Modeling the impact of the COVID-19 outbreak on environment, health sector and energy market

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Abstract
The global outbreak of COVID-19 disease had a significant impact on the entire globe. Such a notable public health event can be seen as a “black swan” that brings unpredictable and unusual forces into the economic context and that it could typically lead to a chain of adverse reactions and market disruptions. Hence, the purpose of this study is to examine how COVID-19 affects the environment, health, and the oil and energy markets. To achieve this objective, we used daily data for several measures that refer to the environment, health, and oil and energy, for the first wave of the COVID-19 pandemic (December 31, 2019 – May 22, 2020). The variable integration mix led to the approach of the ARDL model, and the Granger causality test was also employed. These empirical techniques allowed us to examine the cointegration between variables and causal relationships. The econometric results of the ARDL models exhibited that the global new cases and new deaths of COVID-19 have short and long-term effects on the environment, the health sector, the oil, and energy measures. However, no significant causal connection was found between the pandemic and the environment, the health sector, or the oil and energy industry, according to the Granger causality test. The uniqueness of current approach consists in the investigation of pandemic impact on the health, environment, oil, and energy sector by applying the ARDL model that permits the analysis of cointegration both in the long run and in the short term. This study provides important insights for investors and policy makers.

KEYWORDS
ARDL model, CO2, COVID-19, environment, Granger causality test, health sector, oil and energy market

1 INTRODUCTION
The pandemic outbreak triggered by the 2019 new coronavirus, also known as SARS-CoV-2 (Gorbalenya et al., 2020), is the most serious global health crises of the modern period and the most severe challenge that humanity has faced since World War Two (United Nations Development Programme, 2020). Unfortunately, it may drive a strong upsurge in conflict, food uncertainty, and poverty as economies shrink, whereas export revenues, transfer funds and leisure industry vanish (United Nations, 2020b). Laing (2020) supported that COVID-19 has the capacity to wipe out individual means of survival, enterprises, branches of activity, and overall nations. Even, if former to the 21st century, coronaviruses (CoVs) were deemed germs of large pertinence in veterinary science but with a lower effect on human health (da Costa et al., 2020), in merely two decades the COVID-19 pandemic become the third serious zoonotic coronavirus disease emergence, succeeding...
the SARS (Severe Acute Respiratory Syndrome) manifestation in 2002–2003 and the MERS (Middle East Respiratory Syndrome) outbreak in 2012 (Nghiem et al., 2020).

Because emerging illnesses have no geographical boundaries (Wu & McGoogan, 2020), globalization has led to disease propagation due to mobility channels including air and ship travel. However, travel bans, movement restrictions, as well as economic and trade lockdowns hindered globalization to reduce the rapidly increasing incidence of COVID-19 cases, but this approach put pressure on the aviation and marine industries, resulting in lost earnings, interruption of world commerce, and the collapse of the tourism sector (Shrestha et al., 2020). Therewith, a decrease in industrial production has befallen, alongside a scarcity of medications, disinfectants, masks, and other merchandises, which has raised the prices of these items (Alia & Alharbi, 2020). Sharif et al. (2020) supported that COVID-19 contagion stroked the oil quotations due to compulsory travel constraints. Das (2020) revealed that the solar energy production segment was affected due to its high reliance on Chinese provisions. Overall, Aharon and Siev (2021) revealed that government constraints are linked with adverse market returns.

The health challenge caused by COVID-19 pandemic was the most distressing event the humanity had seen in this generation (Rita et al., 2021). Until the end of December 2020, there were no definite antivirals or vaccine, and the standard epidemiological advice alike isolation, observation, and monitoring were employed (Reina, 2020). Under such circumstance, so as to restrain the prevalence of coronavirus and to lessen the death rate, public places were closed, whereas flights were canceled, and most of citizens remained home, committed to social distancing and remote working. Nevertheless, such changes engendered the decline in carbon discharges and coal consumption, but also job losses and businesses failures (Saadat et al., 2020). In this regard, Tollefson (2021) noticed that worldwide carbon dioxide releases dropped by 6.4% or 2.3 billion tonnes in 2020. As well, Mandal and Patel (2021) proved a worldwide decline in the pollutant levels of almost 60% throughout the lockdown phase. Nevertheless, United Nations (2020c) claimed that current coronavirus is much more than a health emergency, since it is intensifying and expanding prior disparities, revealing weaknesses in societal, political, economic, and biodiversity structures, which are gradually augmenting the effects of the plague. As long as the whole society is imperiled, a joint action was essential. Therefore, the officials of G20 nations decided to inject over $5 trillion into the world economy to address economic collapse caused by the COVID-19 pandemic (G20 Leaders’ Statement, 2020). As well, COVID-19 Global Humanitarian Response Plan was committed to meet the necessities of the most exposed individuals, particularly women and children, elderly, and those with incapacities or long-lasting sickness (United Nations, 2020a). However, there is a lot of variability among countries. In this regard, International Monetary Fund (2021) projected that in 2022, the advanced markets’ aggregate output is expected to revert to their pre-pandemic trend path, outperforming it by 0.9 percent in 2024. Besides, in 2024, the overall output of emerging and developing nations (except China) is predicted to maintain 5.5 percent behind pre-pandemic estimates, worsening their living standards even further. As well, Caselli and Mishra (2021) claimed that inflation in advanced economies are anticipated to be low in the short term, with the impact fading over time, but in developing markets it appears to be more volatile.

The current coronavirus crisis is producing wider effects than those related to public health, with profound and long-term socioeconomic consequences. Pre-existing factors leading to energy poverty have amplified all this time, by decreasing or losing revenue and increasing bills due to increased energy consumption. The coronavirus outbreak reinforces that energy and energy services are essential elements for a safe, healthy, and decent life. There is noticed a widespread decline in incomes, while energy consumption in the residential environment has increased, amid increasing time spent at home, because of the decree imposing a state of emergency, working at home and by suspending courses throughout the system education. Further, Barua and Nath (2021) argued that in the long-run, indoor or housing mobility increases significantly lower CO discharges, while outside movement rises, mainly in transit stations and offices, significantly expand CO releases. Nevertheless, the release of air impurities diminished due to the decline of fossil fuel power generation as production and transport segment consumption were low down (Nundy et al., 2021). Further, the decrease of noxious waste granted more sunlight to achieve photovoltaic panels and boosted renewable energy production (Naderipour et al., 2020).

COVID-19 is expected to provoke as many or higher human pain than different infectious illnesses in the entire world. Infectious disease may kill fewer people concomitantly than a catastrophic storm or a severe drought, but once it persists in a region, it is hard to eradicate and can expand to other communities (Epstein, 2001). Besides, diverse global ecological instabilities, such as soil deprivation, ozone layer weakening, pollution, and urban sprawl, fluctuating atmosphere generates an undeniable risk to our planet and human health (Chakraborty & Maiti, 2020). For instance, increasing overflows and dryness ensuing from global warming can induce outbreaks by forming conducive milieu for pests, whose desiccated eggs remain viable and incubate in plain water (Epstein, 2000).

The purpose of this research is to examine how COVID-19 affects the environment, the healthcare system, and the oil and energy global markets. The study aims to contribute to the literature in several ways. Different to existing literature, we contribute to the global debate on longstanding pandemic consequences on economic development by assessing the impact of COVID-19 on multiple sectors. First, because global climate change, pollution, and COVID-19 may increase the risk of psychological diseases, we cover the environment, health industry, and oil market simultaneously (Marazziti et al., 2021). Second, the ARDL framework allow the investigation of both short- and long-term associations among pandemic and the three sectors. Third, to the best our knowledge, this is among the first attempts, which explore the impact of COVID-19 on stock returns of major healthcare companies. According to Nammouri et al. (2021), the healthcare segment price is an essential indicator that can support legislators in creating immediate economic and healthcare policy results, particularly throughout this exceptional plague.
This article is organized as follows. Section 2 surveys prior literature. Section 3 presents the research sample and selected variables, alongside quantitative methods. Section 4 discusses the empirical outcomes. Section 5 concludes the paper.

2 | BACKGROUND LITERATURE

2.1 | Prior studies towards COVID-19 and environment

Even if the novel infectious illness critically perils human health and provoke economic downturn, Muhammad et al. (2020) deemed it a “Blessing in Disguise” due to its constructive effect on environment. Shehzad et al. (2020) noticed that the occurrence of COVID-19 has been considered a crucial evil due to alleviating air contamination. In this regard, Rume and Islam (2020) emphasized that the pandemic enhanced air quality in several cities around the world, reduced greenhouse gas emissions, diminished water contamination and noise, and relieved stress on tourist destinations. For instance, Zhang et al. (2021) claimed that the energy supply and utilization of commercial tourism cities displayed descending trends, which drove lowered carbon releases and improved the ecosystem. As such, there occurred a refurbishment of the environmental setting. The hydrosphere, covering seas, waterways, and oceans have prolonged been experiencing an acute contamination on account of quick sprawl, industrial development, and overutilization, but quarantine measures radically fallen the level of pollution (Facciola et al., 2021). Besides, the closure of industry sectors throughout the lockdown lessened the demand for fossil fuel energy, which in turn improved the atmosphere (Nundy et al., 2021). However, Yang et al. (2021) claimed that the new coronavirus has had both beneficial and harmful indirect effects on the environment. Thus, it was suggested that soil pollution has become more serious than in the past as a result of the elimination of recycling methods in many metropolitan areas and the restriction of sustainable waste management. In this regard, Jia et al. (2021) reasoned that the drop in worldwide carbon emissions are attributable to economic slump, but the pandemic and the variation of oil price have double effects on the sustainable economy. Table 1 summarizes prior literature on the effects of the COVID-19 pandemic on environment.

Kerimray et al. (2020) documented for Almaty, Kazakhstan, a decrease in the PM2.5 concentration by 21% during coronavirus lockdown compared to the matching period in 2018–2019, as well as a fall in the concentrations of CO and NO2 by 49% and 35% related to the moment before the isolation, but an increase in O3 by 15%. For the case of China, Wang and Su (2020) confirmed that COVID-19 diminished the CO2 releases and the concentration of NO2 in the air. Likewise, Bao and Zhang (2020) reinforced that the concentrations of pollutant discharges decreased in 44 cities in northern China. With regard to the global financial crisis of 2008–2009, Peters et al. (2012) highlighted a reduction in CO2 emissions of 1.3 percent in 2008 and 7.6 percent in 2009 in developed countries, but a 3.4 percent increase in 2010. As well, World Meteorological Organization (2021) noticed that CO2 emissions from fossil fuels (coal, oil, gas, and cement) soared at 36.64 gigatonnes in 2019, before plummeting by 1.98 gigatonnes (5.6 percent) in 2020 due to the COVID-19 disease outbreak. In the same vein, Le Quere et al. (2020) reported that by early April 2020, daily global CO2 releases had reduced by −17 percent relative to the mean 2019 values, while individual country discharges had decreased by −26 percent on average. However, according to Friedlingstein et al. (2021), in 2021, fossil CO2 releases are expected to rise by 4.9 percent, bringing them back to the similar level as in 2019.

