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The impact of COVID-19 uncertainties on energy market volatility: Evidence from the US markets

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ABSTRACT

This research investigates the influence of the COVID-19 on the returns of energy indexes in the US using daily time series data of WTI and Brent markets for the January 2020 – March 2022 period. The findings reveal compelling evidence of the effects of the COVID-19 on the volatility of energy commodity indexes in the US. Nevertheless, the magnitude of this impact varies across different volatility regimes. Notably, the WTI crude oil exhibits more substantial effects during periods of lower volatility characterised by fewer COVID-19 cases, potentially attributed to market control measures. In contrast, the Brent crude oil displays a more pronounced impact of the COVID-19 during turbulent periods, attributed to the market's openness and the prevalence of speculative participants. The study suggests that participants in the Brent market, driven by a desire to capitalise on price differentials, intensify their activities during turbulent periods, contributing to increased volatility during successive waves of high COVID-19 cases. The observed structural differences between the WTI and Brent commodity markets carry significant policy implications for investors in the energy sector.

1. Introduction

The global energy sector, financial markets, and prices of energy commodities have all been significantly impacted by the COVID-19 pandemic (Guo et al., 2022; Uddin et al., 2024). This crisis has unveiled vulnerabilities in supply chains across the globe (Chowdhury et al. 2021), leading to concerns about the security of energy resources (Friedman, 2022). Moreover, the disruptions in supply chains during this period have resulted in significant fluctuations in the prices of precious metals like gold, base metals (e.g., copper), and rare earth metals (Chen et al., 2020; Moktadir et al., 2023). Additionally, the global consumption of oil experienced an unprecedented decline of 8.6 million barrels per day during the same period, intensifying the fall in oil prices and causing severe repercussions for companies operating in this industry (Jia et al., 2021). The pandemic in particular has exerted a profound influence on global stock markets, leading to increased volatility and declining prices, particularly in sectors such as energy and natural resources (Jiang et al., 2020; Song et al., 2021). Numerous academic investigations have delved into the connection between the COVID-19 and fluctuations in energy commodity prices. For example, Zhang et al. (2020) examined how the pandemic influenced

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energy prices, with a particular focus on its notable impact on oil prices. Meanwhile, Farooq et al. (2021) demonstrated that the economic uncertainty stemming from the COVID-19 led to higher gold prices. Despite extensive research on the relationship between the COVID-19 and stock market volatility, there has been relatively little attention given to exploring the enduring consequences of this pandemic specifically on energy stocks (Batrancea, 2021). Most existing studies have primarily concentrated on short-term impacts, leaving a gap in our understanding of how the long-term effects may manifest within the financial sector (Balcı et al., 2022a; Yadav et al., 2023). Further, there is a need for additional empirical evidence regarding the interaction between the stock index of the energy sector and the broader economic and social consequences stemming from the COVID-19. Therefore, research on examining both the lasting impacts on energy sector stocks and their connections with wider socio-economic factors affected by the COVID-19 (Shahzad et al., 2021; Wang et al. (2023) becomes necessary. Moreover, given that the escalating geopolitical tensions continue to shape the future prospects of the energy sectors (Batrancea, 2021; Batrancea et al., 2021a, 2021b; Goodell et al., 2023; Chen et al., 2023; Zeng et al., 2024) and also the International Monetary Fund (IMF) prediction of a post-pandemic global crisis of a magnitude comparable to the Great Depression makes it a pressing issue for all countries (Ashraf, 2020), directing research efforts towards gaining a deeper understanding of the intricate interconnections amid these factors (Aktar et al., 2021) is vital.

"The US, Spain, Russia, the UK, Italy, Brazil, France, German, Turkey, and Iran were the top-10 countries in terms of the confirmed cumulative total of COVID-19 cases. Among them, the US alone witnessed the highest number of cases" (Bouteska et al., 2023), experiencing profound and far-reaching impacts on various aspects of their societies. As of May 3, 2023, the US reported over 103 million confirmed cases of the virus, resulting in more than 1 million fatalities, according to the World Health Organization (WHO) data from 2023 (Bouteska et al., 2023). Furthermore, this outbreak has significantly disrupted its economy. The US saw its GDP contract by approximately 3.5 %. The economic toll of the pandemic was staggering, with the US facing an estimated financial loss of $16 trillion, as reported by the International Monetary Fund (IMF) in 2023 (Bouteska et al., 2024). Moreover, the US witnessed a surge in unemployment rates, reaching record highs. The US lost nearly 22 million jobs. The COVID-19 outbreak has underscored the critical importance of preparedness for future pandemics and has highlighted the need for a coordinated global response to public health emergencies, as emphasized by the United Nations (UN) in 2023 (Ha et al., 2024). When we contrast the circumstances in the US, it becomes apparent that the US encounters high pronounced fluctuations in the COVID-19 cases and associated deaths. This can be ascribed to frequent policy changes, especially those pertaining to lockdown measures. Apart from the various socio-economic repercussions, the COVID-19 pandemic has continued to exert adverse effects on the stock markets of the US (Balcı et al., 2022b; Rahman et al., 2021; Razmi and Razmi, 2023). For instance, in March 2020, the S&P 500 index experienced a decline of over 30 % from its previous peak, and at the same time, the Dow Jones Industrial Average reached historically low levels, marking its worst single-day crash ever recorded (Baek et al., 2020). Throughout much of 2020 and 2021, the US witnessed significant market fluctuations, resulting in remarkable volatility in its financial markets (Bouteska et al., 2023a, 2023b, 2023c; Wang et al., 2024). Amidst the uncertainties prevailing in the US stock markets, a CNBC report disclosed staggering losses incurred during February-March 2020 alone, amounting to an astonishing $16 trillion in the US, encompassing its respective economic domain. All these reports associated with the world's largest economy witness the intricate connection between the global health crisis and financial markets. A comprehensive examination of this phenomenon has the potential to provide insights into potential solutions for maintaining economic stability during times of crisis. In light of this backdrop, this research aims to conduct an empirical examination to assess the impact of the COVID-19 pandemic on the performance volatility of the energy sector indices in the US, using daily time series data of the two globally recognised oil benchmarks, i.e., West Texas Light (henceforth, WTI) crude oil and North Sea Brent (hereafter, Brent) crude oil markets (Wei et al., 2022), for the January 2020 – March 2022 period. Due to its significance to any economy, particularly vulnerability during crisis periods (Dharani, et al., 2023; Iyke, 2020; Yadav et al., 2024), we set our focus on the energy sector.

The findings reveal compelling evidence of the influence of the COVID-19 on the volatility of energy commodity indexes in the US. Nevertheless, the magnitude of this impact varies across different volatility regimes. Notably, the WTI crude oil exhibits more substantial effects during periods of lower volatility characterized by fewer COVID-19 cases, potentially attributed to market control measures. In contrast, the Brent crude oil displays a more pronounced impact of COVID-19 during turbulent periods, attributed to the market's openness and the prevalence of speculative participants. The study suggests that participants in the Brent market, driven by a desire to capitalize on price differentials, intensify their activities during turbulent periods, contributing to increased volatility during successive waves of high COVID-19 cases.

The novelty of this paper lies in the contributions it makes to literature. First, there is plethora of research (e.g., Chai et al., 2022; Phan and Narayan, 2020; Ramelli and Wagner, 2020; Balcı et al., 2022b; Bouteska et al., 2023a, 2023b, 2023c, 2024) on the recent pandemic's impact on the reactions of stock prices. Also, extant research (e.g., Apergis and Apergis, 2020; Fu and Shen, 2020; Gil-Alana and Monge, 2020; Iyke, 2020; Liu et al., 2020; Narayan, 2020; Qin et al., 2020) focus on investigating the effect of oil price variations on various economic factors during the COVID-19 pandemic. Unlike this study, as Amamou and Bargaoui (2022) argued, the existing investigations have not deeply explored the nature and magnitude of influence of this crisis on crude oil markets. Second, given the substantial losses to investments that were predicted as a consequence of the volatility of the major oil markets in these markets (Dutta et al., 2020), this study tests the impact of the COVID-19 on the oil markets, using the two leading oil markets (i.e., Brent and WTI) as the proxies, for the January 2020–March 2022 period. Third, although "many research papers concentrated on capturing financial market spillover effects, downside risk–return spillovers, and their effects on market volatility" during the pandemic (Mamilla et al., 2023), this is probably the first empirical study to investigate the influence of the COVID-19 on the returns of energy indexes in the US using daily time series data of two pioneering oil markets (Wei et al., 2022). Fourth, although academic literature postulates that the COVID-19 leads to uncertainty and that uncertainty influences the energy sector, little is known about the impacts of COVID-19 related uncertainty on the returns, volatility and investor behaviour in the energy sector (Szczygielski et al., 2021; Goodell et al., 2023). Fifth, the findings underscore the structural differences between these markets, and carry significant policy implications for investors in the energy sector. This outcome in this study fills a gap in research by contradicting the finding of Gharib et al. (2021) that suggested a statistically significant negative financial bubble for both WTI crude oil and Brent crude oil markets during the COVID-19 outbreak. Sixth, given that oil price shocks had substantial effect on the stock markets of the US and Canada than those of the other countries (Yan et al., 2022), we consider investigating the effect of the pandemic-driven uncertainty on returns and volatility for the US energy industry of paramount importance.

