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The historic oil price fluctuation during the Covid-19 pandemic: What are the causes?

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ABSTRACT

On 20 April 2020, the West Texas Intermediate (WTI) crude oil price dropped to negative levels for the first time in history. This study examines the factors underlying the historic oil price fluctuation during the Covid-19 pandemic. The autoregressive distributed lag (ARDL) bounds testing approach incorporating a structural break is applied to the daily series from 17 January to 14 September 2020 to analyze long-run relationships and short-run dynamics. The results reveal that increases in Covid-19 pandemic cases, US economic policy uncertainty, and expected stock market volatility contributed to the fall in the WTI crude oil price, whereas the fall in the global stock markets appears to significantly reduce the fall. Furthermore, the Russia–Saudi Arabia oil price war and speculation on oil futures are shown to play a critical part in the collapse of the oil markets. The findings are consistent with our expectations. Although it is reasonable to assume that the solution to this oil crisis is a pick-up in global oil demand, which will occur only when the novel coronavirus is defeated, this study proposes policy recommendations to cope with the current oil price crash.

1. Introduction

In parallel with the human loss and economic damage figures caused by the Covid-19 pandemic, recently, one figure captured the attention of the public globally—the price of crude oil. Crude oil is often referred to as the lifeblood of an economy, and thus, fluctuations in oil prices have a substantial impact on many countries around the world. The Covid-19 pandemic has restricted movement globally, resulting in a drop in demand of more than 30 million barrels of oil in early April 2020 (International Energy Agency, 2020). In the context of countries issuing traffic blockades and quarantine orders, restricting production and business activities, the oil price war between Russia and Saudi Arabia appeared to "pour oil into the fire," contributing to the steepest drop in oil prices in history. At one point on 20 April 2020, the West Texas Intermediate (WTI) benchmark of crude oil prices dropped to US$–$37.63 per barrel.

Several key events have seemingly been destabilizing for oil markets during this calendar year, but the biggest and most significant

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upset likely was the breakdown of the agreement between Russia and the Organization of the Petroleum Exporting Countries (OPEC)[1] nations regarding limitations on oil production. Saudi Arabia started an oil price war on 9 March 2020[2], slashing the price of crude oil by more than 20 % and crashing financial markets through shock spillovers on the same day (so-called "Black Monday"). The study period saw an oil glut when oil production was high, whereas the demand was much lower due to the effects of containment measures adopted in 187 countries. For example, the demand for oil in April is calculated to be 29 million barrels per day below the one-year-ago level (International Energy Agency, 2020). This type of disagreement between members of the OPEC + is not new, but this particular temper tantrum coincided with the largest market shutdown in modern history.

Traditionally, a lower oil price tends to be good news for emerging markets, especially for China, which is the largest oil importer in the world and thus, can benefit by filling up their strategic reserves at low prices. However, the demand for oil has declined substantially due to national lockdowns during which people have to stay at home, thus diminishing the benefit of lower oil prices. This also affects oil-processing industries. Refined petroleum is four times more expensive than crude oil at the best of times because of the cost of manufacturing. However, due to falling demand, even after purchasing crude oil at low prices, refiners cannot sell many of the processed products to earn a fat margin. Similarly, although lower oil prices mean that airlines and logistics companies have one of their major expenses alleviated, the airline industry worldwide might not be able to capitalize on this benefit due to having been heavily hit in recent months by the pandemic. Shipping companies are profiting from low oil costs since fuel costs are a significant expense for those industries. Nevertheless, these potential benefits are fully realized only if traffic blockades and quarantines are removed, and economic activity returns to normal. Heavy oil-consuming economies, such as the United States (US) and Europe, are still under lockdown, while China only gradually reopened their economy, implying that the demand for oil will remain low for the foreseeable future.

There are mixed results for the factors behind the recent sharp fluctuation in oil prices. We analyze and clarify this emerging question. Specifically, we investigate the potential determinants of the current WTI oil price shock during the Covid-19 pandemic. We focus on the WTI crude price for two reasons.[3] First, the WTI oil price dropped to negative territory on 20 April 2020, making history in the commodities markets for negative prices. Second, the role of WTI as the world's leading oil benchmark has been strengthened. This is attributable to the lift of the 40-year ban on oil exports by the US Congress in December 2015, as US crude oil production hit a record high (i.e., 9.2 million barrels per day at that time and 12.9 million barrels per day as of November 2019, according to the IEA). This has marked historic changes in the booming oil industry in the United States. Thanks to a significant investment in infrastructure, US oil production continues to increase at an impressive rate, and thus, WTI continues to play an increasingly important role in the global economy.

In our model setting, we consider the impacts of the Covid-19 pandemic and the oil price war, while controlling for the roles of the US's economic policy uncertainty, equity market-related economic uncertainty, and market volatility, as well as fluctuations in the US dollar, the world stock market, and speculation on WTI crude oil prices. For this purpose, Pesaran et al., 2001 bounds testing to cointegration (or autoregressive distributed lag (ARDL)) procedure was applied to the daily time-series data covering the period from 17 January to 14 September 2020 to examine the long-run (stable) and short-term relationships in addition to dynamic interactions among the selected variables. When appropriate lags are considered, ARDL can address serial correlation and endogeneity problems (Pesaran and Shin, 1999).

For comparison and completeness, we consider four proxies to assess the impacts of the Covid-19 pandemic on global crude oil prices, namely, (1) the number of new infection cases, (2) the total number of infection cases, (3) the number of new deaths, and (4) the total number of deaths. For robustness checks, we look at three proxies of the world stock market index and two proxies of the US dollar index.

We found that the Covid-19 pandemic, along with economic policy uncertainty, market perceived volatility, the global equity market, and speculation on WTI crude, negatively impacted oil prices in the long run. Meanwhile, in the short run, the number of daily new deaths due to Covid-19, as well as economic policy uncertainty, and global equity market seem to be critical determinants of the recent fluctuation in oil prices. Furthermore, the oil price war between Russia and Saudi Arabia had significantly negative impacts on the price of crude oil. The findings are robust to different proxies and model specifications.

The remainder of this study is organized as follows. In Section 2, we review the related literature that identifies potential determinants of crude oil price shocks, especially during several historical oil price crises, including the current pandemic. In Section 3, we review the model, data, and methodologies employed in this study. In Section 4, we present and discuss the empirical results. In Section 5, we conclude the study and provide implications.

[1] OPEC, founded on 14 September 1960, currently consists of 13 member countries, including a substantial portion of the largest oil-producing countries in the world. As of 2016, OPEC allied with other top, non-OPEC, oil-producing nations to form the OPEC+, a powerful entity that controls more than 50% of global oil supplies and about 90% of proven oil reserves.

[2] Saudi Arabia started a price war after the OPEC+ meeting on Saturday; immediately after, ARAMCO slashed the price for April delivery by 20%. Subsequently, on Monday, 9 March 2020, the oil and stock markets crashed.

[3] We initially investigated WTI and Brent in this study. However, we detected two issues with including Brent crude in the analysis. First, the historic oil price crash (with a negative price) happened only for WTI, so the focus on WTI is more appropriate. Second, the results found for Brent and WTI are not similar, partly due to the different nature of the oil futures contracts, which lead to the different responses of the two crude oils during the study period. We then decided to focus on WTI crude. Furthermore, we later included the SPREAD variable (which is the price difference between Brent and WTI crude oil) to capture the speculation effect on the price of WTI crude, in our empirical modeling. Thus, it is more appropriate to focus on the analysis of the WTI crude oil price.

2. Literature review

In this section, we look at three strands of the nexus between oil prices and macroeconomic variables in the literature. We also review the impact of trading activities on oil prices. More importantly, we found only a few key studies that also analyze oil price behaviors during the Covid-19 pandemic, and we discuss them in this section.