Further, Le Quere et al. (2020) claimed that the economic slump linked with COVID-19 is different, since it is more severely anchored in restricted human conduct. Hence, apart from positive effects on the environment, such as lessened concentrations of NO2 and PM2.5, clean beaches, and drop of environmental noise level, Zambrano-Monserrat et al. (2020) underlined the enlarged waste, alongside decrease in waste recycling. In the same vein, Mostafa et al. (2021) noticed several adverse ecological effects of COVID-19, such as the rise in medical waste generation, urban and solid garbage creation, less effective solid waste reprocessing activity, as well as an expansion in ozone concentration. Klemes et al. (2020) advised that the disease provoked huge issues in the management of urban solid waste and risky medical waste. Mzoughi et al. (2020) noticed that the response of CO2 releases to a shock on COVID-19 infections are negative during the entire interval.

Earlier, studies acknowledged certain atmospheric settings that could serve as forecasters of a topmost of disease. Bull (1980) argued that fluctuations in the meteorological conditions are highly significantly associated with shifts in decease rate from pneumonia. Epstein (2001) concluded that the diffusion of West Nile virus in the United States and Europe may be due to the extreme climate circumstances associated to lasting temperature change. According to Yuan et al. (2006), the highest diffuse of SARS occurred at an average temperature of 16.9°C, with measured humidity levels of 52.2 percent and a wind speed of 2.8 m/s, indicating that the illness was most likely to occur in the spring in northern China. By means of Spearman correlations, Tosepu et al. (2020) revealed a significant relation between average temperature and COVID-19. However, Irfan et al. (2021) proved that the effect of temperature on COVID-19 is unequal and mixed. For instance, Liu (2022) exhibited for a sample of 295 cities in China that the temperature threshold of 16.92°C is the most crucial, with the greatest disease incidence, while propagation diminishes between 28.82°C and 50°C. For six cities of the Kingdom of Saudi Arabia, Ismail et al. (2022) claimed that high daily infections were detected at temperatures among 23 and 34.5°C and humidity levels within 30 and 60 percent, whereas a substantial number of fatalities were identified at temperatures exceeding 28.7°C and humidity levels under 40 percent. Xu et al. (2020) established that air quality index is statistically significantly connected with confirmed cases of COVID-19 in several Chinese cities.

2.2 | Earlier research regarding COVID-19 and health sector

Besides, triggering human contaminations and fatalities, COVID-19 disease also disorders the stock market. In this regard, Hunjra et al.
(2021) reported volatility in the stock indices relating to specific health strategies. He et al. (2020) found that health industry, apart from the manufacturing, information technology, and education strongly reacted to the pandemic in a positive way. Furthermore, according to Harjoto and Rossi (2021), COVID-19 has a favorable impact on the healthcare and telecommunications industries in emerging countries, allowing investors to increase their returns by investing in these sectors. Table 2 reviews earlier literature on the influence of the COVID-19 pandemic on health market.

Further, Carraturo et al. (2020) cautioned that dispersal risk may be amplified in case of a lengthy exposure to polluted ecological sources, the longer interaction with vaporizers formed from sewage
or the deficient washing of food and surfaces. Therefore, Leung et al. (2020) argued that wearing masks may avoid the infectious bases. However, the growing demand of shielding kit driven an increase of prices, such as the cost of medical covers raised six times, N95 ventilators three times and gowns twice as much (World Health Organization, 2020). Because enterprises manufacture a huge quantity of units daily, progressively further mask trash has been shaped and must be discharged. Hence, dismissed masks in unsuitable spaces like busses, train stations, hospitals, and streets may cause secondary contaminations (Wang et al., 2020). However, National Center for Immunization and Respiratory Diseases (NCIRD) (2021) declared that individuals may become ill after interacting with infected items (fomites), but the threat is usually deemed minimal. In this regard, based on the review the existing knowledge, Gonçalves et al. (2021) confirmed that COVID-19 fomite spread has not been proved. As well, Lewis (2021) reinforced that although the coronavirus that caused the pandemic can be found on door handles and other objects, they are not a primary cause of infection.

Besides, Choo and Rajkumar (2020) noticed that the critical pharmaceutical stock tend to be surpassed as long as common distribution chains, mechanisms, and organizational courses are insufficient for this emergency. Giria and Rana (2020) argued that the creation of completely prepared testing facilities would entail massive capital, proficiency and time, which are narrowed throughout COVID-19 period. Nevertheless, Mishra et al. (2021) emphasized that the pandemic differentiates towards people less fortunate. In this vein, Maxmen (2021) claimed that many people in the global south do not have accessibility to COVID-19 immunizations. This fact is argued by the fact that medical enterprises have marketed all of their available doses to the high-ranking purchasers in the aspirations of getting large revenues (Malpani & Maitland, 2021). Hence, Jecker (2022) asserted that rich and influential governments have a moral obligation to share COVID19 treatments with impoverished countries and to mend ties that have been strained by injustice.

In the fight against the SARS-CoV-2 pandemic, successful clinical trial procedures were launched to speed up the course of treatment aimed at the recovery of COVID-19 affected patients. For instance, remdesivir (Cao et al., 2020) or hydroxychloroquine and azithromycin (Gautret et al., 2020) have been suggested in the cure of coronavirus infection. As such, Chabrière (2021) reported that throughout a phase in which many stock prices plummeted, including those of medical corporations, the stock price of Gilead Sciences, the biopharmaceutical company developing the remdesivir molecule, rose substantially. Ahmed et al. (2021) exhibited the potential benefit of using the medicine ivermectin early in the therapy of adult patients with moderate COVID-19. Angélica Jayk Bernal (2021) documented that in at-risk, unvaccinated adults with COVID-19, timely molnupiravir medication lowered the probability of hospitalization or mortality.

### 2.3 Previous literature concerning COVID-19 and energy market

The suspension of economic undertakings during the first wave of COVID-19 period entailed earnings losses for many citizens, whereas stay at home guidance has augmented the electricity bill, thus making

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**TABLE 2**

| Study              | Timeframe                          | Measures                                                                 | Research techniques                           | Econometric outcomes                                                                 |
|--------------------|-----------------------------------|--------------------------------------------------------------------------|-----------------------------------------------|--------------------------------------------------------------------------------------|
| Gurrib (2021)      | November 9, 2018–December 23, 2020| FTSE health-care index, CBOE ETF VIX, health-care and energy stocks       | Impulse responses and Markov Switching regression | Health-care services stocks and three health-care technology stocks showed an expansion in the change of their daily stock prices within the first 2 days following the sharp rise in COVID-19 cases in Italy |
| Mushafiq (2021)    | June 3, 2019–August 21, 2020      | 26 Industries of the Pakistan Stock Exchange                              | Event study methodology                       | The pharmaceutical, refinery industry had displayed a positive response to the COVID-19 |
| Mazur et al. (2021)| March 2020                         | Standard and Poor’s (S&P) 1500 firms                                     | Event study methodology                       | Stocks in the pharmaceutical, food, fuel, and technology sectors performed well during the March 2020 stock market crisis, generating substantial returns |
| Alam et al. (2021) | Before and after the 27th of February, 2020 | Indexes for eight different sectors                                      | Event study methodology                       | The indices for food, pharmaceutical, and health all showed large positive returns on the day of the formal declaration of the COVID-19 pandemic in Australia |

Source: Authors’ processing based on literature review.
a substantial economic and financial burden on households (Qarnain et al., 2020). However, COVID-19 is a distinctive reality in wealthy and deprived nations, but they are connected by means of globalization and mankind (FAO, 2020). For instance, because governments restricted households’ purchasing options, prompting them to spend less (Gropp & McShane, 2021), the pandemic triggered a substantial household savings across developed economies, greatly exceeding previous records. According to European Central Bank (2021), in 2020, household savings gathered in surplus of previous levels in Australia, Canada, Japan, the United Kingdom and the United States amounted to an average of 6.7 percent of GDP and 9.5 percent of available revenue. In several economies, such as the United States, Hungary, Estonia, Ireland, and Romania, household bank deposit balances have also increased (OECD, 2020). With reference to developing countries, Bottan et al. (2020) found that the link among job loss and business closure is monotonically decreasing with income prior to the pandemic, exacerbating existing inequality.

The COVID-19 epidemic has also delayed the transition to renewables by disrupting clean energy manufacturing plants, distribution networks, and enterprises (Hosseini, 2020). The falling aggregate level of energy demand has had a detrimental effect for renewable energy generation and carbon trading price schemes (Hoang et al., 2021). As such, Shah et al. (2021) documented for Denmark that pandemic has a multiplier effect along with a harmful impact on renewable energy production. With reference to shocks propagation, Tiwari et al. (2022) found that clean energy transmits the highest value of shocks to other markets. Li and Meng (2022) confirmed that renewable energy stocks are the primary contributors in the analyzed connectedness system. Mensi et al. (2022) reported that return spillovers to the crude oil (gold) market are mostly transmitted through energy (basic resource) sectors. In addition, Nguyen (2020) documented that energy segment experienced the highest abnormal negative returns among other sectors, such as communications, consumer goods, medical assistance, computer technology, and public service. Table 3 summarizes prior findings on the COVID-19 pandemic impact on the energy sector.

Yilmazkuday (2020) showed by means of a structural vector autoregression (VAR) that a weekly upsurge of 1000 in daily COVID-19 cases in the rest of the world generate a cumulative decrease of 0.4% of in crude oil prices, while the COVID-19 cases in China do not have any significant impact on the crude oil prices. Aloui et al. (2020) demonstrated that energy futures markets, namely crude oil and natural gas S&P GS Indexes, respond to COVID-19 shocks. Mzoughi et al. (2020) confirmed through an unrestricted VAR that a positive shock to the number of COVID-19 cases determines a reduction in the price of crude oil, but the adverse reaction of the oil market is temporary. In addition, Khan et al. (2021) found that a negative effect of COVID-19 on energy prices, the adverse impact being larger on the oil prices as contrasted to the natural gas and the heating oil price. Szczygiełska et al. (2021) strengthened that COVID-19 related insecurity has a harmful effect on returns in the whole energy markets and caused sharp instability in most nations.

On the contrary, Albuluescu (2020) pointed out that the everyday announced cases of coronavirus have a peripheral adverse influence on the crude oil prices in the long term. In the same vein, Maneesjk et al. (2021) revealed that the energy markets perform analogous to both optimistic and adverse COVID-19 shocks.