The remainder of the paper is as follows: Section 2 presents literature review, Section 3 outlines data and methodology, Section 4 highlights empirical results and discussion, and Section 5 presents concluding comments.

2. Review of literature

Extant literature documents studies that investigate the effects of various Black Swan events on financial market returns comprising calamities (Kowalewski and Śpiewanowski, 2020), news of crises (Li, 2018), political issues (Shanaev and Ghimire, 2019) and endemics, such as the SARS (Chen et al., 2009) and Ebola (Ichev and Marinc, 2018). A group of such studies suggest that “big shocks, such as the 2008 global financial crisis (GFC), produce fundamental changes in commodity and financial markets, with potentially asymmetric impacts on market efficiency, portfolio allocation, and volatility fluctuations” (Balci et al., 2022). More recently, a new series of studies (e.g., Ramelli and Wagner, 2020; Balci et al., 2022; Bouteska et al., 2023; Moktadir et al., 2023) highlight more perilous economic and financial effects of the COVID-19, compared with the consequences of the GFC (Shehzad et al., 2020). The pandemic caused widespread disruptions for the global financial markets, resulting in heightened fluctuations in stock prices (Akhtaruzzaman et al., 2020; Jelilov et al., 2020; Yadav et al., 2023).

Stock markets serve as a primary platform for global capital exchange and their performance therefore holds a pivotal role in shaping national economies (Zahedi and Rounaghi, 2015; Bouteska et al., 2023a, 2023b, 2023c, 2024). Given that macroeconomic indicators significantly affect stock markets, extensive research into the relationship between the pandemic, stock markets, and price volatility has ensued (Hui and Chan, 2022). For instance, Ali et al. (2020) documented a worsening volatility in the stock markets of the US, UK, Germany and South Korea during the transition period of the COVID-19 from an epidemic to a pandemic. Gormsen and Koijen (2020) added that the US and German stock markets deteriorated sharply once the COVID-19 had blowed out to Italy, Iran and South Korea. Al-Awadhi et al. (2020) investigated the effects of the COVID-19 pandemic on stock market volatility in the Gulf Cooperation Council (GCC) countries and discovered that the pandemic had a significant impact, leading to increased volatility in the stock markets of these nations. Ashraf (2020) observed a negative influence of the rising number of daily cases and deaths on stock returns across 64 affected countries during the pandemic. Similarly, Shehzad et al. (2020) reported a significant negative influence of the COVID-19 had on S&P 500 Index and an insignificant impact on Nasdaq Composite Index. Liu et al. (2021) found that the COVID-19 pandemic had resulted in notable volatility in the Chinese stock market. Baker et al. (2020) emphasize that the impact of this virus on stock market instability is not only historically significant but also attributes the primary cause of increased volatility to government restrictions on commercial activities. According to their findings, countries with more extensive restrictions in place to combat the spread of the pandemic have experienced higher levels of stock market turbulence due to event cancellations and efforts to inform people about safety precautions. Bhutto et al. (2022) revealed that the COVID-19 had a substantial adverse effect on the stock market performance in Pakistan. More recently, Bouteska et al. (2023) examined the regime-switching and time-varying dependence between the COVID-19 pandemic and the US stock markets, and suggested a simultaneous but significant financial market reaction to any unanticipated occurrence of a natural calamity or a pandemic. Furthermore, research has explored the pandemic's effects on different segments of the stock market. For instance, Lee et al. (2021) observed that the COVID-19 had a substantial adverse effect on the tourism and hospitality sector in China. Similarly, Sun et al. (2021) and Huang et al. (2020) examined the impact of the COVID-19 on the Chinese stock market and revealed that the pandemic had a significant negative influence on sectors including transportation, retail, and tourism. Li et al. (2021) also found that the pandemic had a significant impact on China's stock market, leading to increased volatility and a decrease in asset prices, particularly in sectors such as finance, real estate, and energy.

Research in this field has also delved into the role of various factors in moderating the relationship between the COVID-19 and stock market volatility. For instance, Huang et al. (2020) investigated the influence of the exchange rate volatility and observed a significant impact on stock market volatility in China during the pandemic. Li et al. (2021) investigated the influence of news sentiment and discovered that it played a significant moderating role in the connection between the COVID-19 and stock market returns in the US. In a similar fashion, Smales (2021) and Szczygielski et al. (2021) investigated Google search trends in the G20 countries and various regions of the world respectively, and observed contribution of the COVID-19 related news to swell volatility of various degrees across industries. Recently, Batrancea et al. (2023) examined tweets related to economy, politics and world topics and observed a similar moderating role of news in the COVID-19-stock market nexus in Turkey. Zaremba et al. (2020) examined the effect of the COVID-19 on stock market volatility and revealed that the pandemic had a more pronounced impact on countries with weaker institutional quality and less-developed financial markets. In a similar vein, multiple research studies have examined the moderating role of government interventions, including fiscal and monetary policies, in alleviating the pandemic's impact on financial markets. For instance, Gormez-Gonzalez et al. (2020) found that government policy responses to the pandemic had a noteworthy impact on stock market volatility in the US. Similarly, Balcilar et al. (2021) suggested that government policy response to the pandemic, such as fiscal and monetary measures, had a substantial influence on stock market volatility in emerging economies. Given the substantial losses and declines in stock markets, it became imperative to implement extensive fiscal and monetary policies, along with providing economic support. These measures were put in place to safeguard human health, mitigate further financial losses, and ensure the stability of the stock market during the COVID-19 pandemic (Gourinchas et al., 2020).

Other research studies have delved into the connection between the COVID-19 and commodity prices. For example, Dutta et al.

(2020) observed extremely volatility of crude oil assets during February-March 2020 which led to significant losses in investments in this market, causing strong possibilities of tail-risks in the oil-derived assets. Gao et al. (2022) investigated the influence of the COVID-19 on crude oil prices and observed that the pandemic resulted in a noteworthy decline in the demand for crude oil, leading to a subsequent price decrease. Similarly, Khan et al. (2021) discovered that the volatility of oil prices had a substantial impact on stock market volatility in Pakistan during the pandemic. Nyga-Łukaszewska and Aruga (2020) found evidence of the short and long run influence of the number of COVID-19 cases on crude oil and natural gas markets during 21 January 2020 2 June 2020 in the US and Japan. The authors also observed a negative effect of the cumulative number of COVID-19 cases on the crude oil price and a positive impact on the natural gas price. On the contrary, the results demonstrated a short-run shock in the crude oil market and no effect of the pandemic shock on the natural gas market in Japan. Qadan and Idilbi-Bayaa (2021) analyzed the effects of the COVID-19 on gold prices and found that the pandemic had a significant effect, causing increased demand for gold as a safe-haven asset. Unlike previous pandemics or financial crises, the global economic challenges posed by the COVID-19 have resulted in unprecedented aftershocks, with severe impacts on economies, including China and the US (Ayittey et al., 2020). For example, Alfaro et al. (2020) conducted an analysis for the US, while Ruiz Estrada et al. (2023) conducted an analysis for China, both of which indicate that the negative consequences arising from these stringent measures could lead to a reduction of up to 0.5 % in the extent of global GDP loss across various sectors worldwide.