2.1. Uncertainty and the oil price

Empirically, uncertainty, including but not limited to economic policy uncertainty, financial uncertainty, and market uncertainty, has been identified as a crucial driver of oil price movements. Throughout history, the price of oil has been affiliated with economic outlook and policy, political stability, and regulatory uncertainty in oil-exporting countries as well as countries with large oil consumption (Yergin, 2012). Extensive literature has linked oil price shocks with inflationary episodes and recessions in the US economy. Disruptions in oil supplies resulting from political tension or wars have substantial power in determining oil prices (Kilian, 2010). Following oil demand shocks, political conflicts in OPEC countries impose the second largest positive effect on global oil prices (Chen et al., 2016). For instance, the Arab–Israeli war in 1973 led to a considerable spike in oil prices due to the OPEC oil embargo (Tignor et al., 2008). Similarly, crude oil prices can rise sharply due to political strains between oil-producing countries and their neighbors (Wang and Sun, 2017).

Changes in the oil price are closely connected to macroeconomic activities, such as output (Kilian and Vigfusson, 2011), investment (Elder and Serletis, 2010), inflation (Bhar and Mallik, 2013), unemployment, and gross domestic product (GDP) growth (Huang et al., 2017; Wang and Sun, 2017). These activities are affected by uncertainty through its effects on stocks in equity portfolios (Pastor and Veronesi, 2012, on government policy uncertainty; Pástor and Veronesi, 2013, on political uncertainty; Brogaard and Detzel, 2015, on government economic policy uncertainty), volatility (Bloom, 2009, on major macroeconomic shocks), and investment opportunities (Bloom et al., 2007, for firm-level data). Thus, it can be hypothesized that uncertainty can influence oil prices via its impacts on macroeconomic activities. Therefore, it is important to examine the significance of the influence of uncertainty on global oil prices. However, existing literature has mostly focused on the link between oil prices and uncertainty, and not the other way round. Few studies have critically assessed this relationship in the opposite direction.

Several empirical studies indicated that uncertainty tends to increase the volatility in oil prices. One widely documented channel is through alteration of economic agents' decision-making behaviors (Bloom et al., 2007; Litzenberger and Rabinowitz, 1995; Pindyck, 1993). In the case of high uncertainty, the adaption in quantities is restricted because of a lag in the consumption or production decision that strengthens the change through the price side. Consequently, elevated uncertainty generates higher oil price volatility. Another possible channel is via the oil futures market. Simply put, uncertainty is likely to render the supply and demand sides less sensitive to changes in oil prices through the use of oil futures, thus raising oil price volatility subsequent to shocks. This theory is reinforced by Hubbard's (1986) study where it was found that a significant driver of oil price volatility is market-based trading of oil. Similarly, Baumeister and Peersman (2013) discovered that hedging instruments could reduce price elasticity for oil supply and demand. Because risks can be diversified through futures markets, it is likely that higher macroeconomic uncertainty will boost the use of future contracts, thus reducing the price elasticity of oil supply and demand. However, there also exist studies in which uncertainty had no statistically significant impact on the oil price. For example, Kilian and Vega (2011) found that in the short term, exogenous macroeconomic news does not impose a significant impact on the daily oil price for the US sample.

The issue of uncertainty is further exacerbated by the extensive media coverage of Covid-19 amidst the swift propagation of information. Studies have shown that the media played a pivotal role in this crisis, and posed significant impact on oil and stock prices as well as environmental, social, and governance (ESG) indices. Media frenzy causes panic amongst the people and contributes to investment climate uncertainty and financial market volatility (Haroon and Rizvi, 2020). High stock market volatility is found to be predicted by high Google search volumes for Covid-19 (Lyócsa et al., 2020). Stock returns is also influenced by media coverage, although only for the middle to superior quantiles of the return distribution (Cepoi, 2020). Media coverage facilitates the transmission of financial contagion across economies and thus affecting the ESG volatility indices (Akhtaruzzaman et al., 2021b). Empirical findings by Atri et al., 2021 reveals that media coverage of the Covid-19 pandemic has a positive impact on the dynamics of the oil and gold markets, although changes in gold prices are less susceptible to "bad news".

Economic uncertainty has been shown to influence oil prices (Kang et al., 2017; Kang and Ratti, 2013; Yin, 2016). Because oil producers have to adapt to market demand and lower elasticity of the oil supply, oil pricing is affected. Regarding economic policy uncertainty (EPU), an index constructed by Baker et al. (2016), several studies found that international oil prices are affected by US EPU dynamics (Aloui et al., 2016; Chen et al., 2019; Yang, 2019). For instance, Chen et al. (2019) found that there is unidirectional Granger causality running from economic policy uncertainty to oil prices. Meanwhile, the global oil price appeared to not Granger cause economic policy uncertainty (Chen et al., 2019). This is intuitive, as oil prices impact forecasts for macroeconomic variables and consequently, EPU, while uncertainty resulting from national or international policies affects asset prices in general, and oil prices in particular. Using a quantile regression framework, Reboredo and Uddin (2016) discovered that EPU had a nonlinear effect on oil prices in the US.

Hypothesis 1. In this study, we propose that high economic policy uncertainty reduces the WTI crude oil price.

2.2. Market volatility and the oil price

Due to the increasing globalization of the world economy and financial markets, volatility spillovers likely exist across markets worldwide. The interactions between financial markets and oil markets are strengthened, allowing oil prices to incorporate more characteristics from the other markets. For instance, McMillan and Speight (2001) reported a transfer of speculative activities from the financial markets to the commodity markets. Ding et al. (2017) argued that oil resources possess financial features as opposed to possessing properties of a commodity only as a production input, implying oil is no longer purely determined by the supply and demand of physical oil products. Miao et al. (2017) discovered that financial factors have a greater impact as a driver of crude oil prices than supply and speculation. In mid-2014, the combined effects of demand, financial factors, and commodity markets were to blame for the crash in oil prices. Das et al. (2018) found a bidirectional relationship between oil prices and financial volatility for the US economy.

Oil futures markets also contribute substantially to the determination of global oil prices. According to Silverio and Szklo (2012), the markets can improve risk aversion, price discovery, and associated financial properties. As companies have been able to purchase any amount of crude oil futures they wish to with no restrictions (US Commodity Futures Trading Commission, 1991), investment funds have increased, leading to higher oil prices. This has sparked debates about the effect of speculation on changes in oil prices. Until now, the majority of empirical studies have indicated a modest (Kilian and Murphy, 2014; Liu et al., 2016) or insignificant (Espinasa et al., 2017; Smith, 2009) impact of speculation in explaining changes in oil prices. In contrast, Kaufmann (2011), while examining the oil spike and collapse during 2007–2008, affirmed the significant influence of speculation on oil price fluctuations.

To proxy for market volatility, the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is often adopted as a credible and reliable measurement, and one of the financial markets' most followed indicators. The VIX was introduced in 1993 as a volatility index for the US stock market. Implied volatility is unique due to its properties of being forward-looking and involving expectations of stock market volatility. Thus, employing implied volatility as a proxy for market risks can assist us in gaining insight into how the market's expectations for 30-day forward-looking volatility affect the WTI oil price. Sari et al. (2011), while examining the information transmission mechanism between global oil prices and global risk perceptions, found that in the long run, the VIX has a restraining impact on oil prices. Bašta and Molnár (2019) discovered statistically significant co-movement between the equity market and the oil market, where implied volatility of the stock markets leads to that of the oil market. Basher and Sadorsky (2016) documented bilateral causality between financial volatility (proxied by the VIX) and oil prices for emerging markets' stock prices.

Hypothesis 2. In this study, we propose that high stock market volatility and financial stress reduce the WTI crude oil price.

2.3. The impact of the stock markets on oil prices

Apart from the GDP, another possible proxy for general economic activity is the stock market (Bašta and Molnár, 2018). The nexus between oil prices and stock prices has been discussed intensively given the financialization of commodity markets (Balcilar et al., 2014). Similar to the case of uncertainty and oil price, although the impacts of oil price shocks on stock prices have been widely examined, the feedback link has rarely been explored critically. There exist some studies that suggest an interdependence between oil prices and stock prices. Antonakakis et al. (2017) confirmed a time-varying statistically significant connectedness between stock returns and oil price shocks while examining the dynamic structural relationship between the two variables in net oil-importing and -exporting developed countries. Foroni et al. (2017) discovered that the relationship between US stock returns and changes in oil prices has varied over time since the 1970s. Meanwhile, Le and Chang (2015) found that the nexus between oil price shock and stock market performance depends on the nature of the shocks and economies. Nusair and Al-Khasawneh (2018) suggested that oil and stock markets were likely to flourish or collapse together. External shocks resulting from macroeconomic policies or political tensions also affect the link between the two variables of interest (Bhar and Nikolova, 2010). However, the absolute impact of changes in the stock market on global oil prices remains uncharted territory.