3 | RESEARCH METHODOLOGY

3.1 | Sample and variables

The impact of the pandemic generated by the COVID-19 disease on the world economy is significant, it will manifest itself in the long run and will depend on the intensity of the pandemic manifestation. We used daily data from December 31, 2019 to May 22, 2020, which matches to the first wave of the COVID-19 pandemic. A broad set of factors were selected, including environmental indices on the financial markets, the health care industry, and the oil and energy market. In order to capture COVID-19 pandemic, we included new cases and new deaths of pandemic worldwide as in Le et al. (2021). The selected measures are depicted in Table 4.

3.2 | Quantitative analysis strategy

To investigate the impact of the COVID-19 pandemic on the environment, healthcare system, and oil sector, we will implement the autoregressive distributed lag (ARDL) model developed alike Albuluescu (2020); Atri et al. (2021); Le et al. (2021); Wang, Li, et al. (2022), as well as the Granger causality test similar to Bourghelle et al. (2021). The ARDL framework has the advantage of allowing us to investigate the short and long run relationships between pandemics and the environment, healthcare, and oil markets. The ARDL specification developed by Pesaran et al. (2001) employs a linear transformation to incorporate short-term adjustments into the long-term equilibrium, using an error correction model.

The augmented Dickey–Fuller (ADF) unit root test, as used by Acedeji et al. (2021); Ahmed and Sarkodie (2021); Albuluescu (2020); Atri et al. (2021); Bourghelle et al. (2021); Maneesjk et al. (2021) will be employed to verify the non-stationary of our variables. In addition, in line with Czech and Wieelewski (2021), the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test will be applied. Non-stationary measures generate unsatisfactory outcomes, which are statistically irrelevant. The null hypothesis of ADF assumes that the variable has a unit root and that it is not stationary, while the null hypothesis of KPSS supposes that the variable is stationary. The ADF test entails modeling the following expression:

$$\Delta m_t = \alpha + \beta t + \gamma_0 + \sum_{j=1}^{k} \gamma_j \Delta m_{t-j} + \epsilon_t, t = 1, ..., T,$$  

where, $t$ is the time trend, $T$ is the sample size, and $k$ is the size of the delay in the response variable.

Because of its ability to use a combination of I(0) and I (1) factors, the ARDL model and the bounds testing methodology
are being used. It is critical to select the correct number of lags for the ARDL model, which allows for the investigation of established relationships between variables. Thus, similar to Atri et al. (2021), the Akaike information criteria (AIC) will be evaluated to select the optimal lags for the variables included in the ARDL model.

Hence, an ARDL \((p, q_1,\ldots,q_k)\) is a least squares regression that takes into account the delays of the dependent \((p)\) and explanatory variables \((q_1,\ldots,q_k)\). The ARDL \((p, q)\) model can be illustrated as follows:

\[
H_t = \mu + \beta_1 K_t + \beta_2 K_{t-1} + \ldots + \beta_p K_{t-p} + \delta_1 H_{t-1} + \ldots + \delta_p H_{t-p} + u_t. \tag{2}
\]

Furthermore, we use the following unrestricted error correction models to assess the short-term connections for each of the three main segments:

| Study | Timeframe | Measures | Research techniques | Econometric outcomes |
|-------|-----------|----------|---------------------|---------------------|
| Czech and Wielechowski (2021) | January 1, 2020–October 31, 2020 | Morgan Stanley Capital International (MSCI) Global Alternative Energy Index, MSCI All Country World Index (ACWI) Energy Index, self-developed Average-49 COVID-19 New Cases Index, Average-49 Stringency Index | Markov-switching model | COVID-19 is more resilient to alternate fuels than it is to conventional sources |
| Shaikh (2021a) | December 30, 2019–April 30, 2020 | Daily closing prices of the implied volatility index of Oil ETF, Energy Sector ETF, Gold ETF, Silver ETF, Gold Miners ETF | Regression analysis | The growth of the COVID-19 cases in the United States and China influenced future oil market volatility |
| Le et al. (2021) | January 17, 2020–September 14, 2020 | Crude Oil Prices, Economic Policy Uncertainty Index, COVID-19 pandemic | ARDL cointegration procedure | Rises in COVID-19 cases, US economic policy uncertainty, and expected stock market volatility drive the decrease of the WTI crude oil price |
| Gharib et al. (2021) | November 1, 2019–December 31, 2020 | West Texas Light crude oil and North Sea Brent crude, diesel, and gasoline prices | Supremum augmented Dickey–Fuller (SADF) test, the generalized supremum augmented Dickey–Fuller (GSADF) test, Log Periodic Power-Law Singularity (LPPLS) | West Texas Light crude oil and North Sea Brent crude oil suffered a negative financial bubble throughout the COVID-19 outburst |
| Abedeji et al. (2021) | March 20, 2020–May 28, 2020 | West Texas Intermediate, Brent, Bonny, and Daqing prices for crude oil | Structural vector autoregressive | COVID-19 pandemic impaired Brent and WTI prices |
| Ahmed and Sarkodie (2021) | February 26, 2020–November 30, 2020 | Commodity prices of oil, natural gas, soybean, corn, steel, silver, gold, and copper | Regime-switching model | High COVID-19 cases influence the price of natural gas demand, but high COVID-19 recovery cases lessen natural gas returns |
| Bourghelle et al. (2021) | January 2, 2014–April 1, 2020 | West Texas Index | VARX model | Oil price volatility responded considerably to the pandemic-caused oil shocks |
| Atri et al. (2021) | January 23, 2020–June 23, 2020 | West Texas Intermediate oil price and daily gold price | ARDL model | The number of deaths and the COVID-19 panic negatively impacted crude oil price |
| Shaikh (2021b) | January 2, 2018–June 30, 2020 | West Texas Intermediate, Brent | Ordinary least squares and interaction dummy variables, vector autoregressions | The crude oil market remains more receptive to the pandemic false information |
| Wang, Li, et al. (2022) | January 2020–March 2021 | US oil consumption | Grey prediction model, Metabolic Nonlinear Grey Model | When the COVID-19 was at its worst, the oil decline in the United States was 45% as compared to the state without the pandemic |

Source: Authors’ processing based on literature review.
TABLE 4  Variables’ explanation

| Variables                           | Description                                                                 | Source                                      |
|-------------------------------------|-----------------------------------------------------------------------------|---------------------------------------------|
| COVID-19 pandemic-related variables |                                                                             |                                             |
| NC                                  | Novel pandemic instances that have been registered all over the world        | Our World in Data                           |
| ND                                  | Novel pandemic deaths that have been registered all over the world           | Our World in Data                           |
| Environment-related measures        |                                                                             |                                             |
| CO2                                 | Atmospheric CO2 concentrations (ppm) derived from in situ air measurements at | NOAA ESRL                                   |
| ENVBP                               | Mauna Loa, Observatory, Hawaii                                             | Global Monitoring Laboratory                |
| CLIM                                | The daily return of Ethical Europe Climate Care Equity Index                | Thomson Reuters Eikon                       |
| GENV                                | The daily return of MSCI Global Environment Price Return in USD Index       | Thomson Reuters Eikon                       |
| GGB                                 | The daily return of iShares Global Green Bond ETF                          | Thomson Reuters Eikon                       |
| Gi                                  | The daily return of S&P BSE GREENEX INDEX                                  | Thomson Reuters Eikon                       |
| ENVWP                               | The daily return of FTSE Environmental Opportunities Waste and Pollution    | Thomson Reuters Eikon                       |
|                                    | Control Index                                                             |                                             |
| Variables pertaining to the health-care industry |                                                                             |                                             |
| HEALTH                              | The daily return of STOXX Europe 600 Health Care EUR Price Index            | Thomson Reuters Eikon                       |
| GHEALTH                             | The daily return of Refinitiv Global Healthcare Price Return Index          | Thomson Reuters Eikon                       |
| PHARMA                              | The daily return of Refinitiv Europe Pharmaceuticals-56201040 Price Return | Thomson Reuters Eikon                       |
| GPHARMA                             | Index                                                                     |                                             |
| CVS                                 | The daily return of CVS Health Corp, the largest pharmacy services provider in the United States | Thomson Reuters Eikon                       |
| ROCHE                               | The daily return of Roche Holding AG, one of the world top producers of coronavirus test maker | Thomson Reuters Eikon                       |
| GILD                                | The daily return of Gilead Sciences Inc which manufacture the antiviral drug Remdesivir | Thomson Reuters Eikon                       |
| ADM                                 | The daily return of Archer Daniels Midland Co, the top ethanol producer in the world | Thomson Reuters Eikon                       |
| ADVANZ                              | The daily return of Advanz Pharma Corp Ltd, one of the world top manufacturers of hydroxychloroquine | Thomson Reuters Eikon                       |
| 3M                                  | The daily return of 3M Co, one of the world top N95 mask manufacturers      | Thomson Reuters Eikon                       |
| Variables relating to the oil and energy industries |                                                                             |                                             |
| Oil                                 | The daily return of NYMEX Light Sweet Crude Oil (WTI)                      | Thomson Reuters Eikon                       |
| RENEW                               | The daily return of Refinitiv Global Renewable Energy Equipment & Services Price Return Index | Thomson Reuters Eikon                       |

\[
\Delta \text{Environment}_t = \beta_0 + \sum_{i=1}^{p} \gamma_1 \Delta \text{Environment}_{t-1} + \sum_{i=0}^{q1} \gamma_2 \Delta \text{NC}_{t-1} + \sum_{i=0}^{q2} \gamma_3 \Delta \text{ND}_{t-1} + \nu_1 \Delta \text{Environment}_{t-1} + \nu_2 \Delta \text{NC}_{t-1} + \nu_3 \Delta \text{ND}_{t-1} + \lambda \text{ECT}_{t-1} + \epsilon_t, \tag{3}
\]

\[
\Delta \text{Oil Energy}_t = \beta_0 + \sum_{i=1}^{p} \gamma_1 \Delta \text{Oil Energy}_{t-1} + \sum_{i=0}^{q1} \gamma_2 \Delta \text{NC}_{t-1} + \sum_{i=0}^{q2} \gamma_3 \Delta \text{ND}_{t-1} + \nu_1 \Delta \text{Oil Energy}_{t-1} + \nu_2 \Delta \text{NC}_{t-1} + \nu_3 \Delta \text{ND}_{t-1} + \lambda \text{ECT}_{t-1} + \epsilon_t, \tag{5}
\]

\[
\Delta \text{Health}_t = \beta_0 + \sum_{i=1}^{p} \gamma_1 \Delta \text{Health}_{t-1} + \sum_{i=0}^{q1} \gamma_2 \Delta \text{NC}_{t-1} + \sum_{i=0}^{q2} \gamma_3 \Delta \text{ND}_{t-1} + \nu_1 \Delta \text{Health}_{t-1} + \nu_2 \Delta \text{NC}_{t-1} + \nu_3 \Delta \text{ND}_{t-1} + \lambda \text{ECT}_{t-1} + \epsilon_t, \tag{4}
\]

where, \( \text{Environment, Health, and Oil\ Energy} \) depicts the variables related to each of the three segments, \( \beta_0 \) and \( \epsilon \) are the intercept and the error term respectively, \( \Delta \) denotes the short-run terms, \( \nu \) defines
the long-run terms, the error correction term is indicated by ECT, while \( \lambda \) indicates the adjustment speed, which should be negative and significant in order to validate the long-run relationship.

