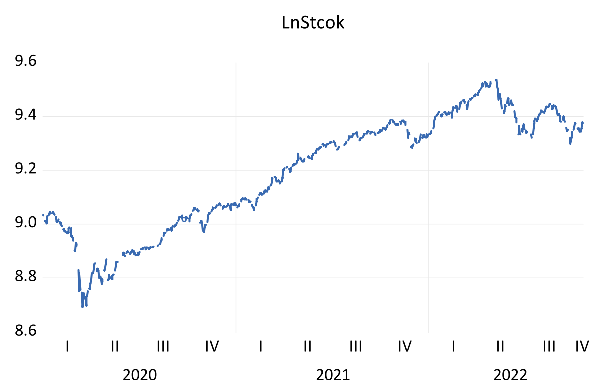

Fig. 2 Stock returns

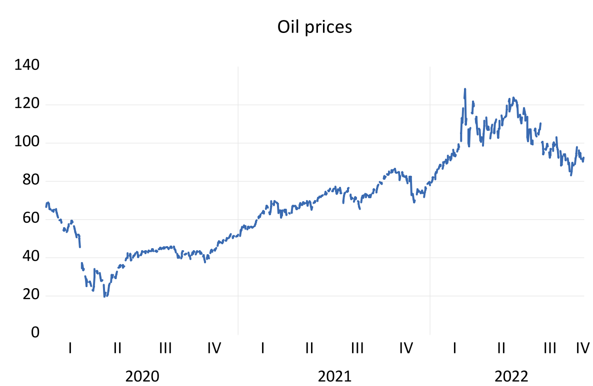

Fig. 3 Oil prices

after COVID-19 cases began being officially monitored, and the total number of COVID-19 infections remained at its initial level for a while. However, from March 8, 2020, stock returns crashed drastically when COVID-19 cases surpassed the psychological threshold of 100,000. Oil prices demonstrated a similar movement in line with global infections starting on March 9, 2020.

Empirical methodology

The empirical methodology consists of conducting newly developed cointegration tests, based on Pesaran et al. [69] and Bayer and Hanck [20], and the ECM Granger causality. The ARDL bounds test of cointegration investigates the long-run relationship. Compared to other cointegration techniques, it has many advantages. First, it is found to be more appropriate because it seems flexible regarding unit root properties of variables. Second, Haug [46] acknowledged that the ARDL approach to cointegration provides better results for small sample databases as in our case. Finally, Laurenceson and Chai [61] showed that unrestricted model of ECM seems to take satisfactory lags that captures the data generating process in a general-to-specific framework of specification. Furthermore, we use Bayer and Hanck's [20] combined cointegration technique to verify the robustness of the model. According to Shahbaz et al. [80], this method combines four major cointegration tests [26, 35, 51], and Banerjee el al. [17]) to give robust results. It overcomes the challenge of possible conflicts in results that may arise while using different types of cointegration tests, thereby preventing random and inconsistent decision taking.

However, prior to all these tests, it was vital to ascertain the order of integration. This was achieved by examining the stationarity of the variables with suitable unit root tests. For macro-finance topics, we generally focus on empirical studies with unbiased results that investigate whether an equilibrium (i.e., long-term) relationship is present between the different variables. A first step here is to examine the stationarity of the different variables. To this end, we adopted the augmented Dickey–Fuller (ADF) [34] and the Phillips–Perron (PP) [72]. These tests continue to be the most commonly used methods to test for the presence of unit roots. While ADF test is a parametric one, PP makes a nonparametric correction to the t-test statistic. These traditional unit root test can yield biased results for time series with a structural break, so empirical studies have suggested that testing for breaks is important when determining the order of integration. Structural breaks can reflect technical, policy or institutional change. They may also because of changes in economic policies or large economic shocks, thereby indicating that they can have a permanent effect on the pattern of the time series. The insertion of a structural break in the unit root tests is particularly important because it could improve the reliability of the econometric tests used improving thus the accuracy of statistical inference [45].

As an example, we could use the unit root test of Perron and Vogelsang [73], because this considers a single structural break in the series when ascertaining the correct order of integration. This unit root test takes two forms to capture immediate and gradual shocks, namely the innovational outlier (IO) and the additive outlier (AO) models, respectively.