Hypothesis 3. In this study, we propose that a high (low) stock market index increases (reduces) the WTI crude oil price.

2.4. The impact of oil market trading activity

The crude oil market has a physical market and a financial market. The physical market is the place where physical oil is traded by businesses. In the financial market, crude oil is commonly traded through futures contracts. These are contracts agreed upon by buyers and sellers to make or take deliveries of barrels of WTI crude oil at a certain time in the future at a predetermined price. A buyer of a WTI crude oil futures contract performs the obligation to buy and take delivery of WTI crude oil when the futures contract expires. Alternatively, the buyer may opt out of taking physical delivery of the oil by selling the futures contract before it expires.

WTI May futures fell more than 300 % from US$17.85 a barrel to US$–37.63 a barrel on Monday (20 April 2020). This is also the first time in history that prices plunged into negative territory. That means the oil seller had to pay the buyer to take the oil. Speculation on WTI crude oil occurs in the financial market. Specifically, many speculators jump into the crude oil market and try to catch the bottom when prices are low and oil prices are expected to turn around soon. That is why speculators poured billions of dollars into exchange traded funds (ETFs) that track the return of WTI crude oil by holding crude oil futures contracts.

Consequently, the collapse of WTI prices to negative levels was also driven by the closing (or rolling) out of long positions in WTI May futures contracts by large ETFs within a few days before the contracts expired on 21 April 2020. Investors were concerned about running out of storage capacity, and therefore, the ETFs had no intention of taking physical delivery of WTI crude oil.

Another possible reason for the drastic plunge in WTI prices is the decline in oil trading volume. Although the mixture of distribution hypothesis (MDH), which is prevalent in the literature, postulates a positive relationship between trading volume and price changes (Clark, 1973; Harris, 1986; Karpoff, 1987), the nature of the relationship in the crude oil futures markets is not as clear-cut. A large body of the price volume literature in the WTI crude oil futures markets supports the MDH. For example, Foster's (1995) pioneering work claimed that the relationship between price variability and trading volume in the WTI and Brent markets is positive. A positive correlation between the variables in the WTI market was also found by Kocagil and Shachmurove (1998); Moosa and Silvapulle (2000), and Moosa et al. (2003). Wang and Chen (2016) found that the relationship is positive for light sweet crude oil contracts but negative for Brent crude oil contracts. However, other scholars found contrasting findings, most of which indicate a lack of causality running between these variables or mixed findings (Abdullahi et al., 2014; Bhar and Hamori, 2005; Fujihara and Mougoué, 1997).

Speculation on WTI crude oil prices during this period contributed to the large drop in the price, causing the spread between WTI and Brent prices to widen significantly. Therefore, to take into account this speculation effect on the price of WTI crude, we include the price difference between Brent and WTI crude oil (the SPREAD variable) in our empirical modeling.

Hypothesis 4. In this study, we propose that a high price difference between Brent and WTI (proxied for high speculation on WTI crude oil) reduces the WTI crude oil price.

2.5. The Covid-19 pandemic and oil prices

The momentous event of crude oil reaching negative prices for the first time in history in April 2020 has prompted researchers to investigate the impact of the novel coronavirus on oil price volatility. As the issue is recent, literature is scarce. Several studies have examined the nexus between oil price and macroeconomic variables, such as the stock market, during the first wave of the pandemic and crisis. Overall, most studies agree on a simple tenet that the Covid-19 pandemic has reduced the global aggregate demand for oil with its economic lockdowns while increasing market uncertainty, particularly through disruptions in the global supply chain (Vidya and Prabheesh, 2020). Thus, the price of the commodity is negatively influenced (Albulescu, 2020; Devpura and Narayan, 2020; Prabheesh et al., 2020, to name only a few). As the adverse impact of the pandemic appears to be obvious, existing literature tends to focus on the nexus between the two variables of interest in a specific context or market, or in the presence of other economic factors. Moreover, because most of the (published) empirical studies utilized daily data only up to May 2020, the results should not be generalized to the second wave of the Covid-19 pandemic.

Using hourly data for the first six months of 2020, Devpura and Narayan (2020) controlled for oil trading volume, price returns, and liquidity, and found that the number of Covid-19 cases and deaths increased daily oil price volatility by at least 8% and at most 22 %. Prabheesh et al. (2020) used the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model fitted to daily oil price data and discovered that the global pandemic fortified the connection between stock prices and oil prices in the four largest Asian net oil-importing countries (China, India, South Korea, and India). Controlling for financial volatility and US EPU, Albulescu's (2020) ARDL estimation results suggested a marginally negative impact of daily newly reported Covid-19 cases on crude oil prices in the long run in comparison with the effect of EPU and financial volatility on oil prices, and the influence seemed indirect. The results also showed that the relationship was more significant for cases reported in China compared to cases reported outside the country, implying that the situation affects nations differently. Mensi et al. (2020) showed the negative impact of the pandemic on market efficiency for commodities such as gold and oil, and that these markets are sensitive to scales, market trends, and the Covid-19 pandemic. The findings are consistent with those from Akhtaruzzaman et al. (2020b).

Other empirical studies also found that the Covid-19 pandemic, particularly in regard to the number of reported deaths, has statistically significant impacts on oil prices, and this result is robust to different estimation methods. Huang and Zheng (2020) employed the Gregory-Hansen regime shift cointegration test and identified a structural change in the long-run relationship between crude oil volatility and WTI oil future prices due to the pandemic. Narayan (2020) identified a threshold value of Covid-19 infection cases above which oil prices would be more severely affected by the pandemic and discovered an association between Covid-19 cases and negative oil price news and oil prices. Corbet et al. (2020) examined the sectoral transmission mechanisms of volatility shocks and contagion in the energy sector during the Covid-19 pandemic. They found positive and economically meaningful spillovers from falling oil prices to coal and renewable energy markets. Nevertheless, this finding applies only to a short period surrounding the negative WTI oil price event. In the branch of energy demand and environmental conservation, the Covid-19 pandemic has been shown to possibly shift consumers, firms, and organizations toward prosocial and responsible consumption (He and Harris, 2020). This may include the consumption of "dirty" energies, such as crude oil.

In relation to the stock markets, Salisu et al. (2020) utilized a panel vector autoregressive (pVAR) model and a panel logit model for panel data covering 15 countries with the highest number of deaths from the coronavirus from early January to the end of May 2020, split into sub-samples of pre- and post-Covid-19 announcements. The findings indicated that stock markets and oil markets undergo more prominent initial and prolonged effects of own and cross-shocks during the post-pandemic announcement, with the impact more pronounced for oil prices. Sharif et al. (2020) discovered with a wavelet-based approach that the Covid-19 pandemic affected oil prices, and that the oil slump had a stronger influence on the US stock markets compared to the coronavirus and other macroeconomic variables, including the EPU and Geopolitical Risk (GPR) indexes. Akhtaruzzaman et al. (2020a) analyzed oil price risk exposure of financial and non-financial industries worldwide during the Covid-19 pandemic. They showed that the pandemic moderated exposure to the oil price risk of financial and non-financial industries. Moreover, Akhtaruzzaman et al. (2021a) pointed out the existence of financial contagion through increased dynamic conditional correlations between countries during the pandemic. To ameliorate the negative impacts of the pandemic on stock returns, several measures have been adopted by firms and corporations. For example, investing in corporate social responsibility (CSR) during the pandemic may help increase stock returns and protect firm values (He and Harris, 2020; Qiu et al., 2021). Another measure is for firms to increase their ESG investment as an indicator of share price resilience, which has been proven to mitigate financial risk during the Covid-19 pandemic (Broadstock et al., 2021). However, Folger-Laronde et al. (2020) claimed that the sustainability performance of investments may not be a good indicator of a firm's financial performance during the financial crisis and global pandemic, and that these investments would not likely be resilient during a crisis-induced market downturn.