The Granger causality test will be used to examine the relationship between variables pertaining to each industry and COVID-19 indicators. The null hypothesis states that \( h \) does not Granger-cause \( k \) and \( k \) does not Granger-cause \( h \). The empirical pattern is centered on the bivariate regressions listed below:

\[
k_t = a_0 + a_1 k_{t-1} + \ldots + a_p k_{t-p} + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p} + \epsilon_t, \tag{6}
\]

\[
h_t = a_0 + a_1 h_{t-1} + \ldots + a_p h_{t-p} + \beta_1 k_{t-1} + \ldots + \beta_p k_{t-p} + \epsilon_t. \tag{7}
\]

4 | **EMPIRICAL FINDINGS**

4.1 | **Summary statistics**

Table 5 shows the summary statistics for the variables. The Skewness and Kurtosis indicators show the deviation from a symmetric distribution around the average, and the degree of flattening or sharpening. The majority of the variables have data that is negatively skewed, with the “tail” of the distribution pointing to the left. The Kurtosis value for the majority of the variables is greater than 3, indicating a leptokurtic distribution. Consistent with Bourghelle et al. (2021), the high value of kurtosis associated with OIL suggests additional evidence of oil price volatility excess.

Figure 1 depicts the daily evolution of atmospheric CO\(2\) concentrations as well as the daily returns of environmental indices. Hence, the drop in atmospheric CO\(2\) concentrations do match with the dispersal of the COVID-19 across the globe. Due to lockdown and spending more time in homes, cities have started consuming more and more global energy, which will lead to more and more increases in carbon emissions, which can be seen in the graph as an increase starting with April 2020.

Figure 2 depicts the expansion of the incidence rate and deaths caused by the pandemic. Cássaro and Pires (2020) argued that the number of cases register a fast growing succeeded by steadiness later, this manner being termed a step-like function.

Figure 3 shows the evolution of health sector variables. It is observed that during March 2020 are registered the highest episodes of volatility. There are some impressive evolutions, especially in April, of the M3 Co producing masks, due to the downgrading of the first wave of COVID-19 and the population had to deal with a wave of protection measures that implicitly found in wearing the mask. Additionally, Gilead Sciences Inc, which produces the antiviral drug remdesivir, and Archer Daniels Midland Co, the world’s largest ethanol producer, have seen some expansion during the analyzed period.

Figure 4 reveals the advancement of the returns on oil futures and the Refinitiv Global Renewable Energy Equipment & Services Price Return Index. On April 20, 2020, there was a significant drop.

| Variables | Mean | Std. dev. | Skewness | Kurtosis | Jarque-Bera | Prob. |
|-----------|------|-----------|----------|----------|-------------|-------|
| 3M        | 0.00 | 0.03      | 0.29     | 5.63     | 29.99       | 0.00  |
| ADM       | 0.00 | 0.03      | 0.25     | 4.34     | 8.48        | 0.01  |
| CLIM      | 0.00 | 0.02      | -1.37    | 11.06    | 299.28      | 0.00  |
| CO2       | 414.97 | 1.47      | 0.18     | 1.95     | 5.09        | 0.08  |
| CVS       | 0.00 | 0.03      | 0.02     | 6.77     | 58.60       | 0.00  |
| ENVBP     | 0.00 | 0.02      | -1.13    | 8.72     | 156.33      | 0.00  |
| ENWBP     | 0.00 | 0.02      | -0.74    | 5.73     | 39.56       | 0.00  |
| GENV      | 0.00 | 0.03      | -0.92    | 6.61     | 67.89       | 0.00  |
| GGB       | 0.00 | 0.00      | -1.60    | 7.42     | 122.73      | 0.00  |
| GHEALTH   | 0.00 | 0.02      | -0.40    | 5.75     | 33.73       | 0.00  |
| GI        | 0.00 | 0.03      | -0.98    | 8.49     | 140.20      | 0.00  |
| GILD      | 0.00 | 0.03      | 0.40     | 3.61     | 4.19        | 0.12  |
| GPHARMA   | 0.00 | 0.02      | -0.46    | 6.07     | 42.54       | 0.00  |
| HEALTH    | 0.00 | 0.02      | -1.36    | 8.37     | 149.52      | 0.00  |
| NC        | 35,539.61 | 37,478.60 | 0.37      | 1.37     | 13.30       | 0.00  |
| ND        | 2337.66 | 2752.06   | 0.79      | 2.38     | 11.84       | 0.00  |
| OIL       | -0.04 | 0.34      | -7.34    | 62.70    | 15,587.83   | 0.00  |
| PHARMA    | 0.00 | 0.02      | -1.51    | 9.61     | 218.03      | 0.00  |
| RENEW     | 0.00 | 0.03      | -0.38    | 6.14     | 43.02       | 0.00  |
| ROCHE     | 0.00 | 0.02      | -0.67    | 4.96     | 23.19       | 0.00  |

Note: For the definition of variables, please see Table 4.
Source: Authors’ own work.
WTI oil prices fell in April 2020 as the coronavirus pandemic continued to erode demand for crude, and growing concerns about a global recession fueled fears of longer-term demand destruction.

Table 6 shows the correlations between variables. Strongly positive correlations were found between the indicators that describe the evolution of the COVID-19 pandemic and CO₂, which is also the only high correlation established with the coronavirus.

One notable finding is that no correlation has been found between oil futures and other variables. Besides, the renewable energy index has positive correlations with environmental variables (CLIM, ENVBP, GENV, and ENVWP). In addition, the indices in the health sector are strongly positively correlated with the CLIM, GENV, and ENVWP indices.

The Jarque–Bera test is used to investigate the normality of the variable distribution. Table 5 also includes the corresponding results, which show that the variable distribution is not normally distributed, because the probability associated with it is 0, with the exception of the data series GILD, which is normally distributed.

Stationarity tests must be performed to confirm that the regressors in the system are not I(2) series in order to avoid the issue of
spurious findings (Le et al., 2021). In this regard, Table 7 displays the results of the ADF and KPSS tests at the level and first difference. Except for the indicators related to the evolution of COVID-19 and CO2, for which we can reject the null hypothesis and conclude that the series are not stationary, the majority of the variables are stationary, with an integration order of I(0). The findings are also supported by the KPSS test results.

4.2 | The outcomes of time series investigation

4.2.1 | Quantitative evidence from ARDL cointegration and Granger causality analysis towards COVID-19 and environment

The primary goal of our research is to investigate how the COVID-19 pandemic affects the environment, health sector, and energy market on a global scale. The stationarity test revealed that the variables are of order 0 and 1, allowing us to proceed with the ARDL analysis technique. This technique investigates the existence of cointegration between the studied variables, which can be stationary or non-stationary. It is critical to select the appropriate number of lags for the ARDL model, which will permit us to investigate the relationships that have been established between variables. Thus, we will use the AIC to determine the best lags for the variables in the ARDL model.

We will use the criteria graph to determine the appropriate lags for the ARDL model, with the lowest value preferred. Appendix D contains the results of the criteria graph for the ARDL model, which takes into account the number of new cases and deaths worldwide. The horizontal axis of the chart represents the estimated ARDL models, and the vertical axis represents the models’ AIC values. The criteria graph displays the top 20 results.

The results of the ARDL bound test for cointegration are shown in Table 8. The cointegration test has two critical values: the lower critical bound assumes that all variables are I(0), implying that there is no cointegration, and the upper critical bound presumes that all variables are I(1), suggesting that there is cointegration among the variables. If the F-statistics value is greater than the critical value of bounds, it signifies that the variables have a long run connection.

The outcomes of the ARDL models that explore the relations between COVID-19 measures and environmental indicators exhibit several cointegration associations. Hence, pandemic is cointegrated with the atmospheric CO2 concentrations, Refinitiv/S-Network Europe Environmental Best Practices Index, Ethical Europe Climate Care Equity Index, MSCI Global Environment Price Return in USD Index, S&P BSE GREENEX INDEX, and FTSE Environmental Opportunities Waste and Pollution Control Index. The F-statistic for GGB (iShares Global Green Bond ETF) is less than the upper bound of bounds value of 5%, so we cannot reject the null hypothesis that no cointegration relationship exists between GGB and COVID-19 variables.

Table 9 displays the results of the long-term connection between COVID-19 new cases and deaths and environmental measures. The coefficient of the error correction term recorded for all environmental variables is significant at the 5% level of significance. Thus, the negative and significant error correction term, which indicates the speed of conversion, suggests that the dependent variable will reach equilibrium with a speed of between 55.17 percent and 113.4 percent the following day.

In the long-run, there was not noticed any statistically significant effect from the number of novel cases and new deaths of pandemic on Refinitiv/S-Network Europe Environmental Best Practices Index, Ethical Europe Climate Care Equity Index, MSCI Global Environment Price Return in USD Index, S&P BSE GREENEX INDEX, FTSE Environmental Opportunities Waste, Pollution Control Index, and iShares Global Green Bond ETF. However, contrary to previous research (Ju et al., 2020; Othmana & Latif, 2021; Wu et al., 2021), the number of new COVID-19 cases has a positive impact on atmospheric CO2 concentrations in both the long and short term. CO2 releases are the main air pollutant associated to manufacturing energy consumption and traffic volume (Ju et al., 2020). Consistent with Barua and Nath (2021), greater movement across outdoor areas significantly increased
the level of pollutant emissions. As well, in line with Chang et al. (2021), the rise of pandemic figures triggered a turn from public transport use to personal vehicle use, hence a boost in pollution. Another justification is related to the expanded usages of household fuel for cooking and heating due to restricted interior events, which boosted the dirty indoor air (Zhang et al., 2022).

In the short term, there was a negative effect from the number of new cases of COVID-19 and a positive effect from the number of new deaths of COVID-19 for the Refinitiv Global Renewable Energy Equipment & Services Price Return Index. Furthermore, Appendices G and J demonstrate that serial correlation and heteroscedasticity have no effect on ARDL outcomes.

In addition, the Granger causality test is used to investigate the relationship between variables. The data series must be stationary, so they were converted into stationary series as a requirement for using the Granger causality test. Appendix A shows the results of the Granger causality test for the environment variables and COVID-19 measures. Nevertheless, there was identified no causal connection between environmental variables and COVID-19 indicators.