Common statistical measures used to assess volatility include standard deviation (SD), skewness, and kurtosis. However, the primary measure, SD, has limitations because it relies on assumptions of a normal distribution regarding returns. Additionally, Gençay et al. (2001) found that skewness primarily focuses on high-data approaches rather than considering average profits. Financial time series data possesses unique characteristics that differentiate it from ordinary data, requiring specialized methods for the analysis of financial asset returns. These distinctive features encompass characteristics such as leptokurtic dispersion, volatility clustering, and the influence of leverage. In periods of economic turmoil, such as a crisis induced by a pandemic, conventional modeling approaches prove inadequate in accurately measuring return volatility. Consequently, time-varying models become more preferable. Researchers have put forth various techniques to address this issue, including the Autoregressive Conditional Heteroscedasticity (ARCH) model, which accommodates changes in volatility over time. Another notable approach is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, introduced by Engle (1982) and popularised by Bollerslev (1986). The GARCH models are known to stand out for its precision, making it a reliable method for modeling return volatilities in financial time series data (Brooks et al., 2002). In particular, these models perform well in measuring time-varying volatility which is typically characterised by a non-normal distribution of the financial series that generally display heteroskedasticity. Andersen and Bollerslev (1998) observed that the GARCH models made a more precise prediction than the realized volatility proxy for FX data. Likewise, Blair et al. (2001) reiterated a similar finding, generating an R2 of about 50 %. More recently, Bouteska et al. (2023) reiterated the suitability of using a Markov-switching GARCH model in examining the regime-switching and time-varying dependence between a Black Swan event and stock returns, proxied by the COVID-19 and the US stock markets respectively.

It is evident from the above review that a plethora of research (e.g., Phan and Narayan, 2020; Ramelli and Wagner, 2020; Balcı et al., 2022b) have been conducted on the impact of the recent pandemic's impact on stock prices. Also, a group of researchers (e.g., Apergis and Apergis, 2020; Fu and Shen, 2020; Gil-Alana and Monge, 2020; Iyke, 2020; Liu et al., 2020; Narayan, 2020; Qin et al., 2020) have focused on assessing the influence of oil price fluctuations on various economic factors during the COVID-19 pandemic. As Amamou and Bargaoui (2022) argued, the current studies have failed to make an in-depth investigation of the nature and magnitude of influence of this crisis on crude oil markets. Although "many research papers concentrated on capturing financial market spillover effects, downside risk–return spillovers, and their effects on market volatility" during the pandemic (Mamilla et al., 2023), no study can be found to investigate the influence of the COVID-19 on the returns of energy indexes in the US using daily time series data of two pioneering oil markets (Wei et al., 2022). Also, although academic literature postulates that the COVID-19 leads to uncertainty and that uncertainty influences the energy sector, little is known about the impacts of COVID-19 related uncertainty on the returns, volatility and investor behaviour in the energy sector (Szczygielski et al., 2021). Moreover, the extant literature does not have sufficient investigations regarding the substantial effect that oil price shocks have on the stock markets of the US and Canada compared to those of the other countries (Yan et al., 2022). Given these gaps in literature, it is significant to investigate the impact of the pandemic-driven uncertainty on returns and volatility for the US energy industry of paramount importance. Also, due to the predicted significant losses to investments as a result of the volatility of the leading oil markets (Dutta et al., 2020), it is vital to examine the effects of the COVID-19 on the oil markets, using the two leading oil markets (i.e., Brent and WTI) as the proxies.

3. Data and methodology

3.1. Data

In selecting data for analysis, we employed specific criteria to ensure the relevance and accuracy of our findings. Firstly, regarding COVID-19 data, we focused on daily confirmed case counts within the United States from January 20, 2020, to March 31, 2022. This timeframe aligns with the onset and aftermath of the COVID-19 pandemic, allowing us to capture its full impact on the energy sector. For the energy sector indices, namely the Brent crude oil index and West Texas Intermediate (WTI) crude oil index, we collected daily price information. These indices serve as key indicators of market performance within the energy sector, particularly in the context of the United States. Our selection criteria prioritize inclusivity by encompassing a comprehensive dataset spanning from the early stages of the pandemic to its later phases. By including data from both the Brent and WTI crude oil indices, we ensure a holistic representation of the energy sector's performance. The choice to focus exclusively on the United States enables us to analyze the pandemic's impact within a specific economic context, allowing for more nuanced insights into how volatility in stock returns within the energy sector was influenced. Overall, our data selection criteria aim to provide a thorough understanding of the relationship between the COVID-19 pandemic and stock market volatility within the energy sector, thereby shaping the scope and depth of our analysis. Table 1 provides a comprehensive overview of the variables and data used in the study.

3.2. Method

One of the oldest techniques used by the scientific community (Hamilton, 1989; Van Norden, 1996; Lammerding et al., 2013; Gharib et al., 2021) to explore the presence of financial market volatility is Markov regime switching (MRS). Moreover, scholars such as Engle (1982), Bollerslev (1986), Leung et al. (2000), among others, endorsed GARCH as the best model for analysing the capricious nature of stock returns, with a relatively large sum of observations. To produce unbiased conditional volatilities for the returns of the natural resource commodity index, this study employs various configurations of the Markov switching GARCH model (Ardia et al., 2019). The GARCH entails the use of three distinct distribution functions, namely normal, Student-t, and generalized random term.

Our methodology encompasses not only a fundamental GARCH specification within the Markov switching framework but also integrates T-GARCH specifications to account for potential asymmetries across different regimes. We investigate the MS-GARCH model due to its inherent ability to identify structural breaks in variance, thereby reducing the risk of overestimation. To address serial correlation, we assume an $AR(1)$ criterion for the conditional mean of all analyzed vectors. The model assumes errors following one of the three aforementioned distributions: normal $\varepsilon \sim N(0, h_t)$, Student-t $\varepsilon \sim x(0, h_t, v)$, and generalized error distribution $\varepsilon \sim GED(0, h_t, k)$. The subsequent presentation of regime-switching GARCH specifications follows a sequential order — simple GARCH and TGARCH in Eqs. (1) and (2), respectively.

$$h_t = \omega_x + \alpha_{2x}\omega_{t-1}^2 + \beta_{3x}h_{t-1} \tag{1}$$

$$h_t = \omega_{1x} + a_{2x}h_{t-1}\omega_{t-1}^2 + \beta_{3x}h_{t-1} + \delta_{4x}h_{t-1}\omega_{t-1}^2 I_{t-1} = \begin{cases} 1 \text{ if } \varepsilon_{t-1} \text{ if } < 0 \\ 0 \text{ if } \varepsilon_{t-1} \text{ if } > 0 \end{cases} \tag{2}$$

In this context, h_t denotes 'conditional volatility,' ω is a constant dependent on the state, and α and β measure the ARCH and GARCH effects within the x regime. δ acts as the 'regime-switching coefficient,' evaluating the nonlinear response of volatility to positive and negative shocks in T-GARCH models. The estimation of all models adheres to the 'maximum-likelihood methodology' as specified in Eq. (3).

$$L = \sum_{t-1}^{T} \log\left[q_{1t}\frac{1}{\sqrt{2\Phi h_{1t}}}\exp\left\{-\frac{(r_t - u_{1t})^2}{2h_{1t}}\right\} + (1 - q_{1t})q_{1t}\frac{1}{\sqrt{2\Phi h_{2t}}}\exp\left\{-\frac{(r_t - u_{2t})^2}{2h_{2t}}\right\}\right] \tag{3}$$

The existing literature posits that regime switching models can modify specific or all variables based on a Markov process (Bouteska et al., 2023). This process is governed by a state variable (x). The progression of the state variable (x) adheres to a first-order Markov chain, characterized by transition probabilities. In every specification of the GARCH model, we assume the presence of two potential regimes: low volatility (regime 1) and high volatility (regime 2). The dynamics of this process are influenced by the switching matrix Q, where q_i represents the probability of transitioning from regime 1 to regime 2. Given a statistical set Y_{t-1}, $q_{1t} = Pr(x = 1|Y_{t-1})$ discloses the probability, conditioned on Y_{t-1}, that the unidentified regime variable x belongs to regime 1. These probabilities are structured into the switching matrix using the formulation outlined in Eq. (4).

$$Q = \begin{bmatrix} q_{11} & q_{21} \\ q_{12} & q_{22} \end{bmatrix} \tag{4}$$

However, Hamilton and Susmel (1994) argued against incorporating the GARCH model into a regime-switching framework where past conditional variances depend on the regime. This impracticality stems from the conditional variances relying on factors such as the observable information set Y_{t-1}, the current regime x, and all preceding states $x - 1$, covering the complete history of the time

Table 1
Variables description.