After researching the existence of relationships among the variables in the long run through cointegration techniques, it was possible to estimate the dynamic short- and long-run relationships with the *ARDL* model that was developed by Pesaran et al. [69]. This model can be applied irrespective of $I(0)$ or $I(1)$ series [68] and meets the need to consider the dependent variable's dynamic responses due to variations in its lags in addition to the other explanatory variables' lagged values [64]. Finally, by applying a simple linear transformation of the ARDL specification, the dynamic ECM can be generated thereby obtaining consistent coefficients of the short- and long-run relationships and proclaiming on the causality direction between the variables.

In a nutshell, ARDL models have been widely used in empirical literature and proved their capacity in analyzing long- and short-run dynamics [3, 4, 22–25, 39, 53], Naser et al. [66], [10]). Besides, since the main aim of this paper consists at empirically examining the short- and long-run relationships between COVID-19, stock returns and oil prices, the ARDL specification is given by the following expression:

$$\Delta SR_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta SR_{t-i} + \sum_{i=1}^{q} \beta_{2i} \Delta Covid_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta Oil_{t-i} + \pi_1 SR_{t-1} + \pi_2 Covid_{t-1} + \pi_3 Oil_{t-1} + u_t \quad (2)$$

where u_t is the white noise error term and Δ indicates first difference. The Wald test or joint F-statistic was used to jointly test the short-run coefficients, while the bounds test was applied to analyze the degree of cointegration among the considered variables. The F-statistic value was compared with the critical lower and upper bounds [69], such that an F-statistic value above the upper bound suggests there is a long-run relationship among the variables.

Under the ARDL framework, the short-run version can be expressed as follows:

$$\Delta SR_t = \gamma_0 + \sum_{j=1}^{m1} \gamma_{1j} \Delta SR_{t-j} + \sum_{j=1}^{m2} \gamma_{2j} \Delta Covid_{t-j} + \sum_{j=1}^{m3} \gamma_{3j} \Delta Oil_{t-j} + \psi ECT_{t-1} + \vartheta_t \quad (3)$$

where ECT is an error correction term that was included in the model.

Finally, the Granger causality test was applied to establish the causality's direction. Once a long-run relationship has been indicated by the cointegration test, Granger-type causality can be investigated by adding a single-period, lagged error correction term to the model. The ECM is expressed as follows:

$$\Delta SR_t = \theta_0 + \sum_{i=1}^{p} \mu_{1i} \Delta SR_{t-1} + \sum_{i=1}^{q} \mu_{1i} \Delta covid_{t-1} + \sum_{i=1}^{r} \mu_{1i} \Delta oil_{t-1} + \varphi_1 ECT_{t-1} + \epsilon_{1t} \quad (4)$$

Results and discussion

Summary statistics

Table 1 gives the data series' descriptive statistics, with total COVID-19 cases showing a high level of volatility.

Unit root testing

Performing unit root tests (ADF and PP unit root tests) enabled us to establish the order of integration for the series, and Table 2 gives the results of these tests.

The results presented in Tables 2 and 3 show that the variables are not stationary at level, but they are stationary when considering the first difference, so all variables have the I(1) order of integration. Furthermore, the unit root test with a structural break (Table 3) indicated that a unique order of integration exists. An analysis of the structural breakpoint of these variables suggests that the Saudi stock market has gone through a structural change after May 2022. The estimating ARDL model with automatic lag selection is ARDL (1,0,2) model. It was selected depending on the least AIC, as shown in Fig. 4.

Based on these results, it was deemed suitable to apply the ARDL bounds test to explore how the confirmed COVID-19 cases and the oil market prices affect stock market returns.

The results of the estimated short-run and long-run ARDL cointegration models (1,0,2), which were automatically selected based on the Akaike Information Criterion from 20 models, are presented in the tables below.

The bounds test for cointegration results

Table 4 gives the ARDL bounds test results, and this gives compelling evidence of cointegration between the various variables. Furthermore, the F-statistic was 5.285 which exceeds the 5% critical bounds value. We consequently concluded that a cointegration relationship exists, meaning that a long-run relationship is present among this study's variables.