### 4.2.2 Quantitative evidence from ARDL cointegration and Granger causality analysis towards COVID-19 and health sector

Appendix E encloses the criteria graph, which will show the appropriate lags for the ARDL model among COVID-19 and health sector variables. In the health sector, the presence of cointegration is confirmed.

| Variables | (1) 3M | (2) ADM | (3) CLIM | (4) CO2 | (5) CVS | (6) ENVB | (7) ENWP | (8) GENV | (9) GGB | (10) GHEALTH | (11) GI | (12) GILD | (13) GPHARMA | (14) HEALTH | (15) NC | (16) ND | (17) OIL | (18) PHARMA | (19) RENEW | (20) ROCHE |
|-----------|-------|--------|---------|--------|--------|---------|---------|--------|-------|-------------|-------|-------|-------------|-----------|-------|-------|-------|-------|---------|--------|
| (1) 3M    | 1     |        |         |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (2) ADM   | 0.77  | 1      |         |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (3) CLIM  | 0.61  | 0.67   | 1       |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (4) CO2   | 0.02  | 0.09   | 0.08    | 1      |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (5) CVS   | 0.6   | 0.73   | 0.55    | 0.09   | 1      |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (6) ENVB  | 0.61  | 0.69   | 0.98    | 0.1    | 0.56   | 1       |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (7) ENWP  | 0.74  | 0.81   | 0.84    | 0.13   | 0.71   | 0.87    | 1       |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (8) GENV  | 0.6   | 0.71   | 0.81    | 0.12   | 0.63   | 0.84    | 0.91    | 1      |       |              |      |      |              |           |       |       |       |       |         |        |
| (9) GGB   | 0.15  | 0.01   | 0.13    | 0.06   | 0.07   | 0.13    | 0.18    | 0.25   | 1     |              |      |      |              |           |       |       |       |       |         |        |
| (10) GHEALTH | 0.76 | 0.83   | 0.77    | 0.13   | 0.81   | 0.78    | 0.89    | 0.11   | 1     |              |      |      |              |           |       |       |       |       |         |        |
| (11) GI   | 0.18  | 0.25   | 0.26    | 0.11   | 0.11   | 0.25    | 0.09    | 0.14   | 0.28  | 0.18        |      |      |              |           |       |       |       |       |         |        |
| (12) GILD | 0.39  | 0.44   | 0.33    | 0.01   | 0.42   | 0.28    | 0.33    | 0.29   | 0.08  | 0.47        |      |      |              |           |       |       |       |       |         |        |
| (13) GPHARMA | 0.72 | 0.82   | 0.77    | 0.13   | 0.8    | 0.78    | 0.86    | 0.79   | 0.11  | 0.98        |      |      |              |           |       |       |       |       |         |        |
| (14) HEALTH | 0.18  | 0.24   | 0.14    | 0.13   | 0.09   | 0.16    | 0.06    | 0.08   | 0.06  | 0.04        |      |      |              |           |       |       |       |       |         |        |
| (15) NC   | 0.1   | 0.11   | 0.14    | 0.88   | 0.11   | 0.16    | 0.19    | 0.15   | 0.08  | 0.17        |      |      |              |           |       |       |       |       |         |        |
| (16) ND   | 0.08  | 0.11   | 0.12    | 0.81   | 0.12   | 0.14    | 0.17    | 0.14   | 0.12  | 0.18        |      |      |              |           |       |       |       |       |         |        |
| (17) OIL  | 0.09  | 0.15   | 0.06    | 0.07   | 0.09   | 0.08    | 0.14    | 0.15   | 0.1   | 0.1         |      |      |              |           |       |       |       |       |         |        |
| (18) PHARMA | 0.46 | 0.58   | 0.76    | 0.11   | 0.5    | 0.78    | 0.7     | 0.64   | 0.11  | 0.73        |      |      |              |           |       |       |       |       |         |        |
| (19) RENEW | 0.53  | 0.61   | 0.8     | 0.07   | 0.52   | 0.84    | 0.86    | 0.16   | 0.75  | 0.1         |      |      |              |           |       |       |       |       |         |        |
| (20) ROCHE | 0.41  | 0.52   | 0.58    | 0.03   | 0.34   | 0.47    | 0.39    | 0.11   | 0.57  | 0.1         |      |      |              |           |       |       |       |       |         |        |
| (11) GI   | 0.26  | 1      |         |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (12) GILD | 0.17  | 0.51   | 1       |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (13) GPHARMA | -0.09 | 0      | 1       |        |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (14) HEALTH | 0.37  | -0.09  | 0       | 1      |        |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (15) NC   | 0.18  | -0.03  | 0.18    | 0.18   | 1      |         |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (16) ND   | 0.17  | 0.03   | 0.18    | 0.17   | 0.92   | 1       |         |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (17) OIL  | -0.1  | 0.17   | 0.07    | -0.1   | -0.07  | -0.06   | 1       |        |       |              |      |      |              |           |       |       |       |       |         |        |
| (18) PHARMA | -0.25 | 0.18   | 0.73    | 0.16   | 0.1    | 0.12    | 0.66    | 1      |       |              |      |      |              |           |       |       |       |       |         |        |
| (19) RENEW | -0.22 | 0.26   | 0.63    | 0.07   | 0.1    | 0.1     | -0.03   | 0.83   | 0.45  | 1           |      |      |              |           |       |       |       |       |         |        |

Note: For the definition of variables, please see Table 4.
Source: Authors' own work.
in all nine estimated ARDL models, according to the ARDL bounds test results in Table 10, with the $F$-statistic being significantly higher than the critical values in $I(0)$ and $I(1)$. Therefore, the variables under consideration are cointegrated and will move together in the long term.

Cointegration relations were found between the studied variables in frameworks that take into account the effects of new cases and deaths, as well as health variables. Table 11 shows that for all health variables, there is a coefficient of the error correction term that is significant at the 5% level of significance. As a result, the negative and significant error correction term, which denotes the speed of convergence, signifies that the dependent variable will reach equilibrium with a speed of between 96.3 percent and 183.6 percent the following day. In the long term, the number of new cases and deaths attributed to COVID-19 have a positive effect on Gilead Sciences Inc, which manufactures the antiviral drug remdesivir. The reason for this outcome could be that the COVID-19 outbreak prompted major pharmaceutical corporations to respond quickly by developing antiviral drugs to aid in the fight against the pandemic. However, in the shorter term, new cases of COVID-19 have a negative impact on Gilead Sciences Inc, which specializes in the production of the antiviral drug remdesivir, and Archer Daniels Midland Co, the world’s largest ethanol manufacturer.

Furthermore, in the short run, new COVID-19 death cases have a positive impact on the Refinitiv Global Healthcare Price Return Index and the Refinitiv Global Pharmaceuticals & Medical Research Price

| TABLE 7 | The outcomes of the augmented Dickey–Fuller test & KPSS test |
|---------|-----------------------------------------------------------|
|         | Augmented Dickey–Fuller test statistic                     | Kwiatkowski–Phillips–Schmidt–Shin test statistic |
|         | Level | 1st Diff. | Level | 1st Diff. | |
| CO₂     | -2.708908*** | -8.608755* | 29.898 | 0.01239*** |
| 3M      | -12.22276*   |          | 0.082193*** |          |
| ADM     | -13.21489*   |          | 0.075621*** |          |
| CLIM    | -5.430739*   |          | 0.247471*** |          |
| CVS     | -6.437243*   |          | 0.00147*** |          |
| ENVBP   | -10.12205*   |          | 0.180587*** |          |
| ENVWP   | -5.36322*    |          | 0.343941*** |          |
| GENV    | -5.36322*    |          | 0.268128*** |          |
| GGB     | -7.3189*     |          | 0.175104*** |          |
| GHEALTH | -5.67817*    |          | 0.293606*** |          |
| GI      | -10.80136*   |          | 0.194274*** |          |
| GILD    | -12.81579*   |          | 0.047649*** |          |
| GPHARMA | -5.6595*     |          | 0.298602*** |          |
| HEALTH  | -9.152589*   |          | 0.192537*** |          |
| NC      | -2.286607*** | -13.59642* | 0.201081* | 0.072553*** |
| ND      | -1.602846*** | -9.14883* | 0.167098* | 0.091213*** |
| OIL     | -7.334988*   |          | 0.082125*** |          |
| PHARMA  | -9.383311*   |          | 0.164832*** |          |
| RENEW   | -9.195755*   |          | 0.102442*** |          |
| ROCHE   | -9.514979*   |          | 0.078068*** |          |

Note: Test critical values: *1% level. **5% level. ***10% level. For the definition of variables, please see Table 4. Source: Authors’ own work.

| TABLE 8 | The results of the ARDL bounds test for the model environment & COVID-19 |
|---------|-----------------------------------------------------------|
| Test statistic: $F$-stat. |
| CO₂     | 11.84 | |
| ENVBP   | 35.99 | |
| CLIM    | 10.48 | |
| GENV    | 7.69  | |
| GGB     | 3.78  | |
| GI      | 41.87 | |
| ENVWP   | 11.23 | |

Critical value bounds

| Significance (%) | I₀ bound | I₁ bound |
|------------------|----------|----------|
| 10               | 3.17     | 4.14     |
| 5                | 3.79     | 4.85     |
| 2.50             | 4.41     | 5.52     |
| 1                | 5.15     | 6.36     |

Note: Null hypothesis: No long-run relationships exist. For the definition of variables, please see Table 4. Source: Authors’ own work.
### Table 9

ARDL cointegrating and long-term form, long-term & short-term coefficients, for the model environment & COVID-19

|        | CointEq(-1) | Long run coefficients | Short run coefficients |
|--------|-------------|-----------------------|------------------------|
|        |             | NC        | ND        | D(NC)   | D(ND)   | D(ND(-1)) |
| **CO2**|             |           |           |         |         |           |
| Coeff. | -0.560      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.091    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -6.140      | 3.669     | 0.502     | 2.912   | 0.510   |           |
| Prob.  | 0.000       | 0.000     | 0.617     | 0.005   | 0.612   |           |
| **ENVBP**|            |           |           |         |         |           |
| Coeff. | -1.059      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.103    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -10.327     | 0.989     | -0.347    | 0.986   | -0.347  |           |
| Prob.  | 0.000       | 0.325     | 0.729     | 0.327   | 0.729   |           |
| **CLIM**|             |           |           |         |         |           |
| Coeff. | -0.815      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.147    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -5.538      | 0.821     | -0.397    | 0.820   | -0.398  |           |
| Prob.  | 0.000       | 0.414     | 0.693     | 0.414   | 0.692   |           |
| **GENV**|             |           |           |         |         |           |
| Coeff. | -0.817      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.172    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -4.745      | 0.465     | 0.097     | -1.359  | 0.097   |           |
| Prob.  | 0.000       | 0.643     | 0.923     | 0.178   | 0.923   |           |
| **GGB**|             |           |           |         |         |           |
| Coeff. | -0.552      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.162    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -3.399      | -0.263    | 0.552     | -0.261  | 0.541   |           |
| Prob.  | 0.001       | 0.793     | 0.582     | 0.795   | 0.590   |           |
| **GI** |             |           |           |         |         |           |
| Coeff. | -1.134      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.102    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -11.161     | 0.868     | 0.047     | -0.975  | 0.047   |           |
| Prob.  | 0.000       | 0.388     | 0.962     | 0.332   | 0.962   |           |
| **ENVWP**|            |           |           |         |         |           |
| Coeff. | -1.062      | 0.000     | 0.000     | 0.000   | 0.000   |           |
| Std. Err. | 0.186    | 0.000     | 0.000     | 0.000   | 0.000   |           |
| t-Stat. | -5.704      | 1.485     | -0.767    | -2.120  | -0.406  | 2.466     |
| Prob.  | 0.000       | 0.141     | 0.445     | 0.037   | 0.686   | 0.016     |
Return Index, as argued by Gurrib (2021); Harjoto and Rossi (2021); He et al. (2020); Mazur et al. (2021); Mushafiq (2021). Likewise, according to Alam et al. (2021), the positive influence is asserted by rising demand for medical devices and pharmaceutics. Besides, serial correlation and heteroscedasticity have no impact on the quantitative results (see Appendices H and K).