Variable	Proxy	Methodology	Data range	Source
CV	COVID-19 Cases	Daily COVID-19 confirmed case counts in the United States	20.01.2020 to 31.03.2022	WHO
BRENT	Daily Brent crude oil Index	BRENT is the international benchmark for crude oil market and oil spot price.	20.01.2020 to 31.03.2022	Bloomberg database
WTI	Daily WTI crude oil index	WTI is the main benchmark in the North American crude oil market and oil spot price.	20.01.2020 to 31.03.2022	Bloomberg database

Source: Authors' own work.
Note: All monetary amounts are expressed in their respective US dollars.

series $(y_{t-1},\ y_{t-2},\cdots,y_0,x_t,\ x_{t-1},\cdots,x_1\ )$. This complexity makes estimation challenging due to the exponential increase in the number of potential paths as t increases. Gray (1996) proposes a suggested resolution for this issue. In the context of a symmetric GARCH model, he recommends generating the conditional variance according to Eq. (5) rather than Eq. (1).

$$h_t = \omega + ah_{t-1}\varepsilon_{t-1}^2 + \beta\widetilde{h}_{t-1} \tag{5}$$

The expression $\widetilde{h}_{t-1}$ can be elucidated as follows:

$$\widetilde{h}_{t-1} = \sum_{i=1}^{K} \Pi_{i,t-1|t-2}\left(\omega + ah_{t-1}\varepsilon_{t-2}^2 + \beta\widetilde{h}_{t-2}\right) \tag{6}$$

In Eq. (6), $\Pi_{i,t-1|t-2}$ denotes a probability vector, where the i^{th} element corresponds to $P(x_{t-1} = i|\varphi, \Upsilon_{t-2})$. Here, k represents the number of regimes, , Υ_t signifies information derived exclusively from observations up to time t, and φ is a set of parameters in the model. A practical implication is that a conclusive determination h_t relies solely on the past trajectory of observations Υ_{t-2}, without taking into account the history of states. This approach makes estimating the MS-GARCH model more manageable.

To capture the nonlinear dynamics resembling the impact of the COVID-19 on returns in the crude oil energy commodity indexes in the US (WTI and Brent), the study utilizes a Markov-based regime-switching model within the mean. Similar to the regime-switching process in the GARCH model, the study assumes two regimes, but the characteristics of the regimes differ from the MS-GARCH model. Specifically, when the value of (x) is 1, the index returns display increased volatility. Conversely, when the (x) value is 2, the index returns enter a state of low volatility. The study also allows the variance of the random term to transition simultaneously between these regimes. Eq. (7) is employed to assess the COVID-19 hypotheses in the Brent market, while Eq. (8) is used to evaluate the hypotheses in the WTI market. The symbol h_t denotes 'conditional variance' computed through the most appropriate MS-GARCH model, also accounting for the three distinct distribution functions $N(0,\ h_t)$, $x(0,\ h_t,\nu)$, and $GED(0,\ h_t,k)$.

$$h_t^{\text{returns.Brent}} = \phi_x + \alpha_x^{\text{returns}} h_{t-1}^{\text{returns}} + \beta_x^{\text{returns}} h_{t-1}^{\text{covid}} + \Upsilon_t, \Upsilon_t \sim N\left(o, \sigma_{x,h}^2\right) \tag{7}$$

$$h_t^{\text{returns.WTI}} = \pi_x + \alpha_x^{\text{returns}} h_{t-1}^{\text{returns}} + \beta_x^{\text{returns}} h_{t-1}^{\text{covid}} + \mu_t, \mu_t \sim N\left(o, \sigma_{x,\tau}^2\right) \tag{8}$$

The constants ϕ_x and π_x vary with the market regime in the given equations, while α_x^{covid} and β_x^{covid} serve as coefficients for regime switching, reflecting nonlinear influences resembling COVID-19 in the crude oil energy commodity indexes returns of the Brent and WTI markets. Eq. (7) demonstrates that the Markov switching model provides insights into how much importance is assigned to conditional volatility in the Brent market by volatility shocks from the previous day. The same principle, outlined in Eq. (8), applies to the WTI market. The transition between regimes in both Eqs. (7) and (8) is not deterministic but occurs with a certain probability. The unobserved and discrete state variable x is dependent on, $x_{t-1}, x_{t-2},\ x_{t-r}$, in a serial manner, constituting an r^{rt}order Markov switching process governed by an expression (9):

$$\left.\begin{array}{l} P(x_t = 1|x_{t-1} = 1) = p_{11} \\ P(x_t = 1|x_{t-1} = 2) = p_{12} \\ P(x_t = 1|x_{t-1} = 1) = p_{21} \\ P(x_t = 1|x_{t-1} = 1) = p_{22} \end{array}\right\} \text{where}, p_{11} + p_{12} = p_{21} + p_{22} = 1 \tag{9}$$

The probabilities specified in Eq. (9) govern the likelihood of a particular state occurring at any given moment, without predefining specific dates. This approach allows empirical data to reveal the characteristics and occurrences of regime changes.

3.3. Methodological limitations and mitigation

Acknowledging the limitations inherent in the methodology outlined, such as potential model biases or data inaccuracies, is crucial for ensuring the credibility and robustness of the empirical analysis conducted. Firstly, while the Markov switching GARCH model (MS-GARCH) is a sophisticated framework known for its capability to capture time-varying volatility dynamics, it is important to recognize that no model is entirely immune to biases. In the case of employing various configurations of the MS-GARCH model, there might exist certain assumptions or simplifications inherent in the model specifications that could introduce biases into the estimation results. For instance, the choice of distribution functions, namely normal, Student-t, and generalized random term, could potentially impact the estimation outcomes, especially if the underlying data exhibits characteristics deviating significantly from the assumed distributions. Furthermore, the integration of T-GARCH specifications to address potential asymmetries across different regimes is commendable. However, it is essential to acknowledge that the effectiveness of these specifications in capturing asymmetries may vary depending on the underlying data properties and the appropriateness of the chosen model parameters. Moreover, while the MS-GARCH model is adept at identifying structural breaks in variance, thereby reducing the risk of overestimation, it is important to recognize that the identification of such breaks might be subject to certain limitations. These could include, but are not limited to, the sensitivity of the model to the choice of breakpoints and the possibility of false break detections, particularly in the presence of noisy or insufficient data. Additionally, assuming an AR(1) criterion for the conditional mean of all analyzed vectors to address serial correlation is a reasonable approach. However, it is essential to acknowledge that the adequacy of this assumption may depend on the underlying dynamics of the time series data being analyzed. In some cases, more complex autoregressive structures or alternative approaches might be necessary to adequately capture serial correlation.

To mitigate the aforementioned limitations, we have made a thorough sensitivity analysis conducted to assess the robustness of the results to changes in model specifications and assumptions. Additionally, we have incorporated alternative methodologies or conducted comparative analyses with other models to provide valuable insights into the robustness of the findings. Moreover, we note that the transparent reporting of our methodology, including detailed discussions of the assumptions made and their potential implications, is essential for facilitating informed interpretation and enhancing the credibility of our empirical analysis (please refer to our discussion in Section 3.2).

4. Results and discussion

4.1. Descriptive statistics

Table 2 presents descriptive statistics for the log transformation of Brent and WTI crude oil indices, respectively, and the change of the COVID-19 cases. It is evident that both energy price indices, when subjected to a logarithmic transformation, do not exhibit a normal distribution. The data shows negative skewness, indicating a thicker lower tail compared to the upper tail. Moreover, the kurtosis in the log-transformed price series is significantly higher than the expected value of 3, as confirmed by the Jarque-Bera test, which yields high values. For the daily variation in confirmed COVID-19 cases, its mean stands at −0.019419, with a standard deviation (SD) of 0.669244. The skewness of these daily confirmed cases is 1.133489, and the kurtosis is notably high at 6.579963. This distribution of daily confirmed cases leans toward being leptokurtic, with a heavier right tail.