Hypothesis 5. In this study, we propose that a high number of Covid-19 cases and deaths reduces the WTI crude oil price.

3. Data and methodology

3.1. Data

In this study, we analyze the impacts of the Covid-19 pandemic, the Russia–Saudi Arabia oil price war, the roles of US economic policy uncertainty, equity market–related economic uncertainty, and market volatility, in addition to fluctuations in the US dollar, the global stock markets, and the speculation of WTI crude on the WTI oil price. We employ daily data with the sample period starting on 17 January 2020, the date when data on Covid-19 infection cases and deaths at the global level were first made available, and ending on 14 September 2020; the closest date data were collected for this study. The global crude oil price is proxied by the WTI - Cushing, Oklahoma (the unit is US dollars per barrel). The two volatility variables are captured by the US EPU and the Equity Market-related Economic Uncertainty Index (EUI). The financial stress/volatility is proxied by the VIX. The US dollar index is employed to account for the fluctuation of the US dollar. The global equity market is proxied by the MSCI Morgan Stanley Capital International (MSCI) World Index (the largest world index of global stocks) which is a market cap-weighted stock market index of 1644 stocks from companies across the globe. Two other proxies, the FTSE All-World index and the S&P Global 100 Index, are employed for robustness checks. For the impacts of the Covid-19 pandemic, four proxies are considered for comparison and completeness: (1) the number of new infection cases, (2) the total number of infection cases, (3) the number of new deaths, and (4) the total number of deaths. The definitions and data sources of the variables are presented in Table 1. Regarding speculation on WTI crude oil prices, the price difference between the Brent and WTI crude oil prices is used as a proxy. The impact of the oil price war between Russia and Saudi Arabia is captured by a dummy which is discussed in section 4.1.

Tables 2 and 3 report the descriptive statistics of the series in levels and percentage changes. Overall, we can observe that the WTI crude oil price reached a negative number in value for the first time in history at US$–36.98 (its minimum).[4] The difference between the maximum and minimum points is substantial at about US$96 during the sample period. In terms of percentage changes, the oil price drops at a daily rate of 2% and has an all-time-high reduction rate of 302 % (from US$18.31 on 17 April to US$–36.98 on 20 April). Significant differences between maximum and minimum values are also recorded for the three uncertainty and volatility indicators. Furthermore, the sample period witnesses explosive growth in Covid-19 cases and deaths. On average, the daily percentage growth in the number of Covid-19 infections is 14 % for new cases and 9.7 % for total cases. Meanwhile, the daily percentage growth for Covid-19 deaths is 14.67 % for new deaths and about 10 % for the total number of deaths.

The trends for the selected variables in the empirical investigation, crude oil prices (WTI, Brent, and the price difference), Covid-19 cases and deaths (new and total), uncertainty and financial volatility, and global equity markets are plotted in Figs. 1,2, 3 and 4 respectively. Based on the plots, we can observe that during the sample period, the trend for the WTI crude is a V-shape with the lowest point observed on 18 April, while the price difference between Brent and WTI moves in the opposite direction. However, the trend for the total numbers of Covid-19 cases and deaths is rising due to the accumulating effect. An inverted U-shaped trend (skewed to the right) is generally observed for the policy uncertainty trend, while an inverted V-shaped trend (skewed to the right) seems to apply to equity market–related economic uncertainty and financial volatility. Meanwhile, the three indicators of global equity markets move closely together and depict a V-shaped trend.

3.2. Methodology

In the empirical analysis, Pesaran et al., 2001 ARDL cointegration procedure is applied to daily time-series data covering the period from 17 January to 14 September 2020. ARDL is selected for a number of reasons. When ARDL is modeled with an appropriate selection of the number of lags, serial correlation and endogeneity problems can be eliminated (Pesaran and Shin, 1999). Endogeneity is also argued to be less of a problem if there is no serial correlation in the estimated ARDL model (Jalil et al., 2013). In the ARDL system, specific driving forces for regressors can be identified.

ARDL modeling enables us to examine the relationships between the oil price and other selected variables in the short and long run. The long run is when there is a stable co-movement relationship between nonstationary variables (i.e., I(1) series). The greater the number of cointegrating vectors between variables, the stronger the long-run relationship between variables. This is because of the

[4] This figure is different from the historic negative figure of US$–$37.63 because they are two distinct crude oil prices. Specifically, US–$37.63 is the closing price of the US benchmark WTI for May delivery (the WTI May futures contract) on Monday, 20 April 2020. Meanwhile, US$–36.98 is the minimum of the WTI crude oil spot price also happening on Monday, 20 April 2020.

Table 1
Definitions and data sources of the variables.

Variable	Description	Source
WTI	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Daily, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis
BRENT	Crude Oil Prices: Brent - Europe, Dollars per Barrel, Daily, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis
SPREAD	The price difference between Brent and WTI (i.e., SPREAD = BRENT – WTI)	Authors' calculation
EPU	Economic Policy Uncertainty Index for the United States	Federal Reserve Bank of St. Louis
EUI	Equity Market-related Economic Uncertainty Index	Federal Reserve Bank of St. Louis
VIX	Chicago Board Options Exchange (CBOE) Volatility Index (VIX): a real-time market index that represents the market's expectation for 30-day forward-looking volatility.	Federal Reserve Bank of St. Louis/ Investing.com
USDI	US Dollar Index: an index (or measure) of the value of the US dollar relative to a basket of foreign currencies, often referred to as a basket of US trade partners' currencies	Investing.com
USDT	Trade-Weighted US Dollar Index: Broad, Goods and Services, Index Jan 2006 = 100	Federal Reserve Bank of St. Louis
MSCI	The MSCI World Index captures large and mid-cap representation across 23 developed market (DM) countries. The MSCI World is a market cap-weighted stock market index of 1644 stocks from companies throughout the world. It is maintained by MSCI, formerly Morgan Stanley Capital International, and is used as a common benchmark for "world" or "global" stock funds intended to represent a broad cross-section of global markets	Investing.com
FTSE	The FTSE All-World index series is a stock market index that covers more than 3100 companies in 47 countries starting in 1986. It is calculated and published by the FTSE Group	Investing.com
SP100	The S&P Global 100 Index is a stock market index of global stocks from Standard & Poor. The S&P Global 100 measures the performance of 100 multi-national, blue-chip companies of major importance in the global equity markets.	Investing.com
COVID1 (NCASE)	Number of new global cases of confirmed Covid-19 infections	European Center for Disease Prevention and Control (ECDC)
COVID2 (NDEATH)	Number of new global deaths due to Covid-19	European Center for Disease Prevention and Control (ECDC)
COVID3 (TCASE)	Number of total global cases of confirmed Covid-19 infections	European Center for Disease Prevention and Control (ECDC)
COVID4 (TDEATH)	Number of total global deaths due to Covid-19	European Center for Disease Prevention and Control (ECDC)
DUMMY	The dummy variable captures the impact of the oil price war between Russia and Saudi Arabia. The dummy takes the value 1 from 6 March 2020 (the break date detected by the Zivot-Andrews test) and onward, and takes the value of 0 for the period before that.	Authors' calculation

Table 1 presents the definitions and data sources of the variables. This study employs daily data from 17 January 2020 to 14 September 2020. The global crude oil price is proxied by the West Texas Intermediate (WTI) - Cushing, Oklahoma (the unit is in US dollars per barrel). The two volatility variables are captured by the US economic policy uncertainty (EPU) and the Equity Market-related Economic Uncertainty Index (EUI). The financial stress/volatility is proxied by the Chicago Board Options Exchange (CBOE) Volatility Index (VIX). In addition to the US dollar index (USDI), the trade-weighted US dollar index (USDT) is employed for the robustness check. The global equity market is proxied by the Morgan Stanley Capital International (MSCI) World Index. Additionally, two other proxies, the FTSE All-World index and the S&P Global 100 Index, are employed for robustness checks. For the impacts of the Covid-19 pandemic, four proxies are considered for comparison and completeness: (1) the number of new infection cases, (2) the total number of infection cases, (3) the number of new deaths, and (4) the total number of deaths. Regarding speculation on WTI crude, the price difference between Brent and WTI crude oil (SPREAD) is used as a proxy. The impact of the oil price war between Russia and Saudi Arabia is captured by a dummy which is discussed in section 4.1.

underlying forces; the variables would always have a (tight) connection in the long run. A long run cannot exist without cointegration between variables. In that case, the estimation will result in short-run impacts or effects. In other words, the short run is the period needed for variables to cointegrate into the long-run equilibrium. That is, before the variables reach a long-run equilibrium (if any), they will undergo a short run. Specifically, a simple linear transformation could derive the error correction model (ECM) from the ARDL model of the cointegrating vector, in which short-run adjustments are integrated with long-run equilibrium, and long-run information is retained. With a sufficient number of lags, the associated ECM model of the ARDL model is able to capture the data-generating process in general-to-specific modeling frameworks, thus incorporating long- and short-run information.