The findings in Appendix B are consistent with those in Appendix A, namely that variables in the health sector have no causal relationship with COVID-19 variables. The pandemic’s impact on global health services is still unquantifiable. The pandemic has also accelerated the adoption of digital technologies or process automation, both of which are required to optimize the delivery of medical facilities. However, the emergence of the COVID-19 pandemic rendered the previous progressions appear to be frozen in time. Faced with an unprecedented situation, medical systems around the world have had to recreate themselves instantly in order to limit the virus’s propagation.

### 4.2.3 Quantitative evidence from ARDL cointegration and Granger causality analysis towards COVID-19 and energy market

Appendix F provides a criteria graph that will support the ARDL model determine the appropriate lags between the COVID-19 measure and oil and energy market variables. Table 12 shows the results of the ARDL bounds test for the model oil and energy market and COVID-19, which confirms the presence of cointegration relationships between variables. The F-statistic is significantly greater than the critical values in I(0) and I(1). As a result, the variables under consideration are cointegrated and will move together in the long run.

Table 13 shows the long-term relationship between variables for the model oil and energy market and COVID-19. Thus, several statistically significant relationships are noticed. In the oil model, the number of new cases and new death cases of COVID-19 had a mixed effect

**Table 9 (Continued)**

| CointEq(−1) | Long run coefficients | Short run coefficients |
|-------------|-----------------------|------------------------|
|             | NEW_CASES  | NEW_DEATHS | D(NEW_CASES) | D(NEW_DEATHS) | D(ND(−1)) |
| t-Statistic | −10.327    | 0.989      | −0.347       | 0.986         | −0.347     |
| Prob.       | 0.000      | 0.325      | 0.729        | 0.327         | 0.729      |
| CLIM        | Coefficient | −0.815     | 0.000        | 0.000         | 0.000      |
|             | Std. Error  | 0.147      | 0.000        | 0.000         | 0.000      |
| t-Statistic | −5.538     | 0.821      | −0.397       | 0.820         | −0.398     |
| Prob.       | 0.000      | 0.414      | 0.693        | 0.414         | 0.692      |
| GENV        | Coefficient | −0.817     | 0.000        | 0.000         | 0.000      |
|             | Std. Error  | 0.172      | 0.000        | 0.000         | 0.000      |
| t-Statistic | −4.745     | 0.465      | 0.097        | −1.359        | 0.097      |
| Prob.       | 0.000      | 0.643      | 0.923        | 0.178         | 0.923      |
| GGB         | Coefficient | −0.552     | 0.000        | 0.000         | 0.000      |
|             | Std. Error  | 0.162      | 0.000        | 0.000         | 0.000      |
| t-Statistic | −3.399     | −0.263     | 0.552        | −0.261        | 0.541      |
| Prob.       | 0.001      | 0.793      | 0.582        | 0.795         | 0.590      |
| GI          | Coefficient | −1.134     | 0.000        | 0.000         | 0.000      |
|             | Std. Error  | 0.102      | 0.000        | 0.000         | 0.000      |
| t-Statistic | −11.161    | 0.868      | 0.047        | −0.975        | 0.047      |
| Prob.       | 0.000      | 0.388      | 0.962        | 0.332         | 0.962      |
| ENVWP       | Coefficient | −1.062     | 0.000        | 0.000         | 0.000      |
|             | Std. Error  | 0.186      | 0.000        | 0.000         | 0.000      |
| t-Statistic | −5.704     | 1.485      | −0.767       | −2.120        | −0.406     |
| Prob.       | 0.000      | 0.141      | 0.445        | 0.037         | 0.686      |

Note: For the definition of variables, please see Table 4. Source: Authors’ own work.
on the long-term above NYMEX Light Sweet Crude Oil (WTI). In addition, new COVID-19 death cases have a positive impact on oil returns in the short run. Therefore, an increase in the number of new cases of COVID-19 worldwide during the analyzed period causes an increase in the price of WTI, whereas an increase in the number of new deaths caused by COVID-19 causes a long-term decrease in the price of WTI.

The adverse economic viewpoint on a global scale caused by enforced travel constraints, closed factories, and self-quarantined people generated a significant fall in the global demand for energy and hence the worldwide oil price declined considerably (Le et al., 2021). Therewith, Bourghelle et al. (2021) argued that the oil price fall occurred due to the oil commercial conflict among the main oil-producing countries (Saudi Arabia and Russia). Besides, the negative effect may be reasoned by greater insecurity triggered by the pandemic, which drive the decline of energy prices (Khan et al., 2021). Consistent with Szczygielski et al. (2021), the uncertainty regarding upcoming profitability of companies within the energy sector driven a negative reaction and increased volatility. Additionally, Atri et al. (2021) contended that COVID-19 health crisis panic strikes oil market and caused oil price collapse. As well, the outcomes confirm, Shaikh (2021a) which found that COVID-19 provoked economic insecurity, which has affected severely most of the commodities.

| TABLE 10 | The results of the ARDL bounds test for the model health sector & COVID-19 |
| Test statistic: F-stat. |
| HEALTH | 29.41746 |
| GHEALTH | 9.425615 |
| PHARMA | 30.79788 |
| GPHARMA | 8.924094 |
| CVS | 15.48152 |
| ROCHE | 8.924094 |
| GILD | 15.12029 |
| ADM | 63.70194 |
| 3M | 52.01012 |

Critical value bounds

| Significance (%) | I0 bound | I1 bound |
|------------------|----------|----------|
| 10 | 3.17 | 4.14 |
| 5 | 3.79 | 4.85 |
| 2.50 | 4.41 | 5.52 |
| 1 | 5.15 | 6.36 |

Note: Null hypothesis: No long-run relationships exist. For the definition of variables, please see Table 4.
Source: Authors’ own work.

| TABLE 11 | ARDL cointegrating and long-term form, long-term & short-term coefficients, for the model health sector & COVID-19 |
| CointEq(-1) | Long term coefficients | Short term coefficients |
| HEALT | NC | ND |
| Coeff. | -0.963 | 0.000 | 0.000 | 0.000 | 0.000 |
| Std. Err. | 0.103 | 0.000 | 0.000 | 0.000 | 0.000 |
| t-Stat. | -9.342 | 0.475 | 0.192 | 0.475 | 0.192 |
| Prob. | 0.000 | 0.636 | 0.848 | 0.636 | 0.848 |

GHEALTH

| Coeff. | -1.090 | 0.000 | 0.000 | 0.000 | 0.000 |
| Std. Err. | 0.206 | 0.000 | 0.000 | 0.000 | 0.000 |
| t-Stat. | -5.294 | 0.209 | 0.370 | -1.964 | 0.750 | 2.446 |
| Prob. | 0.000 | 0.635 | 0.712 | 0.053 | 0.455 | 0.017 |

PHARMA

| Coeff. | -0.984 | 0.000 | 0.000 | 0.000 | 0.000 |
| Std. Err. | 0.103 | 0.000 | 0.000 | 0.000 | 0.000 |
| t-Stat. | -9.541 | 0.590 | 0.029 | 0.589 | 0.029 |
| Prob. | 0.000 | 0.556 | 0.977 | 0.557 | 0.977 |

GPHARMA

| Coeff. | -1.063 | 0.000 | 0.000 | 0.000 | 0.000 |
| Std. Err. | 0.206 | 0.000 | 0.000 | 0.000 | 0.000 |
| t-Stat. | -5.151 | 0.059 | 0.505 | -1.845 | 0.476 | 2.153 |
| Prob. | 0.000 | 0.953 | 0.615 | 0.069 | 0.635 | 0.034 |

CVS
Another noteworthy point from these ARDL models is that new infection cases of COVID-19 have a negative impact on the RENEW variable in the short run, while new death cases of COVID-19 have a positive impact. In line with Maneejuk et al. (2021), the sensitivity of energy markets is attributable to the fact that no large-scale crisis, such as current pandemic was faced in the past and thus the prices cannot quickly adapt.

Furthermore, the results are exempt of serial correlation and heteroscedasticity (see Appendices I and L). Appendix C exhibits the results of causalities for the variables related to the oil and energy markets, along with COVID-19. Consequently, no causal relationship was found in this case.

### TABLE 11 (Continued)

|         | CointEq(−1) | Long term coefficients | Short term coefficients |
|---------|-------------|------------------------|-------------------------|
|         | Coeff.      | NC         | ND         | D(NC) | D(ND) | D(ND(−1)) |
| Coeff.  | −1.479      | 0.000      | 0.000      | 0.000 | 0.000 |
| Std. Err.| 0.218      | 0.000      | 0.000      | 0.000 | 0.000 |
| t-Stat. | −6.773      | 0.126      | 0.658      | 0.126 | 0.657 |
| Prob.   | 0.000       | 0.900      | 0.512      | 0.900 | 0.513 |
| ROCHE   | Coeff.      | −0.980     | 0.000      | 0.000 | 0.000 |
|         | Std. Err.   | 0.103      | 0.000      | 0.000 | 0.000 |
|         | t-Stat.     | −9.519     | 0.119      | 0.286 | 0.119 |
|         | Prob.       | 0.000      | 0.906      | 0.776 | 0.906 |
| GILD    | Coeff.      | −1.837     | 0.000      | 0.000 | 0.000 |
|         | Std. Err.   | 0.273      | 0.000      | 0.000 | 0.000 |
|         | t-Stat.     | −6.734     | −2.616     | 2.481 | −2.585 |
|         | Prob.       | 0.000      | 0.011      | 0.015 | 0.011 |
| ADM     | Coeff.      | −1.346     | 0.000      | 0.000 | 0.000 |
|         | Std. Err.   | 0.098      | 0.000      | 0.000 | 0.000 |
|         | t-Stat.     | −13.805    | 0.750      | −0.413 | −2.356 |
|         | Prob.       | 0.000      | 0.455      | 0.681 | 0.021 |
| 3M      | Coeff.      | −1.242     | 0.000      | 0.000 | 0.000 |
|         | Std. Err.   | 0.099      | 0.000      | 0.000 | 0.000 |
|         | t-Stat.     | −12.504    | 1.021      | −0.425 | −1.116 |
|         | Prob.       | 0.000      | 0.310      | 0.672 | 0.267 |

Note: For the definition of variables, please see Table 4. Source: Authors' own work.