Once the bounds test detected long-run cointegration, we set out to explore the long- and short-run relationships among the variables. The ARDL framework's short-run estimation yielded the results presented in Table 5, and these convey how oil prices and total COVID-19 cases did exert positive and significant influence on stock market prices in Saudi Arabia. Moreover, the lagged error correction term's coefficient had a negative value, with it being statistically significant at the 5% level, thus

Table 1 The descriptive statistics for the series

	Covid-19 CC	SR	Oil
Mean	221,000,000	9.19168	69.8495
Median	170,000,000	9.256417	69.03
Maximum	626,000,000	9.533897	127.98
Minimum	27	8.692774	19.33
Std. Dev	206,000,000	0.211816	25.31847
Skewness	0.663608	−0.37825	0.189946
Kurtosis	2.036732	1.922525	2.147341
Observations	1017	699	725

Table 2 Results of the ADF and PP unit root tests

Variables	ADF		PP	
	t-stat	Prob	*t*-stat	Prob
Oil	−2.8506	0.7198	−2.8156	0.1922
ΔOil	−21.549	0	−21.546	0
SR	−2.084	0.5531	−2.1327	0.5258
ΔSR	−25.329	0	−24.762	0
Covid	−1.9657	0.6187	−1.8695	0.6695
ΔCovid	−4.5292	0.0014	−6.8216	0

The Newey-West Bartlett kernel was utilized to establish PP's bandwidths

*, **, and *** refer to significance at 1%, 5% and 10%

Table 3 The Perron–Vogelsang test results with a single endogenous structural break

	IO model *t*-statistics	BD1	AO model *t*-statistics	BD1	Result
Oil	−3.690	6/28/2022	−3.693	6/28/2022	I(0)
SR	−4.119	3/11/2020	−4.912	5/11/2022	I(0)
Covid	−1.953	12/12/2021	−2.344	10/11/2022	I(0)
First difference					
ΔOil	−22.162	3/09/2022	−22.261	3/09/2022	I(1)
ΔSR	−26.182	5/12/2022	−26.126	5/12/2022	I(1)
ΔCovid	−4.889	2/14/2020	−5.877	12/21/2022	I(1)