Next, unlike other traditional cointegration approaches, such as Johansen-Juselius and Engle-Granger cointegrating techniques that require a pre-test for the existence of unit root in the series, the bounds test is appropriate to apply regardless of whether the variables are purely I(0) or purely I(1), or mutually cointegrated. Thus, one can avoid potential pre-test bias in the standard unit root tests and cointegration tests. However, the ARDL system crashes if the variables are I(2), rendering the computed F-statistics of the bounds test invalid.

The ARDL bounds testing procedure is performed as follows. In the first step, the bounds testing procedure tests the cointegrating relationship among the variables (Pesaran and Pesaran, 1997; Pesaran et al., 2001).

Unrestricted error correction model (UECM) regressions are estimated as follows:

Table 2
Descriptive statistics of variables in levels: 17 January 2020 to 14 September 2020.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Number of observations
WTI	36.44	39.68	58.55	−36.98	12.50	166
BRENT	40.68	42.03	65.66	18.69	11.17	171
SPREAD	4.00	2.665	61.86	0.45	4.99	166
EPU	318.11	300.34	807.66	22.25	163.74	171
EUI	192.66	156.05	939.58	12.1	151.90	171
VIX	31.91	28.195	82.69	12.1	13.92	166
USDI	97.27	97.464	103.61	92.13	2.68	171
USDT	119.72	119.49	126.47	115.11	2.98	165
MSCI	2192.37	2236.04	2494.1	1602.11	207.74	171
FTSE	345.18	351.86	391.19	253.51	32.73	171
SP100	2111.08	2146.92	2442.5	1574.04	189.12	171
COVID1 (NCASE)	117497.01	88,843	310,287	5	97222.08	171
COVID2 (NDEATH)	3782.55	4226	10,491	0	2595.09	171
COVID3 (TCASE)	7,940,000	4,666,271	29,100,000	66	8,670,000	171
COVID4 (TDEATH)	335711.60	314,093	924,835	2	301,000	171

Note: Authors' calculation.
Table 2 reports the descriptive statistics of the series in levels. WTI and BRENT are the WTI and Brent crude oil prices, respectively, and SPREAD is their price difference. EPU stands for US economic policy uncertainty, and EUI denotes the Equity Market-related Economic Uncertainty Index. VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. USDI and USDT represent the US dollar index and the trade-weighted US dollar index, respectively. MSCI denotes the global equity market. FTSE and SP100 denote the FTSE All-World index and the S&P Global 100 Index, respectively. COVID1, COVID2, COVID3, and COVID4 represent the number of new infection cases, the number of new deaths, the total number of infection cases and the total number of deaths, respectively.

Table 3
Descriptive statistics of variables in percentage changes: 17 January 2020 to 14 September 2020.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Number of observations
WTI	−1.99	0	26.438	−301.966	53.086	171
BRENT	−0.17	−0.245	4.918	−26.870	17.681	181
SPREAD	7.69	0.376	61.359	−84.190	644.404	171
EPU	5.64	0.219	39.087	−55.817	325.528	181
EUI	27.16	6.608	112.094	−88.622	1016.282	181
VIX	0.86	−1.213	10.954	−23.373	47.951	171
USDI	−0.02	−0.015	0.499	−1.529	2.031	181
USDT	0.01	−0.018	0.425	−1.923	1.929	170
MSCI	0.03	0.149	2.085	−9.915	8.770	181
FTSE	0.02	0.107	1.961	−9.490	8.311	181
SP100	0.04	0.173	2.062	−9.382	8.413	181
COVID1 (NCASE)	14.03	4.316	79.256	−100	665	173
COVID2 (NDEATH)	14.67	6.475	71.354	−100	715.385	168
COVID3 (TCASE)	9.72	2.415	27.185	0	262.121	181
COVID4 (TDEATH)	9.91	2.349	25.147	0	211.539	174

Note: Authors' calculation.
Table 3 reports the descriptive statistics of the series in percentage changes. WTI and BRENT are the WTI and Brent crude oil prices, respectively, and SPREAD is their price differences. EPU represents the US economic policy uncertainty, and EUI denotes the Equity Market-related Economic Uncertainty Index. VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. USDI and USDT represent the US dollar index and the trade-weighted US dollar index, respectively. MSCI denotes the global equity market. FTSE and SP100 denote the FTSE All-World index and the S&P Global 100 Index, respectively. COVID1, COVID2, COVID3, and COVID4 represent the number of new infection cases, the number of new deaths, the total number of infection cases and the total number of deaths, respectively.

$$\begin{aligned}\Delta \mathrm{WTI}_t = {} & \alpha_0 + \alpha_1.\mathrm{WTI}_{t-1} + \alpha_2.\mathrm{EPU}_{t-1} + \alpha_3.\mathrm{EUI}_{t-1} + \alpha_4.\mathrm{VIX}_{t-1} + \alpha_5.\mathrm{USDI}_{t-1} + \alpha_6.\mathrm{GSI}_{t-1} + \alpha_7.\mathrm{COVID}_{t-1} + \alpha_8.\mathrm{SPREAD}_{t-1} \\ & + \sum_{i=1}^{k}\alpha_{9i}.\Delta\mathrm{WTI}_{t-i} + \sum_{i=0}^{m}\alpha_{10i}.\Delta\mathrm{EPU}_{t-i} + \sum_{i=0}^{n}\alpha_{11i}.\Delta\mathrm{EUI}_{t-i} + \sum_{i=0}^{p}\alpha_{12i}.\Delta\mathrm{VIX}_{t-i} + \sum_{i=0}^{q}\alpha_{13i}.\Delta\mathrm{USDI}_{t-i} + \sum_{i=0}^{r}\alpha_{14i}.\Delta\mathrm{GSI}_{t-i} \\ & + \sum_{i=0}^{s}\alpha_{15i}.\Delta\mathrm{COVID}_{t-i} + \sum_{i=0}^{v}\alpha_{16i}.\Delta\mathrm{SPREAD}_{t-i} + \alpha_{17}.\mathrm{DUMMY}_t + \varepsilon_t \end{aligned} \tag{1}$$

On the right side, WTI, EPU, EUI, VIX, USDI, GSI, COVID, and SPREAD are the global crude oil price, economic policy uncertainty, equity market–related economic uncertainty, financial stress and volatility, US dollar index, global stock market index, Covid-19 (infection and death cases), and speculation on the WTI (proxied by the price difference between Brent crude and WTI crude), respectively. DUMMY is the dummy variable, which captures the impacts of the Russia–Saudi Arabia oil price war; Δ is the first difference operator; k, m, n, p, q, r, s, and v are lag lengths; α_0 is the drift, and ε_t is the white noise error. α_i (i = 1–8) are the long-run

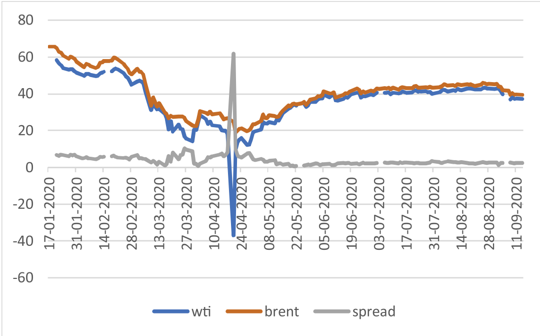

Fig. 1. Global crude oil price trends.