### TABLE 12 The results of the ARDL bounds test for the model oil and energy market & COVID-19

| Test statistic: F-stat. | OIL | 18.65341 |
|-------------------------|-----|----------|
| RENEW                   | 10.8404 |

| Critical value bounds   | I0 bound | I1 bound |
|-------------------------|----------|----------|
| Significance (%)        |          |          |
| 10                      | 3.17     | 4.14     |
| 5                       | 3.79     | 4.85     |
| 2.50                    | 4.41     | 5.52     |
| 1                       | 5.15     | 6.36     |

Note: Null hypothesis: No long-run relationships exist. For the definition of variables, please see Table 4. Source: Authors' own work.

Another noteworthy point from these ARDL models is that new infection cases of COVID-19 have a negative impact on the RENEW variable in the short run, while new death cases of COVID-19 have a positive impact. In line with Maneejuk et al. (2021), the sensitivity of energy markets is attributable to the fact that no large-scale crisis, such as current pandemic was faced in the past and thus the prices cannot quickly adapt.

Furthermore, the results are exempt of serial correlation and heteroscedasticity (see Appendices I and L).

Appendix C exhibits the results of causalities for the variables related to the oil and energy markets, along with COVID-19. Consequently, no causal relationship was found in this case.

### 5 Concluding Remarks and Policy Implications

The pandemic's progression caused uncertainty at all levels of activity, putting significant psychological strain on individuals. The outbreak of the COVID-19 pandemic caused high volatility in the stock markets in the first half of 2020, resulting in uncertainty and fear. We looked at how COVID-19 affects the environment, the health sector, and the
energy market in this article. We used daily data from December 31, 2019 to May 22, 2020, covering the first wave of the pandemic, to achieve our goal. The ARDL framework was applied in order to examine both short and long-term relationships. The results of the ARDL bound test for cointegration revealed the presence of long run relationships between environmental, health sector, and energy market variables, as well as new cases and deaths from the COVID-19 pandemic around the world. We also found long-term and short-term relationships after estimating the ARDL models. It should be noted that the number of short-term relationships was higher, which can be attributed to the short periods of high volatility observed during the study period.

The number of new cases was found to have a positive long-term and short-term impact on atmospheric CO₂ concentrations. Thus, an increase in the number of new cases of COVID-19 will result in an increase in CO₂ emissions both in the long and short term, because the isolation period caused the population to consume more unclean energy (Y. Zhang et al., 2022). In the long run, the number of new cases and deaths related to COVID-19 had a positive impact on the stock returns of Gilead Sciences Inc, which manufactures the antiviral drug remdesivir. This empirical result may be supported by journal publications or press releases relating to the performance of remdesivir, as well as information about the start of clinical studies (Chabrière, 2021). In the short run, however, new cases of COVID-19 had a negative impact on the stock returns of Gilead Sciences Inc and Archer Daniels Midland Co, the world’s largest ethanol producer. This outcome may be attributed to frequent news headlines about drugs competing with remdesivir, political influence, or research articles (Chabrière, 2021). Furthermore, investors who are unfamiliar with the complexities of medicine and biological science are making investment decisions based on short-term news cycles rather than long-term public health consequences (Mukherjee, 2020). In addition, in the short run, new COVID-19 death cases had a positive impact on the Refinitiv Global Healthcare Price Return Index and the Refinitiv Global Pharmaceuticals & Medical Research Price Return Index.

In terms of the oil model, the number of new cases and deaths from COVID-19 were found to have a mixed impact on NYMEX Light Sweet Crude Oil over the long term (WTI). In addition, new COVID-19 death cases had a positive effect on oil returns in the short run. As well, results showed that new infection cases had a negative impact on the daily returns of the index capturing renewable energy, but new death cases had a positive impact. According to the findings of the Granger causality analysis, there are no causal relationships between the COVID-19 variables and the environment, health sector, or oil and energy market.

The pandemic-initiated partnership at the national and international levels have exceeded all expectations and precedents. The public–private partnership formed by regulators, health care providers, the life sciences industry, and technology firms have brought all parties involved together to fight the pandemic, improve people’s health, and assist economies in surviving and recovering. Our findings offer several recommendations to investors for optimizing their portfolios. Investing in alternative energy sources, for example, could reduce reliance on the crude oil market (Gharib et al., 2021). As long as different effects are identified, government assistance is required for those sectors that are negatively impacted by COVID-19, such as the energy sector (Harjoto & Rossi, 2021).

Further, decreasing pollutant emission throughout quarantine measures are not a sustainable approach to clean up the atmosphere. As such, effective guidance for decision makers and regulators are also offered. Thus, in order to lengthen the gains of COVID-19 on air and water contamination, government policies and regulations are necessary so as to design a more inclusive atmosphere supervising procedure (Yang et al., 2021). There is necessary a secure organization of household waste, which should be gathered by dedicated municipal operators (Zhang et al., 2021). At the same time, there is necessary the disconnecting of economic growth from air pollution and the reduction of releases from the industrial segment (Magazzino et al., 2021). Hence, financing renewable energy resources will support the green and clean ecosystem produced by the COVID-19 lockdown.

### Table 13 ARDL cointegrating and long-term form, long-term & short-term coefficients, for the model oil and energy market & COVID-19

|            | Long term coefficients | Short term coefficients |
|------------|------------------------|-------------------------|
|            | CointEq(–1) | NC | ND   | D(NC) | D(ND) | D(NC–1) | D(ND–1) | D(NC–2) | D(ND–1) |
| OIL        |            |    |      |       |       |          |          |          |         |
| Coeff.     | −1.1483    | 0.0000 | −0.0002 | 0.0000 | 0.0001 | 0.0000   | 0.0000   | 0.0000   | 0.0002   |
| Std. Err.  | 0.1595     | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000   | 0.0000   | 0.0000   | 0.0001   |
| t-Stat.    | −7.2009    | 4.3872 | −4.9837 | −1.7179 | 2.3491 | −1.5918  | 1.9415   | 4.3427   |
| Prob.      | 0.0000     | 0.0000 | 0.0000 | 0.0896 | 0.0212 | 0.1153   | 0.0556   | 0.0000   |
| RENEW      |            |    |      |       |       |          |          |          |         |
| Coeff.     | −0.7900    | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000   | 0.0000   | 0.0000   | 0.0000   |
| Std. Err.  | 0.1393     | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000   | 0.0000   | 0.0000   | 0.0000   |
| t-Stat.    | −5.6721    | 1.0828 | −0.9030 | −1.3302 | −0.9217 | −2.2107  | −0.8455  | 3.0637   |
| Prob.      | 0.0000     | 0.2820 | 0.3691 | 0.1870 | 0.3593 | 0.0298   | 0.4003   | 0.0029   |

Note: For the definition of variables, please see Table 4.
Source: Authors’ own work.
(Rita et al., 2021). In terms of mobility, in order to curtail traffic discharges, which considerably enhance air quality (Wu et al., 2021) and improve health, there is necessary the shift to environmentally friendly transport means. Not least, more commitments from the authorities are essential so as to establish green employment and strengthen ecological resilience.

The study is limited only to the first wave of the pandemic period. At the same time, a global analysis is employed. As well, stock trading volume or residential mobility are not considered. Besides, merely atmospheric CO₂ concentrations are covered. Hence, upcoming investigations could concentrate on additional COVID-19 wave series, while also taking a multi-country approach. Therewith, another future research direction may consider the air pollution emanated from transportation, along with other individual pollutants, such as ozone, as well as meteorological variables alike daily temperature. Likewise, since the impact of COVID-19 may vary across different sectors, other segments, such as financials, should be included. Besides, as long as the link among COVID-19 and considered sectors may be asymmetric, employing quantile-on-quantile estimation technique or non-linear autoregressive distributed lag model may be considered.

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### APPENDIX A: THE RESULTS OF THE GRANGER CAUSALITY TEST FOR THE ENVIRONMENT AND COVID-19 VARIABLES

| Pairwise Granger causality tests | Null hypothesis | F-stat. | Prob. |
|----------------------------------|-----------------|--------|-------|
| DNC does not Granger Cause DCO2  | 0.52786         | 0.7546 |
| DCO2 does not Granger Cause DNC  | 1.68414         | 0.1476 |
| DND does not Granger Cause DCO2  | 2.27801         | 0.0543 |
| DCO2 does not Granger Cause DND  | 1.09454         | 0.3698 |
| DNC does not Granger Cause ENVBP | 1.13182         | 0.3502 |
| ENVBP does not Granger Cause DNC | 1.49402         | 0.2008 |
| DND does not Granger Cause ENVBP | 0.53582         | 0.7486 |
| ENVBP does not Granger Cause DND | 0.2881          | 0.9183 |
| DNC does not Granger Cause CLIM  | 1.39759         | 0.2338 |
| CLIM does not Granger Cause DNC  | 1.31137         | 0.2673 |
| DNC does not Granger Cause GENV  | 0.78687         | 0.5621 |
| GENV does not Granger Cause DNC  | 1.63051         | 0.1611 |
| DND does not Granger Cause GENV  | 0.62227         | 0.6832 |
| GENV does not Granger Cause DND  | 0.77971         | 0.5672 |
| DNC does not Granger Cause GGB   | 0.15749         | 0.7772 |
| GGB does not Granger Cause DNC   | 1.41422         | 0.2278 |
| DND does not Granger Cause GGB   | 0.65373         | 0.6959 |
| GGB does not Granger Cause DND   | 1.03424         | 0.4032 |
| DNC does not Granger Cause GI    | 0.59275         | 0.7055 |
| GI does not Granger Cause GI     | 1.16545         | 0.3333 |
| DND does not Granger Cause Gl    | 0.5169          | 0.7628 |
| Gl does not Granger Cause DND    | 0.30405         | 0.9092 |
| DNC does not Granger Cause ENVWP | 0.66246         | 0.6529 |
| ENVWP does not Granger Cause DNC | 1.83892         | 0.1143 |
| DND does not Granger Cause ENVWP | 0.6694          | 0.6477 |
| ENVWP does not Granger Cause DND | 0.75877         | 0.5821 |

Note: Sample: 1/02/2020–5/22/2020. For the definition of variables, please see Table 4.
Source: Authors’ own work.