BD Break date. *IO* Innovational outlier. *AO* Additive outlier

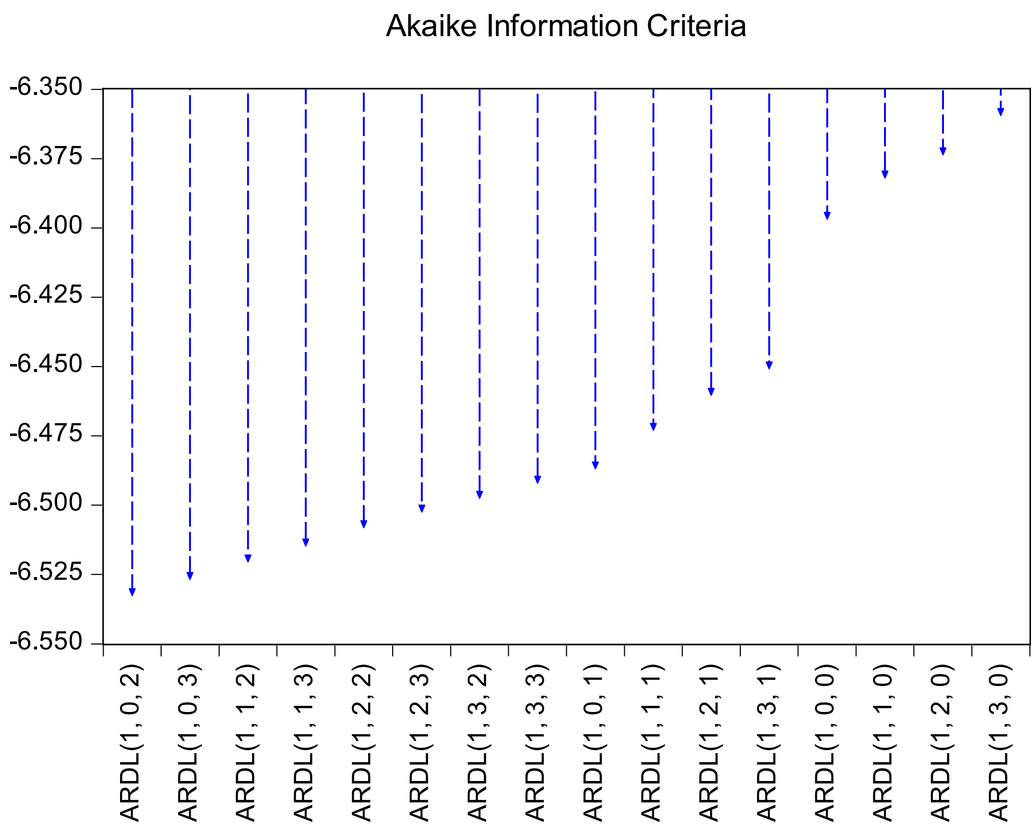

Fig. 4 Optimal lag length selection

Table 4 Results for the cointegration bounds test

Estimated Model	$F_{SR}(SR/LnCovid, LnOil)$			
$OptimalLagLength(SIC)$	**(1,0,2)**			
$F-Statistics(BoundTest)$ [a]	5.285*			
$CriticalValues$	1 Percent	2.5 Percent	5 Percent	10 Percent
$LowerBoundsI(0)$	5.15	4.41	3.79	3.17
$UpperBoundsI(1)$	6.36	5.52	4.85	4.14
$R-squared$	0.997			
$Adj.R-squared$	0.992			
DW	1.941			
$F-Statistics$	349.619*			

* represents the 1% significance level. The ARDL model's optimal lag length was selected by SIC. The critical values were sourced from the study of Pesaran et al. [69]

[a] The ARDL model using in this study featured an unrestricted constant and no trend (Case 3). DW refers to the Durbin–Watson test statistics

Table 5 Results for the ARDL short-run estimation

Dependentvariable : *SR* (1,0,2)			
Variable	**Coefficient**	**StandardError**	**t − statistics**
SR_{t-1}	1.227	0.185	6.187*
$LnOil$	0.086	0.045	2.667**
$LnCovid$	0.273	0.087	3.225**
$Constant$	1.776	0.333	5.123**
ECT_{t-1}	−0.082	0.002	-3.928**
$R-squared$	0.888		
$Adj.R-squared$	0.877		
$F-Statistics$	8.634*		
$S.Eofregression$	0.008		
$SumSquaredresid$	0.025		

* and ** represents significance at 1% and 5% level respectively

suggesting the presence of long-run cointegration relationships among the considered variables and suggesting convergence to a long-run equilibrium from a short-run disequilibrium. Moreover, its value is (-0.082), which implies a speed of adjustment of about 8.2%.

In addition to the short-run results, the ARDL model's long-run estimation further supported the positive impacts of oil prices and COVID-19 cases on Saudi stock market prices (Table 6). The coefficient for the oil prices term was 0.177, suggesting that it had the greatest significant impact on stock market prices, which is

Table 6 The long-run results for ARDL (1,0,2)

Dependentvariable : ΔSR			
Variable	**Coefficient**	**StandardError**	**t − statistics**
LnOil	0.177	0.017	4.392*
LnCovid	0.030	0.022	3.042**
Trend	0.002	0.003	0.911

* and ** represents the 1% and 5% significance level, respectively

unsurprising and in line with many previous studies [14, 87]. Saudi Arabia is a major exporter of oil, so it makes sense that its stock market will be sensitive to shocks in oil market prices. Indeed, changes in oil prices, especially for Brent Crude, significantly influence financial markets in oil-exporting countries. For example, an increase in the price oil means greater revenue for such countries, enabling them to invest more in capital and operational projects, which in turn leads to increasing demand and consumption in the economy. This then increases the profitability of local companies, which is then reflected in their share prices. Additionally, increased government spending leads to greater liquidity in the economy, and much of this undoubtedly finds its way into the financial markets, so the demand for shares increases and their prices rise. The above findings indicate that oil prices are the most important driver of the variance in Saudi stock market returns, which is consistent with those of Kang et al. [55], Clements et al. [31], Hwang and Kim [50], and Al-Najjar [9]. The opposite happens in the case of declining oil revenues.