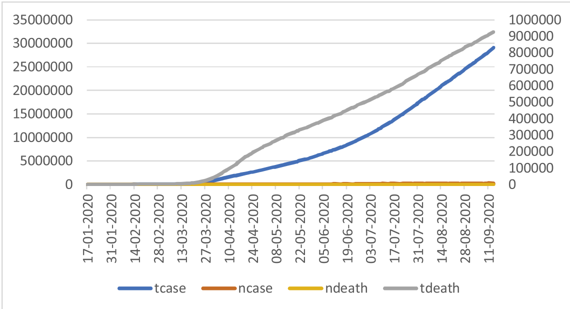

Fig. 2. Covid-19 cases and deaths trends.

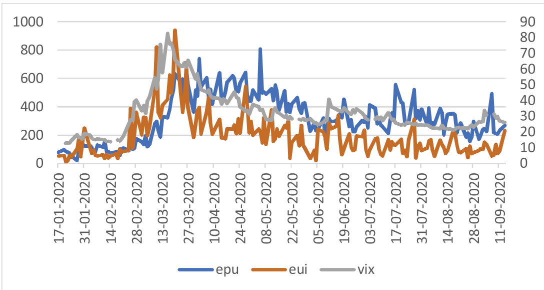

Fig. 3. Uncertainty and financial volatility trends.

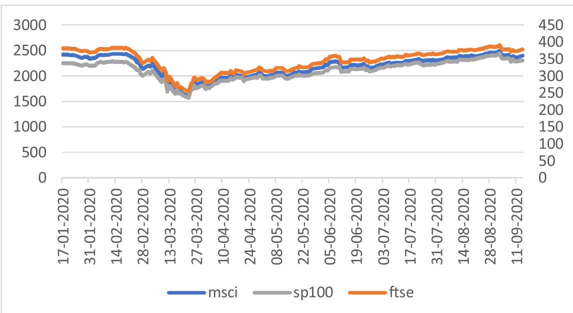

Fig. 4. Global equity market trends.

Note: The trends of the selected variables in the empirical investigation, crude oil prices (WTI, Brent, and the price difference); Covid-19 cases and deaths (new and total); uncertainty and financial volatility; and global equity markets, are plotted in Figs. 1,2,3, and 4, respectively.

multipliers; α_i ($i = 8$–16) are the short-run multipliers. The optimal lag lengths are determined with the Akaike information criterion (AIC).

Then, the F-test is carried out on the joint-level significance of the lagged variables, implying the existence of a long-run relationship. The null hypothesis of "no cointegration" in the equation (Eq. [1]), i.e., the coefficients of the lag-level variables are zero, is tested as follows:

$$F(WTI_t|EPU_t, EUI_t, VIX_t, USD_t, GSI_t, COVID_t, SPREAD_t): \ \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = 0 \tag{2}$$

The hypothesis is tested by producing general F-statistics based on the variables computed in levels. We then use critical values taken from Pesaran et al. (2001) for comparison. Based on the properties of the series, two sets of critical values are considered: the lower critical bound assuming the variables in the ARDL model are all stationary I(0), and the upper critical bound for the purely I(1) series. If the variables are fractionally integrated, the computed F-statistics are then compared with these upper and lower critical bounds. If the computed F-statistic for the joint significance of the variables in the level is smaller than the lower critical bound, then the null hypothesis of no cointegration cannot be rejected at the confidence level, implying no cointegration among the variables. However, if the computed F-statistic is greater than the upper critical bound, the null hypothesis is rejected, implying cointegrated variables. Meanwhile, if the computed F-statistic falls within the critical value band, the cointegration outcome is inconclusive.

The error correction representation associated with the selected ARDL can be specified as follows:

$$\begin{aligned}\Delta WTI_t = {} & \beta_0 + \sum_{i=1}^{k} \beta_{1i}.\Delta WTI_{t-i} + \sum_{i=0}^{m} \beta_{2i}.\Delta EPU_{t-i} + \sum_{i=0}^{n} \beta_{3i}.\Delta EUI_{t-i} + \sum_{i=0}^{p} \beta_{4i}.\Delta VIX_{t-i} + \sum_{i=0}^{q} \beta_{5i}.\Delta USDI_{t-i} + \sum_{i=0}^{r} \beta_{6i}.\Delta GSI_{t-i} \\ & + \sum_{i=0}^{s} \beta_{7i}.\Delta COVID_{t-i} + \sum_{i=0}^{s} \beta_{8i}.\Delta SPREAD_{t-i} + \beta_9.DUMMY_t + \varphi ECM_{t-1} + u_t\end{aligned} \tag{3}$$

where the parameters β_{ij} are the short-run dynamic coefficients, ECM_t is the residual obtained from Eq. [1], i.e., the error correction term, and the coefficient of the lagged error correction term (φ) indicates the speed of adjustment back to long-run equilibrium after a short run shock. φ is expected to be statistically significant and negative.

4. Empirical results

4.1. Stationarity test

Although the ARDL bounds testing approach to cointegration does not require an examination of the integrated order of all the variables, this approach is feasible only when the variables are not integrated of an order higher than one. Otherwise, Pesaran et al.'s (2001) computed F-statistics are no longer valid. Thus, to avoid the problem of spurious results, stationarity tests must be performed to ensure that the regressors in the system are not I(2) series. For this purpose, we employed the Zivot and Andrews, 1992 unit root test, which takes into account one endogenous structural break in the data series, to test the null hypothesis of the unit root against the break-stationary alternative.

The results of unit root tests for the Zivot and Andrews, 1992 test (with one break) are presented in Table 4. There seems to be a mixture of I(0) and I(1) series, but no risk of I(2) variables. This finding supports the use of the ARDL bounds testing approach to cointegration in this study.

As shown in Table 4, the Zivot-Andrews test detects the structural break on 7 March 2020 for the WTI crude oil price series. This break date corresponds to the start date of the oil price war between Saudi Arabia and Russia, two of the world's largest oil producers, triggered by the failure of OPEC + countries to reach an agreement on oil production cuts. To capture the effects of the 2020 Saudi Arabia–Russia oil price war as implied by the structural break in the dependent variable (WTI crude oil price) of the baseline model, Eq. [1], a dummy variable is incorporated in the empirical estimations. The dummy takes the value 1 from 6 March 2020 and onward, and takes the value of 0 for the period before that.[5]

4.2. Bounds test results and findings

We examine whether there exist stable long-run relationships among the variables, based on Eq. [1]. A general-to-specific approach is applied, and based on a maximum lag of 4, the AIC is used to determine the optimal lag structure for the conditional autoregressive distributed lag-vector error correction model (ARDL-VECM). For the first difference part of the system, we estimate Eq. [1] with the ordinary least squares (OLS) estimation procedure as in Pesaran and Pesaran (1997, p. 305), and then compute the F-statistics to test the joint significance of the parameters of the lagged level variables when added to the first regression. However, according to Pesaran and Pesaran (1997), "this OLS regression in first differences are of no direct interest to the bounds test to cointegration." The F-test examines the null hypothesis that the coefficients of the lagged level variables are zero (i.e., no long-run relationship exists among the variables).

[5] The dummy variable captures the single break as identified by the Zivot-Andrews unit root test results (i.e., 6 March 2020). This date is consistent with the start of the oil price war between Russia and Saudi Arabia.

Table 4
Zivot-Andrews unit root test results (with intercept).