4.2. Preliminary analysis

Before delving into the main analysis, we first scrutinize the price trends using data from the energy sector in the US, as illustrated in Fig. 1. This data reveals significant fluctuations in the both indices, evident in the presence of peaks and valleys. Additionally, to assess the returns on these indices as a performance metric, we calculate the logarithmic differences, as illustrated in Fig. 2. Nevertheless, in order to ascertain the true connection between the COVID-19 cases and energy price indices, whether it leans towards a positive or negative correlation, the study investigates the correlation between these variables, and the outcomes are detailed in the subsequent Table 3. The findings indicate a positive correlation between the COVID-19 cases and energy Brent crude oil price index, whereas in the case of WTI crude oil, there is an inverse correlation between the COVID-19 cases and price index. The latter has a similarity with the findings of Gillingham et al. (2020), Qin et al. (2020), Aruga et al. (2020), Norouzi et al. (2020), among others, which reported a negative association of the rising pandemic related cases and deaths with price index for fuel in the US, China and India. As we work with time series data, we have performed augmented Dickey-Fuller (ADF) both conventional and with structural break, and Phillips-Perron (PP) unit root tests to verify stationarity. Table 4 presents the outcomes of these unit root tests, affirming that the series achieve stationarity after the first differencing, corresponding to an order of integration I(1) and identification of single breakpoint for each series.

Afterwards, we examine the data sets for multicollinearity, aiming to determine whether the variables exhibit significant correlation. In this process, we employ the Variance Inflation Factor (VIF), which gauges the extent to which multicollinearity within the model inflates the variance of regression. Should the VIF value surpass 10, issues stemming from collinearity are anticipated. The outcomes of the VIF examination are showcased in Table 5 (Panel A) provided underneath. The table reveals that none of the values exceed 1.3, indicating no cause for concern regarding multicollinearity within the data sets. Endogeneity can arise as a result of omitted variables. In analyzing the energy oil-Covid-19 cases nexus, it is possible that the estimations are biased and inconsistent due to the correlation of variables and the error term. Prior to conducting any estimation, the variables undergo examination for endogeneity using the Hausman test. We computed the Hausman's test in the models, to check for any confounding effect or enodogeneity in the regression models. Table 5 (Panel B) shows the results of the Hausman endogeneity test, which confirm the absence of endogeneity in all the models, with the null hypothesis of no endogeneity accepted. Specifically, we fail to reject the null hypothesis since the estimated *p*-value is 0.610 for model (WTI), and 0.351 for model (BRENT). This demonstrates the lack of endogeneity in the two models we estimate. Also, the test of ARCH-LM is presented in Table 5 (Panel C), which strongly supports the rejection of the null

Table 2
Descriptive statistics on LNBRENT and LNWTI crude oil indices and the change of novel coronavirus pandemic.

	Ln*BRENT*	LN*WTI*	*CV*
Mean	4.516895	4.451003	−0.019419
Median	4.530311	4.494650	−0.019609
Maximum	5.244935	5.254859	2.534601
Minimum	2.333001	2.308414	−1.650770
SD	0.404700	0.387200	0.669244
Skewness	−0.604751	−0.642650	1.133489
Kurtosis	3.442675	3.673165	6.579963
Jarque-Bera	200.9601	247.8621	45.539505
Probability	0.000000	0.000000	0.000000

Source: Authors' own calculations.

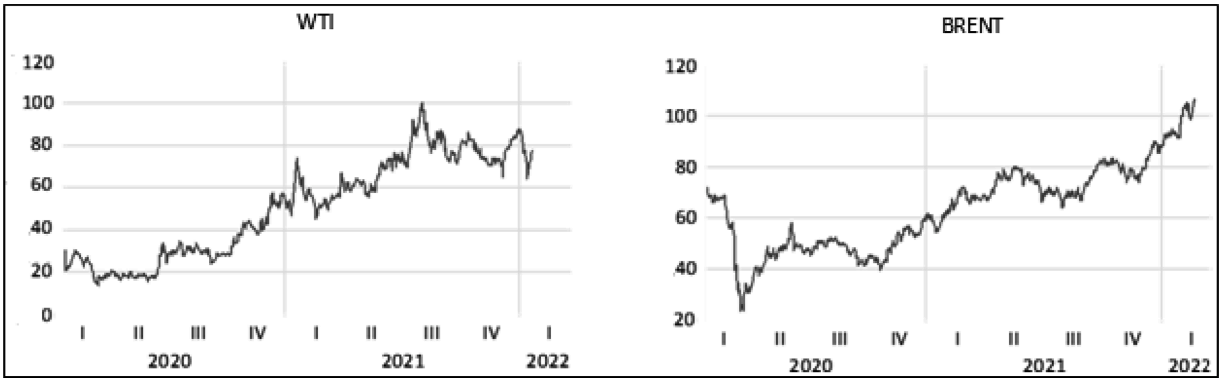

Fig. 1. Price pattern in the energy indices for both the Brent and WTI crude oil.
Source: Authors' own work.

hypothesis asserting the absence of an ARCH effect in the residual series. Both the ARCH(10) and ARCH (20) test indicates the presence of Autorregresive Conditional Heteroskedasticity for the oil variables identified (WTI and Brent). In other words, we find degree of heteroscedasticity and autocorrelation up to at least lag 20, and this demonstrates that we have established that the conditional variance as time-varying, requiring that the models be explored through GARCH approach.

4.3. GARCH (p, q) and non-parametric results for WTI and BRENT crude oil

Assuming that the impact of the COVID-19 cases on price indices returns varies, this could lead to new avenues of research in other parts of the world. To delve deeper into the relationship between the COVID-19 energy price index volatility, this study employs GARCH (1.1)-S models for estimation. The outcomes for WTI and BRENT are presented in Tables 6 and 8, respectively, contributing to the study's goal of analyzing and predicting volatility. In Table 6 for WTI crude oil, the results are divided into three sections: the mean equation, the variance equation, and diagnostic tests. In the mean equation, the constant (C) represents the average positive and statistically significant energy price index. However, the lnCV, i.e. the logarithm of the COVID-19 cases in the US has a negative and statistically significant impact on the energy stock price (lnWTI). This suggests that the COVID-19 has a negative effect on current energy price indices. This outcome can possibly be explained by the plummeting demand for fuel by 50 % in the US aviation industry as a consequence of the COVID-19 (Gillingham et al., 2020). The decline aggravated to 80 % in the first quarter of 2020 due to the Russia-Saudi Arabia price war in March 2020 (Qin et al., 2020). China and India witnessed a similar drop in energy demand (Aruga et al., 2020; Norouzi et al., 2020). However, the above result in the US context corroborates a broader body of scholarly works (e.g., Anderson et al., 2009; Bams et al., 2017; Naeem et al., 2020) that reported negative effects of uncertainty on asset prices. Moving on to the second part, the variance equation assesses time-varying volatility using GARCH. The coefficients for the constant (C) and the ARCH, i.e. conditional value of lagged error squared, RESID(−1)ˆ2, are positive and statistically significant. Conversely, the conditional value of lagged GARCH, i.e. GARCH (−1), is negative and statistically significant. This indicates that the GARCH model's result comprises a constant (0.001), its past value (−0.050), and a component dependent on a past error (1.038). While these findings establish time-varying conditional volatility of returns, the persistence of volatility shocks is statistically insignificant. This means that the impact of today's shock likely does not endure in the forecasted variance for many future periods. Thus, the GARCH effect is negative and statistically insignificant for WTI crude oil. Additionally, for the long-term dynamic impact, Table 7 reports the results of FMOLS and DOLS. These findings reveal that the pandemic has a negative and statistically significant impact on energy commodity prices. This implies that the pandemic's influence on prices persists in the long run, resulting in a negative impact. This finding can possibly be validated by the fact that effect of uncertainty on energy sector stocks is not limited to crisis periods. For example, Bianconi and Yoshino (2014) measured employed implied volatility indices and discovered negative influence of greater uncertainty on the returns on oil and gas stocks in 24 countries. Likewise, Fazelabdolabadi (2019) reported negative effect of uncertainties associated with implied crude oil price and economic policy on the energy sector returns, bolstering volatility in Iran. Zhu et al. (2020) observed that investor sentiment that arose during the COVID-19 significantly contributed to pricing anomalies in the oil and gas stocks and securities.