In contrast, the coefficient for the total COVID-19 cases was 0.030, highlighting the limited effect this had on stock prices. A likely explanation for this lies in how the coronavirus pandemic reduced the demand for oil, because industrial production and transportation dropped in many countries due to quarantine measures. This in turn had a profound effect on the Saudi stock market due to the inevitable drop in oil prices. This confirms that the pandemic had an indirect effect on stock prices through the consequences of low oil prices, and this was much stronger than any direct effect. In spite the limited effect, it is clearly shown the existence of positive relationship between world oil prices and stock market returns. A reduction in oil prices will dampen stock market performance. Our findings are in line with those of Yan et al. [90], Zhang et al. [92] and Alamgir and Amin [6] who demonstrate substantial stock market returns and WTI oil prices moving in lockstep.

Table 7 Diagnostic test results for the long-run estimation

Diagnostictest	χ^2_{SC}	χ^2_{BPG}	χ^2_{ARCH}	*RamseyResetTest (F − Statistics)*
	0.129 (0.732)	1.986 (0.269)	1.277 (0.301)	6.166 (0.211)

SC, *BPG*, and *ARCH* represent the Lagrange multipliers (LMs) for the serial correlation test, the Breusch–Pagan–Godfrey test, and the ARCH heteroscedasticity test, respectively. The P values are given in brackets, while the F-Statistics were accounted for in the Ramsey RESET test

Table 7 reports the long-run ARDL model's results for the diagnostic tests, with all the estimations passing all the diagnostic tests, thus verifying the fundamental assumptions for a classical linear regression model. There was no indication of any heteroscedasticity or serial correlation between the residuals.

We used the Ramsey RESET test to evaluate the results' stability, and this indicated that the model was indeed stable. Thus, the validity and reliability of the ARDL estimates were confirmed by the diagnostic tests.

Finally, for checking the stability of the ARDL estimated model CUSUM is used. Figure 5 confirms the stability condition since CUSUM lines are within the boundaries thereby lying inside the significance level.

Demonstrating the ARDL Model's robustness with the Bayer–Hanck cointegration test

The ARDL model was tested for robustness with the Bayer–Hanck [20] test for combined cointegration. This test uses multiple statistics to test the null hypothesis of there being no cointegration. Bayer and Hanck [20] suggested combining the calculated significance levels (*p values*) of the various cointegration tests into Fisher [38]'s formula as shown as follows:

$$EG - JOH = -2[ln(pEG) + ln(pJOH)]$$

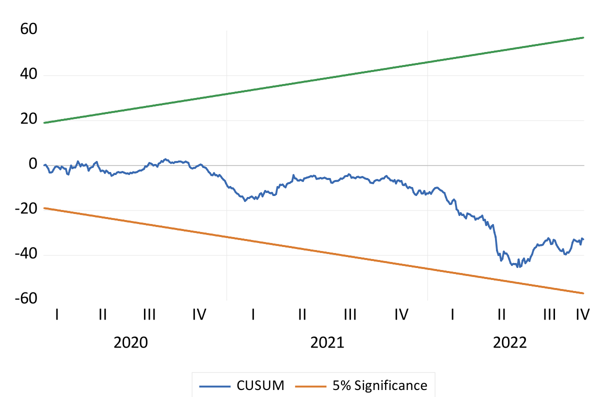

Fig. 5 CUSUM long-run analysis stability test

Table 8 Bayer–Hanck test results

Model specification	Fisher Statistics	Cointegration decision	
	EG–JOH	EG–JOH–BOS–BDM	
$SR = f(LnCovid, LnOil)$	14.138*	37.668*	Cointegration exists
Significance level	Critical values		
Significance level at 1%	18.2234	32.854	
Significance level at 5%	12.223	21.099	
Significance level at 10%	07.925	17.695	

* significant at the level of 1%

$$EG - JOH - BO - BDM = -2[ln(pEG) + ln(pJOH) + ln(pBO) + ln(pBDM)]$$

where pEG, $pJOH$, pBO and $pBDM$ are the *p values* for the various tests of cointegration. When the calculated Fisher statistic exceeds the critical values proposed by Bayer and Hanck [20], we can reject the null hypothesis (i.e., there being no cointegration).