Variable	Level		First difference	
	T-statistic (lag)	Break	T-statistic (lag)	Break
WTI	−3.9083 (3)	06-March-2020	−9.8182*** (3)	21-April-2020
BRENT	−4.9691* (0)	06-March-2020	−13.4575*** (0)	22-April-2020
SPREAD	−8.3795*** (0)	15-April-2020	−6.8309*** (3)	07-April-2020
EPU	−4.5304 (3)	09-March-2020	−9.1629*** (4)	27-March-2020
EUI	−4.9621 (4)	27-March-2020	−11.3968*** (3)	23-March-2020
VIX	−3.284904 (4)	05-March-2020	−6.6221*** (4)	19-March-2020
USDI	−6.0300*** (2)	10-March-2020	−10.1902** (0)	20-March-2020
USDT	−5.1209** (3)	10-March-2020	−5.7783*** (3)	24-March-2020
MSCI	−5.0563** (4)	05-March-2020	−7.8329*** (3)	24-March-2020
FTSE	−5.192721** (4)	05-March-2020	−7.7163** (2)	24-March-2020
SP100	−4.9577** (3)	05-March-2020	−6.5281*** (4)	24-March-2020
COVID1 (NCASE)	−3.5802 (4)	17-June-2020	−7.9884*** (4)	31-July-2020
COVID2 (NDEATH)	−3.4959 (4)	23-March-2020	−9.3815*** (4)	20-April-2020
COVID3 (TCASE)	−0.3956 (4)	13-July-2020	−6.2240*** (4)	22-June-2020
COVID4 (TDEATH)	−4.0808 (0)	23-April-2020	−7.5516*** (4)	23-March-2020

Note: Maximum lags are set at 4. Source: Authors' calculation. Note: *, **, and *** denote statistical significance at the 10 %, 5%, and 1% levels, respectively.
Table 4 presents the results of the Zivot and Andrews, 1992 unit root test (with one break). There seems to be a mixture of I(0) and I(1) series, but no risk of I(2) variables. This finding supports the use of the ARDL bounds testing approach to cointegration in this study.

The calculated F-statistics for the cointegrating relationships among the seven variables as shown in Eq. [1] are presented in Table 5. The calculated F-statistics are compared with the critical values from Table C1.iii in Appendix C, Case III: unrestricted intercept and no trend in Pesaran et al. (2001) for k = 7. The results reveal that at the 5% significance level, there is not enough evidence to accept the null hypothesis of no cointegration for all the models. The existence of cointegrating vectors among the group of the variables indicates that these variables move together in the long run. The first cointegrating vector shows that economic policy uncertainty, equity market–related economic uncertainty, financial volatility, US dollar index, global stock market index, Covid-19 new infection cases, and the price difference between the Brent and WTI crudes oil prices, controlling for the impact of Russia–Saudi Arabia oil price war as a fixed regressor, are the forcing variables of the WTI crude oil price. Meanwhile, the second, third, and fourth cointegrating vectors support the cointegration evidence of the first vector with different proxies of the global stock index (GSI; i.e., the FTSE and the SP100 instead of the MSCI) and different proxy of the US dollar index (USDT in lieu of USDI). The fifth, sixth and seventh cointegrating vectors indicate similar evidence per the first cointegrating vector; but instead of Covid-19 new infection cases as one of the driving forces, these vectors suggest for Covid-19 total cases, new deaths and total deaths, respectively.

Table 6 reports the coefficient estimates of the long-run relationships of the cointegrating vectors detected from the previous stage at the 5% significance level. First, the results reveal that at the 1% significance level, there is a long-run relationship between US economic policy uncertainty and the WTI crude oil price. Specifically, EPU is shown to have a significantly negative impact on the WTI in the long run. This is consistent with our expectation, as economic policy uncertainty is expected to have a significant impact on the economy at the macro- and micro-levels (Chen et al., 2019). Specifically, high uncertainty in the economy and policy implies greater risks, thus negatively affecting economic activity, investors' perspectives, and firms' decisions about investment and output plans. Consequently, the demand for crude oil is reduced, and therefore, its price is lowered, because oil is a critical input in the production process. However, the result implies an increase in the price of crude oil when uncertainty about economic policy decisions is reduced.

Table 5
Bounds test to cointegration: results.

Cointegration hypothesis	Lag structure	F-statistic	Outcome at 10 % level	Outcome at 5% level
Baseline model				
F(WTIO, EPU, EUI, VIX, USDI, MSCI, NCASE, SPREAD, DUMMY)	1,3,1,2,0,3,0,2	8.957	Cointegration	Cointegration
Robustness checks				
F(WTIO, EPU, EUI, VIX, USDI, FTSE, NCASE, SPREAD, DUMMY)	2,3,1,2,0,2,0,1	7.2757	Cointegration	Cointegration
F(WTIO, EPU, EUI, VIX, USDI, SP100, NCASE, SPREAD, DUMMY)	1,3,1,2,0,3,0,2	6.8899	Cointegration	Cointegration
F(WTIO, EPU, EUI, VIX, USDT, MSCI, NCASE, SPREAD, DUMMY)	2,3,0,2,2,2,0,1	6.9311	Cointegration	Cointegration
F(WTIO, EPU, EUI, VIX, USDI, MSCI, TCASE, SPREAD, DUMMY)	2,3,1,2,0,2,1,1	6.8750	Cointegration	Cointegration
F(WTIO, EPU, EUI, VIX, USDI, MSCI, NDEATH, SPREAD, DUMMY)	1,3,3,2,4,3,1,1	6.8021	Cointegration	Cointegration
F(WTIO, EPU, EUI, VIX, USDI, MSCI, TDEATH, SPREAD, DUMMY)	2,3,1,2,0,2,1,1	6.9218	Cointegration	Cointegration

Table 5 presents the calculated F-statistics for the cointegrating relationships among the seven variables as shown in Eq. [1]. The calculated F-statistics are compared with the critical values from Table C1.iii in Appendix C, Case III: unrestricted intercept and no trend in Pesaran et al. (2001) for k = 7. The results reveal that at the 5% significance level, there is not enough evidence to accept the null hypothesis of no cointegration for all the models.
Source: Authors' calculation. Note: *, **, and *** denote statistical significance at the 10 %, 5%, and 1% levels, respectively. DUMMY is included as a fixed regressor. Maximum lag length = 4.

Table 6
Long-run estimation results.

Variable	Model 1	Model 2	Model 3	Model 4
L.EPU	−2.963***	−2.726**	−3.083**	−3.259**
	[0.269]	[1.273]	[1.373]	[1.395]
L.EUI	−0.896	−0.899	−0.668	−1.010
	[1.199]	[1.195]	[1.256]	[1.241]
L.VIX	−5.865**	−3.456**	−4.828***	−4.902**
	[2.868]	[1.644]	[2.403]	[2.500]
L.USDI	−33.734	−22.797	−19.690	
	[56.881]	[54.312]	[55.107]	
L.USDT				−12.852
				[89.811]
L.MSCI	7.484**			5.237**
	[3.677]			[2.512]
L.FTSE		26.325**		
		[12.793]		
L.SP100			17.284**	
			[26.766]	
L.NCASE	−2.405	−3.5837***	−4.084***	−4.315***
	[1.782]	[1.302]	[1.477]	[1.466]
SPREAD	−2.224***	−2.248***	−2.321***	−2.235***
	[0.244]	[0.244]	[0.260]	[0.277]

	Model 5	Model 6	Model 7
L.EPU	−3.789**	−4.120**	−3.062***
	[1.890]	[2.033]	[0.801]
L.EUI	−1.216	−1.344	−1.432
	[1.389]	[1.442]	[1.339]
L.VIX	−13.447**	−7.442***	−10.464**
	[7.833]	[1.937]	[5.323]
L.USDI	−81.237	−27.942	−34.358
	[112.471]	[61.758]	[59.445]
L.MSCI	52.263**	4.576**	13.766***
	[24.769]	[2.215]	[5.368]
L.TCASE	−3.824**		
	[1.608]		
L.NDEATH		−4.183**	
		[1.926]	
L.TDEATH			−2.123**
			[1.059]
SPREAD	−2.367***	−2.523***	−2.327***
	[0.351]	[0.344]	[0.289]

Note: Robust standard errors are in brackets. *, **, and *** denote statistical significance at the 10 %, 5%, and 1% levels, respectively. The optimal lag lengths are determined with the Akaike information criterion (AIC).
Table 6 presents the long-run estimation results for the WTI crude oil price as the dependent variable, based on the ARDL bounds testing approach. The independent variables include EPU, EUI, VIX, USDI, USDT, MSCI, FTSE, SP100, NCASE, TCASE, NDEATH, TDEATH, and SPREAD, which represent economic policy uncertainty, equity market–related economic uncertainty, financial stress and volatility, the US dollar index, the trade-weighted US dollar index, the global stock market index (the MSCI World Index, FTSE All-World Index, and S&P Global 100 Index), Covid-19 proxies (new/total infection cases and new/total death cases), and speculation on the WTI (proxied by the price difference between Brent crude oil and WTI crude oil), respectively.