Likewise, Table 8 presents findings for the Brent crude oil, organized into three segments: the mean equation, the variance equation, and diagnostic tests. In the mean equation segment, the constant (C) signifies the average energy price index, displaying a positive and statistically significant association. Additionally, the lnCV, i.e. the logarithm of the COVID-19 cases in the US, also exhibits a positive and statistically significant influence on the energy stock price (lnBRENT). This suggests that the COVID-19 has a favorable impact on current energy stock prices, implying a contradiction with the findings of Ashraf (2020) and Al-Awadhi et al. (2020) that suggested a negative correlation of the rising daily case and deaths with the returns on stocks (including energy stocks) in 64 pandemic-affected countries and China, respectively. In the second part of our analysis, we investigate the variance equation employing GARCH to track fluctuations in volatility over time. Our findings disclose that both the constant (C) and two crucial variables, ARCH represented by the conditional value of lagged error squared, RESID (−1)ˆ2, and lagged GARCH indicated as GARCH

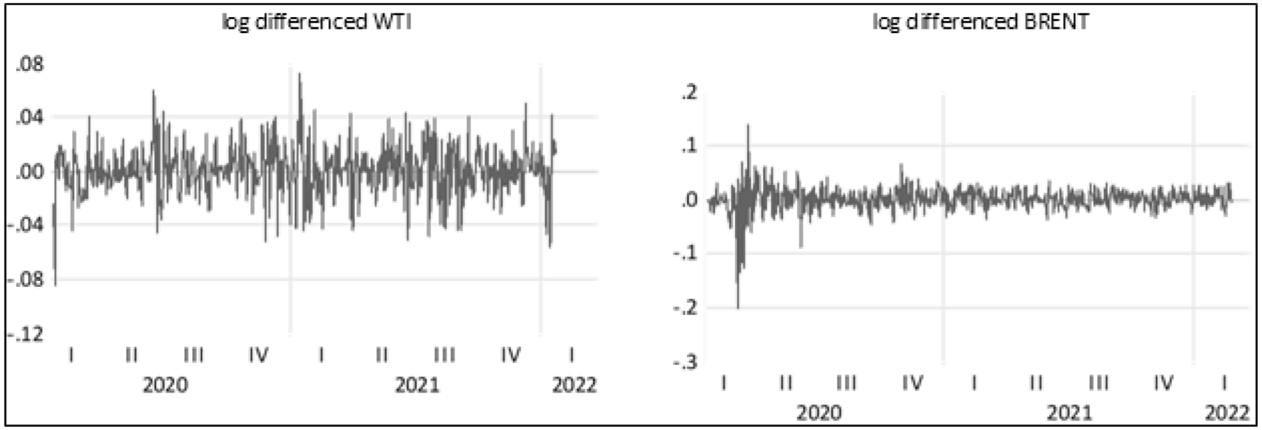

Fig. 2. Return pattern in the energy indices for both the Brent and Wti crude oil.
Source: Authors' own work.

Table 3
Correlation matrix.

For WTI crude oil			For BRENT crude oil		
Variables	WTI_t	CV_t	Variables	$BRENT_t$	CV_t
WTI_t	1	–	$BRENT_t$	1	–
CV_t	−0.143	1	CV_t	0.403	1

Source: Authors' own work.

Table 4
Tests for the presence of a unit root.

Variables	For WTI crude oil				Variables	For BRENT crude oil			
	ADF	PP	ADF-BP	Break		ADF	PP	ADF-BP	Break
$lnWTI_t$	−5.058***	−2.996	−3.473	26.04.2020	$lnBRENT_t$	−4.108	−2.885	−3.639	15.02.2021
$\Delta\ lnWTI_t$	−6.855***	−5.259***	−24.281*	17.03.2022	$\Delta lnBRENT_t$	−4.590***	−5.717***	−28.687***	26.04.2020
$lnCV_t$	−3.310	−4.390	−4.129	19.03.2022	$lnCV_t$	−2.433	−2.406	−7.304***	11.03.2020
$\Delta\ lnCV_t$	−5.307***	−6.548***	−35.667*	24.02.2020	$\Delta\ lnCV_t$	−5.115***	−4.486***	–	–

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 5
Statistical tests of the oil data.

Statistic	*WTI*	*BRENT*
Panel A:	Tests for the multicollinearity using Variance Inflation Factor (VIF)	
CV	1.269	1.108
Panel B:	Endogeneity test	
Hausman test	74.429	38.301
	(0.610)	(0.351)
Panel C:	Heteroscedasticity test using ARCH-LM test statistic	
ARCH(10)	123.65***	213.10*** (0.000)
	(0.000)	
ARCH(20)	68.297***	107.06***
	(0.000)	(0.000)

Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 6
Volatility of WTI crude oil stock prices in relation to COVID-19 cases.

Dependent Variable: lnWTI				
Mean equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
$lnCV_t$	−0.002*	0.002	−2.540	0.072
C	8.556***	0.006	1576.279	0.000
Variance Equation				
C	0.001***	0.000	2.939	0.006
RESID(−1)ˆ2	1.038***	0.377	2.930	0.007
GARCH(−1)	−0.050	0.122	−0.429	0.722
Diagnostic Tests				
R^2	0.790	Mean dependent var	8.484	
Adjusted R^2	0.798	S.D. dependent var	0.081	
S.E. of regression	0.107	Akaike info criterion	−3.250	
Sum squared resid.	2.264	Schwarz criterion	−3.166	
Log likelihood	346.590	Hannan-Quinn criter.	−3.217	
Durbin-Watson stat	0.020			

Method: ML-ARCH - Normal distribution (BFGS / Marquardt steps) Sample: 1/20/2020 03/31/2022 Included observations: 520 Convergence achieved after 76 iterations' Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(3) + C(4)*RESID(−1)ˆ2 + C(5)*GARCH(−1) + C(6)*lnCV

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 7
FMOLS and DOLS analyses conducted for WTI crude oil.

WTI	FMOLS			DOLS		
Regressor	Coefficient	t-stats	Prob.	Coefficient	t-stats	Prob.
lnCV	−0.920***	−3.994	0.001	−1.073***	−3.807	0.002
R^2	0.92			0.91		
Adj R^2	0.87			0.84		
SE	0.0034			0.0028		

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 8
Volatility of BRENT crude oil stock prices in relation to COVID-19 cases.

Dependent Variable: lnBRENT				
Mean equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
$lnCV_t$	0.002***	0.001	3.804	0.000
C	8.555***	0.005	2403.931	0.000
Variance Equation				
C	0.001	0.001	1.337	0.216
RESID(−1)^2	0.910***	0.289	3.321	0.001
GARCH(−1)	0.195	0.175	1.171	0.281
Diagnostic Tests				
R^2	0.489	Mean dependent var		8.496
Adjusted R^2	0.497	S.D. dependent var		0.104
S.E. of regression	0.126	Akaike info criterion		−3.231
Sum squared resid.	3.187	Schwarz criterion		−3.130
Log likelihood	345.669	Hannan-Quinn criter.		−3.190
Durbin-Watson stat	0.042			

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps) Sample: 1/20/2020 03/31/2022 Included observations: 520 Convergence achieved after 76 iterations Coefficient covariance computed using outer product of gradients Presample variance: backcast (parameter = 0.7) GARCH = C(3) + C(4)*RESID(−1)^2 + C(5)*GARCH(−1) + C(6)*lnCV

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

(−1), demonstrate positive and statistically significant coefficient values. This information contributes to the expansion of our academic comprehension. The GARCH model was applied to investigate the dynamic nature of volatility and its influence on returns. The outcomes reveal the presence of time-varying conditional volatility, comprising a constant value (0.001), an autoregressive element based on past values (0.195), and a component linked to prior errors (0.910). These findings emphasize the enduring effects of shock-induced volatility fluctuations over time, establishing significant long-term implications for predicting future variance. Importantly, today's unexpected events can exert a substantial impact on market outcomes for extended periods, a phenomenon referred to as volatility persistence. This positive correlation between historical data and current conditions underscores how past trends not only forecast but also shape future realities within US energy markets. This effect has been statistically validated by the findings of this study. Furthermore, Table 9 reports the results of FMOLS and DOLS, revealing a positive and statistically significant influence of a pandemic on energy commodity price indices.