Table 8 gives the actual results. These indicate the presence of cointegration, because the F-statistic value for the Engle–Granger–Johansen (EG-JOH) test is greater than the critical level for 5% significance, while the Engle–Granger–Johansen–Banerjee–Dolado–Mestre–Boswijk (EG–JOH–BOS–BDM) yielded a high enough value to qualify for 1% significance. Thus, we rejected the no cointegration null hypothesis, further confirming the ARDL bounds test's previous results.

ECM Granger causality analysis

Guided by the presence of cointegration in the series, to establish the direction of causality between the various considered variables, an error correction model (ECM) was applied. Granger causality testing helps indicate if some variables are cointegrated in a long-run relationship. The results given in Table 9 represent the causal relations between stock market returns, oil prices, and total COVID-19 cases. Three Granger causality tests have been performed: the short-run test, the long-run test, and the joint short- and long-run test. While the first test indicates the significance of the sum of lagged terms of each explanatory variable, the one indicates the significance of the error correction term. Finally, the third test is the short-run adjustment to restore the long-run equilibrium.

For causality in the long run, the lagged error correction terms' coefficients are significant and negative, thus confirming the existence of bidirectional causality and long-run relationships among the variables. More specifically, significant lagged error correction terms were identified for stock market prices and total COVID-19 cases. However, only an insignificant coefficient was found for the oil price variable. In the short run, total COVID-19 cases and oil prices caused movements in stock market returns.

In the longer term, oil market prices and COVID-19 infected cases were found to "Granger-cause" stock market prices with an ECT of (−0.002), thus indicating the speed of adjustment, whereby in the long run, the relationships that stock returns have with oil prices and total COVID-19 cases converges back to equilibrium by 0.2% in each period. Over the same longer term, stock prices and total COVID-19 cases together "Granger-cause" oil prices with an ECT of (−0.026), with this being statistically significant at the 1% level. This relationship therefore approaches the long-run equilibrium by about 2.6% every period.

Results of the significance of interactive terms of change in stock returns ($\Delta LnStock$) along with the ECT in the COVID-19 cases equation are consistent with the presence of Granger causality running from COVID-19 infected cases to stock returns. These indicate that whenever there is the presence of a shock to the system, stock returns would make short-run adjustments to re-establish long-run equilibrium. Furthermore, results of the significance of interactive terms of change in oil prices ($\Delta LnOil$) along with the ECT in the COVID-19 cases equation are consistent with the presence of Granger causality running from COVID-19 infected cases to oil prices. These indicate that whenever there is the presence of a shock to the system, oil prices would make short-run

Table 9 Granger causality test results

Dependent Variable	*F*-Statistics short-run (Probability)		Long run		Joint short- and long-run *F*-Statistics (Probability)		
	$\Delta LnStock$	$\Delta LnOil$	$\Delta LnCovid$	ECT_{t-1}(t-statistics)	$\Delta LnStock.ECT_{t-1}$	$\Delta LnOil.ECT_{t-1}$	$\Delta LnCovid.ECT_{t-1}$
$\Delta LnStock$	–	1.879 (0.098)	2.230 (0.089)	−0.002 (−2.388)**	–	2.111 (0.065)***	2.665 (0.076)***
$\Delta LnOil$	0.047 (0.866)	–	0.009 (0.901)	−0.026 (−4.546)*	2.066 (0.219)	–	2.325 (0.086)***
$\Delta LnCovid$	0.122 (0.866)	0.069 (0.909)	–	−0.0004 (−0.062)	0.674 (0.807)	6.085 (0.004)*	–

***, ** and * represents 10%, 5% and 1% significance, respectively adjustments to re-establish long-run equilibrium. Henceforth, we confirm the presence of bidirectional Granger causality in the long run.

Finally, such causalities among of oil and stock variations indicate that shocks of both assets tend to move in opposite directions, which can be considered advantages to Saudi investors who, even in the period of crisis, can trade-off between oil and stocks, to reduce investment weight in one of these assets or substitute one another, thereby obtaining the optimal risk-return profile. Our findings are consistent with those of Escribano et al. [37] and Younis et al. [91] who argued that correlation between oil and equity markets increased widely in normal and crises conditions but contradict those of Razmi and Razmi [75] in the US context where stock market lost its significant impact on the oil market after the COVID-19 pandemic.