### APPENDIX B: THE RESULTS OF THE GRANGER CAUSALITY TEST FOR THE HEALTH SECTOR AND COVID-19 VARIABLES

| Pairwise Granger causality tests | Null hypothesis | F-stat. | Prob. |
|----------------------------------|-----------------|--------|-------|
| DNC does not Granger Cause HEALTH | 1.58769         | 0.1981 |
| HEALTH does not Granger Cause DNC| 1.60968         | 0.1929 |
| DND does not Granger Cause HEALTH| 0.40891         | 0.747 |
| HEALTH does not Granger Cause DND| 0.82859         | 0.4816 |
| DNC does not Granger Cause GHEALTH| 1.63676         | 0.1866 |
| GHEALTH does not Granger Cause DNC| 0.65106         | 0.5844 |
| DND does not Granger Cause GHEALTH| 1.25846         | 0.2936 |
| GHEALTH does not Granger Cause DND| 1.20077         | 0.3143 |
| DNC does not Granger Cause PHARMA| 1.79915         | 0.1532 |
| PHARMA does not Granger Cause DNC| 1.07596         | 0.3635 |
| DND does not Granger Cause PHARMA| 0.93626         | 0.4267 |
| DNC does not Granger Cause CVS   | 1.24989         | 0.2966 |
| CVS does not Granger Cause DND   | 1.50968         | 0.1114 |
| DND does not Granger Cause CVS   | 0.94531         | 0.4224 |
| DNC does not Granger Cause GPHARMA| 1.30859         | 0.2767 |
| GPHARMA does not Granger Cause DND| 1.3832          | 0.2532 |
| DNC does not Granger Cause CVS   | 0.46721         | 0.7059 |
| CVS does not Granger Cause DND   | 0.63423         | 0.5949 |
| DND does not Granger Cause CVS   | 0.75767         | 0.5208 |
| CVS does not Granger Cause DND   | 0.12025         | 0.948 |
| DNC does not Granger Cause ROCHE | 0.93028         | 0.4296 |
| ROCHE does not Granger Cause DNC | 0.58531         | 0.6262 |
| DND does not Granger Cause ROCHE | 0.27192         | 0.8455 |
| ROCHE does not Granger Cause DND | 0.74933         | 0.5256 |
| DNC does not Granger Cause GILD  | 0.41752         | 0.7409 |
| GILD does not Granger Cause DNC  | 1.71568         | 0.1696 |
| DNC does not Granger Cause GILD  | 2.23461         | 0.0898 |
| GILD does not Granger Cause DND  | 2.52626         | 0.0626 |
| DNC does not Granger Cause ADM   | 1.92098         | 0.132 |
| ADM does not Granger Cause DND  | 1.37224         | 0.2565 |
| DND does not Granger Cause ADM   | 1.86326         | 0.1417 |
| ADM does not Granger Cause DND  | 0.61486         | 0.6072 |
| DNC does not Granger Cause _3M   | 1.119           | 0.3458 |
| _3M does not Granger Cause DNC   | 1.04272         | 0.3778 |
| DND does not Granger Cause _3M   | 0.91326         | 0.438 |
| _3M does not Granger Cause DND   | 0.54483         | 0.6529 |

Note: Sample: 1/02/2020–5/22/2020. For the definition of variables, please see Table 4.
Source: Authors’ own work.
**APPENDIX C: THE RESULTS OF THE GRANGER CAUSALITY TEST FOR THE OIL AND ENERGY MARKET AND COVID-19 VARIABLES**

| Null hypothesis                        | F-stat.     | Prob.  |
|----------------------------------------|-------------|--------|
| LNND does not Granger Cause OIL        | 0.40225     | 0.8749 |
| OIL does not Granger Cause LNND        | 0.3045      | 0.9324 |
| LNNC does not Granger Cause OIL        | 0.0918      | 0.9970 |
| OIL does not Granger Cause LNNC        | 0.18627     | 0.9797 |
| LNND does not Granger Cause RENEW      | 1.37897     | 0.2364 |
| RENEW does not Granger Cause LNND      | 0.24955     | 0.9578 |
| LNNC does not Granger Cause RENEW      | 0.41198     | 0.8687 |
| RENEW does not Granger Cause LNNC      | 0.96386     | 0.4562 |

**Note:** Sample: 1/02/2020–5/22/2020. For the definition of variables, please see Table 4.

**Source:** Authors' own work.
APPENDIX E: OPTIMAL LAGS FOR THE MODEL HEALTH SECTOR & COVID-19 [Colour figure can be viewed at wileyonlinelibrary.com]
APPENDIX F: OPTIMAL LAGS FOR THE MODEL OIL AND ENERGY MARKET & COVID-19 [Colour figure can be viewed at wileyonlinelibrary.com]
### APPENDIX G: BREUSCH–GODFREY SERIAL CORRELATION LAGRANGE MULTIPLIER (LM) TEST FOR THE MODEL ENVIRONMENT AND COVID-19

| Variable | F-stat. | Prob. F(2, 92) | Obs * R-square | Prob. Chi-Sq.(2) |
|----------|---------|----------------|----------------|-----------------|
| CO₂      | 0.33231 | 0.7181         | 0.702886       | 0.7037          |
| ENVBP    | 0.12671 | 0.8811         | 0.272364       | 0.8727          |
| CLIM     | 0.12671 | 0.8811         | 0.272364       | 0.8727          |
| GENV     | 1.399862| 0.2523         | 3.029323       | 0.2199          |
| GGB      | 0.571227| 0.567          | 1.245467       | 0.5365          |
| GI       | 0.077654| 0.9253         | 0.16697        | 0.9199          |
| ENVWP    | 0.423844| 0.656          | 0.972028       | 0.6151          |

**Note:** For the definition of variables, please see Table 4. 
**Source:** Authors’ own work.

### APPENDIX H: BREUSCH–GODFREY SERIAL CORRELATION LAGRANGE MULTIPLIER (LM) TEST FOR THE MODEL HEALTH SECTOR AND COVID-19

| Variable | F-stat. | Prob. F(2, 92) | Obs * R-square | Prob. Chi-Sq.(2) |
|----------|---------|----------------|----------------|-----------------|
| HEALTH   | 0.320006| 0.7269         | 0.677042       | 0.7128          |
| GHEALTH  | 0.818732| 0.4447         | 1.905487       | 0.3857          |
| PHARMA   | 0.424331| 0.6555         | 0.895746       | 0.639           |
| GPHARMA  | 0.982369| 0.3789         | 2.2772         | 0.3203          |
| CVS      | 1.560399| 0.2159         | 3.326673       | 0.1895          |
| ROCHE    | 0.681367| 0.5085         | 1.43042        | 0.4891          |
| GILD     | 0.680343| 0.5092         | 1.496805       | 0.4731          |
| ADM      | 0.282281| 0.7548         | 0.641821       | 0.7255          |
| 3M       | 0.270989| 0.7632         | 0.580212       | 0.7482          |

**Note:** For the definition of variables, please see Table 4. 
**Source:** Authors’ own work.
## APPENDIX I: BREUSSCH–GODFREY SERIAL CORRELATION LAGRANGE MULTIPLIER (LM) TEST FOR THE MODEL OIL AND ENERGY MARKET AND COVID-19

| VARIABLE | F-stat. | Prob. F(2, 80) | Obs * R-sq. | Prob. Chi-Sq.(2) | Scaled explained SS |
|----------|---------|----------------|-------------|------------------|--------------------|
| OIL      | 3.065789| 0.0521         | 6.762908    | 0.034            |
| RENEW    | 0.030048| 0.9704         | 0.069572    | 0.9658           |

Note: For the definition of variables, please see Table 4. Source: Authors' own work.

## APPENDIX J: HETEROSCEDASTICITY TEST: BREUSSCH–PAGAN–GODFREY FOR THE MODEL ENVIRONMENT AND COVID-19

| VARIABLE | F-stat. | Prob. F(3, 94) | Obs * R-sq. | Prob. Chi-Sq.(3) | Scaled explained SS |
|----------|---------|----------------|-------------|------------------|--------------------|
| CO2      | 0.416042| 0.7419         | 1.284188    | 0.7329           |
| ENVBP    | 0.487961| 0.6915         | 1.502773    | 0.6816           |
| CLIM     | 0.450899| 0.7715         | 1.865053    | 0.7606           |
| GENV     | 1.556721| 0.1592         | 10.57457    | 0.1583           |
| GGB      | 4.145999| 0.001          | 20.93642    | 0.0019           |
| GI       | 1.457784| 0.2214         | 5.782097    | 0.216            |
| ENVWP    | 1.07227 | 0.3927         | 10.75409    | 0.377            |

Note: For the definition of variables, please see Table 4. Source: Authors' own work.

## APPENDIX K: HETEROSCEDASTICITY TEST: BREUSSCH–PAGAN–GODFREY FOR THE MODEL HEALTH SECTOR AND COVID-19 VARIABLES

| VARIABLE | F-stat. | Prob. F(3, 94) | Obs * R-sq. | Prob. Chi-Sq.(3) | Scaled explained SS |
|----------|---------|----------------|-------------|------------------|--------------------|
| HEALTH   | 1.1708  | 0.3251         | 3.529962    | 0.3169           |
| GHEALTH  | 1.20017 | 0.2972         | 14.19195    | 0.2886           |
| PHARMA   | 0.401273| 0.7524         | 1.239176    | 0.7436           |
| GPHARMA  | 1.198826| 0.2981         | 14.17906    | 0.2894           |
| CVS      | 1.313748| 0.2595         | 7.809941    | 0.2524           |
| ROCH     | 1.583461| 0.1986         | 4.714285    | 0.194            |
| GILD     | 0.486461| 0.842          | 3.578295    | 0.8269           |
| ADM      | 2.485865| 0.0143         | 19.79472    | 0.0192           |
| 3M       | 3.532949| 0.0099         | 12.92722    | 0.0116           |

Note: For the definition of variables, please see Table 4. Source: Authors' own work.
APPENDIX L: HETEROSCEDASTICITY TEST: BREUSCH–PAGAN–GODFREY FOR THE MODEL OIL AND ENERGY MARKET AND COVID-19

|       | OIL               |               | RENEW             |               |
|-------|-------------------|---------------|-------------------|---------------|
| F-stat. | 5.400355         | 1.164555      |                    |               |
| Obs * R-sq. | 41.93615       | 11.56695      |                    |               |
| Scaled explained SS | 402.4917       | 22.56875      |                    |               |
| Prob. F(12, 82) | 0               | Prob. F(10, 84) | 0.3262           |               |
| Prob. Chi-Sq.(12) | 0               | Prob. Chi-Sq.(10) | 0.3151          |               |
| Prob. Chi-Sq.(12) | 0               | Prob. Chi-Sq.(10) | 0.0125          |               |

Note: For the definition of variables, please see Table 4.
Source: Authors’ own work.