The study's findings reveal significant differences in the way the COVID-19 affects energy stock market prices in WTI and BRENT. The presence of a statistically significant ARCH effect in both indices suggests that the COVID-19 impacts average price volatility, but with opposing directions, i.e. it has a negative influence on WTI crude oil and a positive one on the BRENT crude oil. These results underscore critical distinctions in how these two energy indices are responding to the global crisis. Further research may be required to investigate potential underlying factors contributing to these observed variations in market reactions. Moreover, concerning the

Table 9
FMOLS and DOLS analyses conducted for BRENT crude oil.

BRENT	FMOLS			DOLS		
Regressor	Coefficient	t-stats	Prob.	Coefficient	t-stats	Prob.
lnCV	0.200***	4.103	0.000	0.240***	4.238	0.000
R^2	0.947			0.982		
Adj R^2	0.906			0.963		
SE	0.000			0.002		

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

GARCH effect, it only exists in the Brent crude oil, indicating that the COVID-19 increases volatility in the energy sector stock prices in the future. Similarly, for returns on energy commodity indices, long-term dynamic estimates, i.e. FMOLS and DOLS, indicate a negative effect in WTI and a positive one in the BRENT. This implies that commodity indices will have opposite impacts on these markets. For example, the negative effect in WTI crude oil may lead to a shortage, while the positive effect in the BRENT crude oil could result in a surplus. The differential outcome in this study contradicts an earlier finding of Gharib et al. (2021) that suggested a statistically significant negative financial bubble for both WTI crude oil and Brent crude oil markets during the COVID-19 outbreak.

4.3. Evolution of volatilities contingent on particular regimes

Given the inclusion of tumultuous global events in our dataset, it is reasonable to assume that multiple structural breaks impact all daily time series. This characteristic can negatively impact the accuracy of computed conditional volatilities in the GARCH process. To mitigate this, we select the most appropriate specification from various MS-GARCH models, using AIC values to identify the optimal model. The MS-GARCH model is particularly advantageous for recognizing endogenous structural breaks. Table 10 presents the AIC values generated for three models for each time series, supporting our choice of the MS-GARCH model. Notably, the MS-GARCH model, combined with both Student t and GED distributions, proves optimal in our cases. However, the MS-TGARCH model takes precedence in an equal number of instances, also with Student *t* and GED distributions. Table 11 displays the probabilities of regime-switching within the optimized MS-GARCH model, revealing the likelihood of being in the low volatility regime (P11) and the high volatility regime (P22). All four values are statistically significant. This observation suggests that the transition between states is not random but is potentially associated with an exogenous factor in this case, the COVID-19.

4.4. Results from the MS-TGARCH model

Table 12 presents the results of Brent and WTI crude oil stock returns under the nonlinear impact of the COVID-19, utilizing asymmetric and regime-switching GARCH estimation. The findings highlight significant volatility transmission, with α parameters capturing the COVID −19 phenomenon and β coefficients indicating its magnitude. Specifically, α_1 and β_1 represent the effect in the high volatility regime, while α_2 and β_2 depict the effect in the low volatility regime. In section (2) of Table 12, there are noticeable rapid shifts between regimes in both markets, with relatively short durations spent in each regime before switching. Despite positive signs, it is important to interpret error variances (σ^2) in absolute values, signifying the standard deviation (SD) of each regime and emphasizing higher σ^2 in the high volatility regime, indicating greater variability as expected in this scenario. The study indicates that all switching computations are highly statistically significant, underscoring a robust presence of the COVID-19 volatility transmissions in crude oil energy commodity returns. By allowing transmission parameters to switch between low- and high-volatility regimes, the model effectively captures the nonlinear nature of spillover effects in the returns. More specifically, Table 12 reveals that the COVID-19 impact is more pronounced in the low volatility regime, occurring during tranquil periods or the low-intensity phase of the COVID-19 cases. This outcome corroborates the observation of Yan et al. (2022) that suggested a negative average return on WTI and Brent oil prices before the COVID-19 but a positive return during the intensity phase of the pandemic. Further, the Brent market exhibits a stronger effect (0.353) compared to WTI (0.201). This discrepancy is likely attributed to the Brent market's larger size, sensitivity to speculation, and prevalent use for diversification and hedging purposes. Consequently, the COVID-19 effect appears more prominent in the Brent market than in WTI. The outcome of this study demonstrates considerable resemblance to the findings of Shaikh (2022), that Brent earns superior returns than the WTI which appears to be more volatile than the former during the COVID-19 period.

5. Conclusion

In this investigation, we aimed to conduct a comprehensive empirical examination of the correlation between the COVID-19 and the volatility in crude oil energy commodity indices, focusing on Brent and WTI. To accomplish this objective, we have employsed time series data with a daily frequency, encompassing the timeframe from 20 January 2020 to 31 March 2022. In our computational analysis, we have prioritised the accuracy of the computed conditional volatilities. To achieve this, we have explored MS-GARCH specifications that incorporate three distinct distribution functions, along with a basic GARCH model. The resulting optimal conditional volatilities are then incorporated into the Markov switching model. This model reveals the nonlinear attributes of volatility spillovers between the COVID-19 and crude oil energy commodity indices within the two markets. Furthermore, for supplementary analyses, we have utilised FMOSL and DOLS methods to investigate long-term dynamics.

Table 10
AIC values for MS-GARCH Model.

ln WTI			*ln Brent*		
TGARCH	Distribution Function			Distribution Function	
	Normal	7014.163	TGARCH	Normal	7780.808
	Student	7026.697		Student	7814.176
	GED	**5955.090**		GED	**6552.173**

Source: Authors' own work.
Note: The lowest AIC values are shown in bold.

Table 11
Regime-switching probabilities.

	ln WTI	*ln Brent*
P11	1.049***	1.054***
P22	0.004***	0.002***

Source: Authors' own work.
Note: *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Table 12
Impact of the COVID-19 pandemic on crude oil energy commodity stock returns.

Dependent variables		
Regime switching parameters	*ln WTI*	*ln Brent*
α_1(AR)	0.201***	0.353***
α_2(AR)	0.463***	0.210***
β_1F	0.516***	0.470***
β_2F	0.613***	0.191***
σ_1^2	0.210***	0.486***
σ_2^2	0.487***	1.170***
Regime properties		
P_{11}	1.049***	1.054***
P_{22}	0.004	0.002***
ED_{11}	0.348	0.524
ED_{22}	0.706	0.530

Source: Authors' own work.
Note: P's represent the probabilities of regime switching, ED's indicate the time duration of each regime, and σ represents the variance of errors. *,**, *** indicate statistical significance at 10 %, 5 %, and 1 % levels, respectively.

Based on our research findings, it is evident that the COVID-19 pandemic has had a substantial impact on the performance of energy indices. This impact is discernible through the presence of the ARCH effect in both scenarios. In the case of WTI crude oil, there is clear evidence of a negative long-term influence, indicating a potential scarcity of energy commodities stemming from the pandemic-induced shock. Conversely, the Brent crude oil exhibits a positive long-term effect, signifying an abundance or surplus of energy due to the same shock. These divergent effects call for distinct policy approaches to reestablish market equilibrium in each index. Furthermore, we have observed notable GARCH effects in price volatility within the Brent Crude oil energy index, implying that the repercussions of the COVID-19-induced shocks will endure over an extended period. In light of the experiences of the previous Black Swan events including the recent COVID-19, counteractive policies will be required to lessen the formation of pessimistic investor sentiments about the demand for energy, oil in particular, that drives capital flows away from energy stocks and aggravates market volatility (Sadorsky, 2001; Ji and Guo, 2015; Szczygielski et al., 2021). Further, such outflows of investment may not only be reflected in oil, gas and other fuels but also in the apparatus and operations associated with the extraction of consumable fuels. Therefore, formulation of financial market policies is required to encounter the future systematic risk associated with crises may have prolonging effects on energy prices and market volatility.