Conclusion

In this study, our primary aim was to comprehensively understand how the COVID-19 pandemic affected the Saudi stock market while considering the oil market. We also attempted to examine the relationship between the COVID-19 confirmed cases, stock returns and oil prices. It can be considered a pioneering study of how the COVID-19 pandemic had financial consequences. Goodell [41] highlighted the importance of such research question. According to the author, "a consideration of possible impacts of COVID-19 on financial markets and institutions, either directly or indirectly, is briefly outlined by drawing on a variety of literatures". Furthermore, "no doubt these questions and many others will be grappled with by financial academics for many years to come".

The main findings shed some light on how oil prices and total cases did exert positive and significant influence on stock market prices in Saudi Arabia. Besides, oil prices are shown as the most important driver of the variance in Saudi stock market. This result seems to be consistent with the findings of Kang et al. [55], Clements et al. [31] and Hwang and Kim [50]. Finally, the results of Granger causality confirm the existence of bidirectional causality and long-run relationships among the variables COVID-19 confirmed cases, Saudi stock market and world oil prices.

Our findings carry prominent and significant policy and practical implications. It is becoming clear that the COVID-19 pandemic is causing a positive response in the Saudi stock market, although in the crisis periods, the impact on stock prices was more negative than positive. The increase in stock prices was likely due to successful government interventions aimed at managing the crisis. This help reduce uncertainty by developing a coherent economic strategy for the pandemic that increased market agents' trust in stocks. Moreover, the pandemic's strong short-term effect on Saudi stock prices should not distract us from the fact that investors may have expected a subsequent recovery in the stock market, especially with continuous government interventions by removing regulatory and legal obstacles and better improving the risk management, allowing thereby a quick decision making in response to any oil price volatilities.

On the other hand, asset managers and policymakers should deal reactively and proactively and with coping strategies for crises to comfort stock investors' anxieties over the increasing oil market crises. They should act in line with more prudent risk management practices, by considering concrete mitigation actions including but not exclusively the reviewing of the overall risk management framework moving from periodic (or on demand) monitoring to a more active and continuous one, the introduction of concrete mechanisms to mitigate non-financial risk, and the adoption of contingency measures on all aspects of valuation particularly in the presence of alternative assets.

Besides, economic policies must be adapted to how oil market fluctuations affect the overall economy. In order to create suitable measures to protect the economy from any negative oil price shocks, policymakers have to understand the nexus between oil and stock markets. Monetary authority (Saudi central bank) may consider the adjustments of interest rates and policy tools to ensure stability and improve market resilience during turbulence periods in oil markets. Finally, considerable efforts should be made to promote renewable energy and reduce dependence on fossil fuels.

Due to the limited sample size and the tests' statistical inference, our findings should be treated with an element of caution. Further observations may contribute to more serious results. Nevertheless, these findings do open opportunities for further studies to look in more detail at how the COVID-19 pandemic affected, over the short and long run, the Saudi stock market, monetary policy, fiscal policy, financial stability, and various other macroeconomic indicators based on a larger sample and possibly even real-time data. Furthermore, alternative empirical strategies, such as artificial neural networks, quantile regressions, and machine learning, can be performed in future research.

Abbreviations

ARDL	Autoregressive distributed lag
ECM	Error correction model
SVAR	Structural vector autoregressive
WHO	World health organization
US	United States
TVC	Time-varying causality
TVP-VAR	Time-Varying Parameter VAR
FMVI	Financial market volatility index
SM	Stock market

SR	Stock returns
OR	Oil returns
EIA	Energy information administration
ADF	Augmented Dickey–Fuller
PP	Phillips–Perron
IO	Innovational outlier
AO	Additive outlier
EG-JOH	Engle–Granger–Johansen
EG-JOH-BOS-BDM	Engle–Granger–Johansen–Banerjee–Dolado–Mestre–Boswijk
ECT	Error correction term
WTI	West Texas Intermediate

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