This study makes some novel contributions to extant literature. First, literature documents flurry of research studies on investigating the effects of the pandemic on stock prices (e.g., Chai et al., 2022; Phan and Narayan, 2020; Ramelli and Wagner, 2020; Balcı et al., 2022b; Bouteska et al., 2023), and the effect of oil price variations on various economic factors during the pandemic (e.g., Apergis and Apergis, 2020; Fu and Shen, 2020; Gil-Alana and Monge, 2020; Iyke, 2020; Liu et al., 2020; Narayan, 2020; Qin et al., 2020). However, unlike this study, much of these studies have missed to deeply explore the nature and magnitude of the impact of this crisis on crude oil markets. Second, "many research papers concentrated on capturing financial market spillover effects, downside risk–return spillovers, and their effects on market volatility" during the pandemic (Mamilla et al., 2023). Given this backdrop, this study pioneers the investigation of the influence of the COVID-19 on the returns of energy indexes in the US using daily time series data of two pioneering oil markets (i.e., WTI crude oil and Brent crude oil) for the January 2020–March 2022 period. Third, although academic literature postulates that the pandemic leads to uncertainty and that uncertainty influences the energy sector, little had been known about the impacts of the COVID-19 related uncertainty on the returns, volatility and investor behaviour in the energy sector (Szczygielski et al., 2021; Goodell et al., 2023) prior to the emergence of this study. Fourth, the findings underscore the structural differences between these markets, and fill a gap in research by contradicting the finding of Gharib et al. (2021) that suggested a statistically significant negative financial bubble for the aforementioned oil markets during the pandemic.

The insights derived from this research hold significance for both crude oil indices engaged in the trade of energy commodities, whether as exporters or importers. Nevertheless, considering the estimated parameters for regime switching, the influence of the COVID-19 is notably significant in the returns of crude oil energy commodity indices in both the WTI and Brent markets. However, the magnitude of this impact varies depending on the volatility levels experienced by the oil market. Specifically, in the WTI market, the spillover effect is more pronounced during periods of calm (characterized by a lower number of the COVID-19 cases) and weaker during turbulent times (marked by a higher number of the COVID-19 cases). This phenomenon may be attributed to market control measures during volatile periods and an increased demand for commodities in tranquil conditions. In contrast, in the Brent market, the impact of the COVID-19 is more prominent during turbulent regimes, which is attributed to the openness of the Brent market. This suggests that participants in the Brent market, particularly speculators aiming to capitalize on price differences, intensify their activities during turbulent times, resulting in heightened volatility transfers during periods of increased the COVID-19 cases. The aforementioned structural differences between the WTI and Brent commodity markets carry significant policy implications for investors in the energy sector.

The overall findings of this study carry some vital implications. First, our findings have insights for the policymakers, financial analysts, investors, and portfolios managers who would like to measure, observe, and effectively manage portfolio risks and accordingly hedge their portfolios to secure higher returns in the wake of any Black Swan events in near future, similar to the COVID-19. Second, the findings could help market actors to apprehend the market behavior across various phases of a crisis and make logical decisions related to their tactics of trading. Third, the findings underscore the structural differences between the WTI crude oil and Brent crude oil markets, and carry significant policy implications for investors in the energy sector. Fourth, the outcomes of our research are useful for regulators and policymakers who need to take into consideration of the existence of jump-tail risks caused by crisis, such as the recent pandemic, and any likely variation to risk levels during period of anxiety while financial systemic risks are calculated, quantified, or ranked. Given the scale of the COVID-19 pandemic consequnces that warranted policymakers to take initiatives to spread market risks and sustain market stability, we suggest the urgency of formulating dynamic policies to smooth the rising systemic risks during crisis and to promote resilience of the financial markets to investors' fear and anxiety. In general, the findings of our study can be piloted by governments or policymakers in preparing for lessening the likely detrimental impacts of any future crisis on global economies and financial markets.

Our research paves the way for future investigations aimed at identifying effective strategies to stabilize the US energy stock in such circumstances. A parallel empirical examination can be carried out for sectors beyond crude oil energy commodity indices, both within a country and in a panel setting. Also, given that these results indicating significant differences in the way the COVID-19 affects energy stock market prices in WTI and Brent, hence underscoring critical distinctions in how these two energy indices are responding to the global crisis, further research may be required to investigate the core underlying factors contributing to these observed variations in market reactions.

CRediT authorship contribution statement

Taimur Sharif: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Jihene Ghouli:** Visualization, Validation, Investigation, Formal analysis, Conceptualization. **Ahmed Bouteska:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Investigation.

Appendix

Fig. A1, Fig. A2

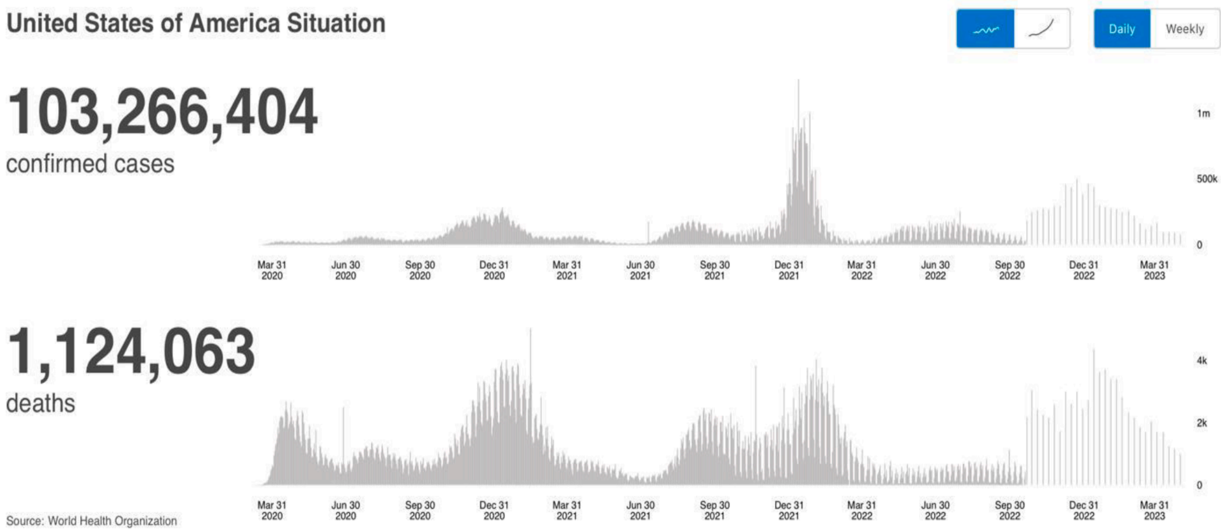

Fig. A1. Daily reported COVID-19 cases and deaths in the United States.

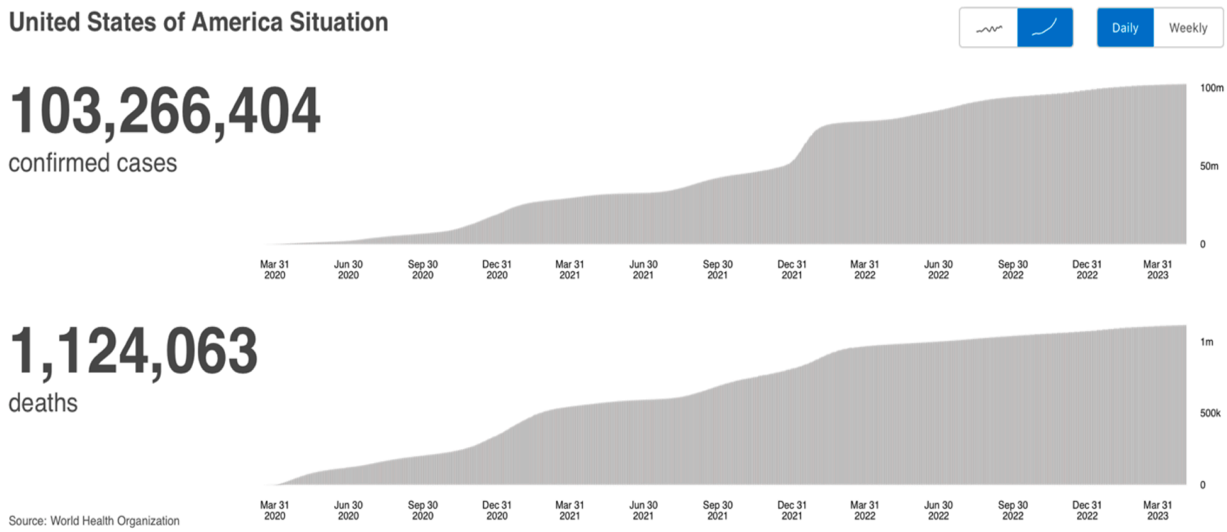

Fig. A2. Cumulative reported COVID-19 cases and deaths in the United States.

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