This finding is in line with Aloui et al. (2016) and Yang (2019) who also documented that international oil prices are affected by US EPU dynamics. This result also supports Kang and Ratti (2013) who found that oil price shocks respond to economic policy uncertainty negatively.

In the long run, financial stress and volatility proxied by the VIX appear to reduce the price of WTI crude oil. This result is consistent with those of Sari et al. (2011) who employed the VIX as a proxy for global risk perceptions and found that the VIX leads oil prices and has a significantly negative impact on oil prices in the long run. This is intuitively understandable. A higher VIX suggests uncertainty about the financial outlook, which represents negative signals about the economic outlook, raising concerns about global economic growth or uncertainty about the global economic recovery (Sari et al., 2011). As a result, downward pressure is put on the global demand for energy including crude oil, and thus, its prices. Furthermore, high VIX readings might induce investors to exit stock markets and invest in T-bills as an alternative channel (Sari et al., 2011). Consequently, the funding opportunities for real investments are narrowed, thus lowering the demand for energy and the prices (Sari et al., 2011).

Furthermore, we found that the global stock market index has a significant and positive impact on the WTI crude oil price in the long run. This is reasonable, as the stock market has been traditionally considered an indicator of expected economic activity (Le and Chang, 2016). Significant decreases in stock prices might reflect expectations of a future economic recession, while considerable increases in stock prices may suggest positive expectations about future real activity (Asprem, 1989). During the Covid-19 pandemic, stock markets worldwide have been heavily impacted, and the effect has been stronger than during any previous infectious disease outbreak (Baker et al., 2020). The fall in the global stock markets reflects a pessimistic economic perspective on a global scale, resulting from imposed travel restrictions, closed factories, and self-quarantined citizens. This implies a substantial reduction in the global demand for energy; thus, the global oil price dropped substantially.

The results also indicate that the Covid-19 pandemic has significantly and negatively affected oil prices. Global demand for oil experienced an unprecedented shock due to lockdown and quarantine measures taken to prevent the spread of the coronavirus. This unprecedented fall in the demand for oil led to oil storage facilities filling up quickly and a significant increase in crude inventories in the US with a rise of 16 million barrels per week, on average, over the first three weeks of April 2020 (Tagliapietra, 2020). The serious surplus of crude oil is evident in Cushing (Oklahoma), the main storage for US crude oil, and the official delivery hub of WTI crude oil that is traded on the US futures market. Cushing has approximately 80 million barrels of oil storage capacity, but given the substantial decrease in the demand for oil and oil products, the remaining available storage capacity can accommodate only 20 million barrels, which was fully booked and was likely to be filled up by the end of May 2020 (Tagliapietra, 2020).

We also found that WTI crude oil speculation in financial markets, represented by the SPREAD variable, has a significantly negative impact on the WTI crude oil price. This result is consistent with our expectations. The US Oil Fund alone received an additional US$1.6 billion in investment within a week just before the price of WTI crude became negative. This is also the largest weekly increase in the fund inflow in the history of this ETF. However, not all investors are fully aware of the risks of investing in crude oil ETFs, especially during the market's historic crises such as this one. We also witnessed the traumatic experience of investors in the Bank of China's ETF oil fund when the ETF had to close out its position in the WTI May futures contract at negative prices. The selling of near month/front-month contracts and the switch to buying far month/back-month contracts put additional pressure on the oil price. This period saw the "super contango" phenomenon when the price of crude oil futures contracts was significantly higher than the spot oil price. The collapse in oil prices, the sharpest plunge in history, has caused many speculators around the world to suffer heavy losses due to incorrectly calling a bottom in the crude oil price.

Table 7 reports the coefficient estimates of the short-run dynamics of the cointegrating vectors detected from the previous stage at the 5% significance level. In the short run, we found that high US economic policy uncertainty, market volatility, and the spread of Brent and WTI crude oil prices seemed to contribute to the decline in the WTI crude oil price. However, the stock market index appeared to have a positive impact on WTI crude oil prices. Note that during the period of the historic oil price crash, as shown in Fig. 4 and Table 2, the trend of global equity markets was on the decline. Thus, one may conclude that the historic plunge in the current oil price is partly attributable to the decrease in the global stock markets, as the latter provide signals about a pessimistic perspective on economic activity, one of the basic drivers of energy demand, besides population and technology.

The dummy variable representing the structural break, which captures the impacts of the Russia–Saudi Arabia oil price war, is negative and statistically significant at the 1% significance level. Saudi Arabia initiated an aggressive oil price war against Russia on 7 March 2020, which was a double hit to the oil price. A massive increase in supply and a massive decrease in demand will certainly lower prices. Storage for crude oil was filling up very quickly. Innovative methods have been utilized to store the extra crude oil that the world did not need, waiting for a future period when demand picks up again. When the options for storing crude oil onshore filled up, people utilized supertankers from shipping companies to store crude oil offshore. And when all storage options started to fill up quickly, it created a big problem for the oil market. Many producers were forced to cut production voluntarily; others were forced to cease operations, or file for bankruptcy. Therefore, given that neither the OPEC + countries nor Russia wanted to give up on the supply side, the price of crude oil continued to decrease despite logical market assumptions. On 12 April 2020, OPEC + members, including other big oil producers such as Russia, agreed to slash global output by 9.7 million barrels per day. The deal was the largest ever cut in oil production in the history of OPEC.

The error correction term in the cointegrating vector is statistically significant and has the right sign (i.e., negative), implying that a given variable returns to equilibrium after deviating from it. The absolute values of the estimated error correction term in the equation are large, suggesting about 17.94 % of the disequilibrium caused by previous day shocks would converge back to the long-run equilibrium. That is, it takes about 5.57 days ($1/0.1794 = 5.57$ days) to correct the disequilibrium in the equation.

For models (2) to (4) in Tables 6 and 7, we perform robustness checks using different proxies of global equity market indices and the US dollar index. The results appear to be strongly robust in terms of the signs and statistical significance of the coefficient estimates. The speed of adjustment is relatively consistent, ranging from 5.51 days to 5.80 days to correct the disequilibrium in the equations.

For comparison and completeness, in models (5) to (7), we perform a similar analysis with different measures for the impact of the Covid-19 pandemic. Specifically, we used the total number of infection cases, new deaths, and total deaths, respectively, in lieu of the number of new cases as in model (1). All the results found in the long run for the model (1) are qualitatively retained for models (5) to (7). Similar to model (1), the influences of the Covid-19 pandemic are statistically significant and negative. Thus, we may conclude that the impact of the pandemic on the WTI crude price is very robust to different measures. The speed of adjustment ranges from 6.01 days to 6.65 days to correct the disequilibrium in the equations.

We conducted several diagnostic and stability tests to confirm the goodness of fit of the ARDL models. Specifically, three diagnostic tests to examine the presence of serial correlation in the residuals, the functional form, and the heteroskedasticity associated with the selected models were applied. The results suggest no major diagnostic problems at the 5% significance level, implying that the estimated models are well specified. Next, Brown et al., 1975 cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests were employed to test the null hypothesis of the stability of the coefficients in the regressions. As the CUSUM and CUSUMQ tests are very general tests for structural change, a prior determination of a structural break is not necessary (Ozturk and Acaravci, 2010). Because the plots of the CUSUM and CUSUMQ statistics stayed within the critical bounds of the 5% level of significance, the coefficients in the given regressions appear to be stable during the sample period for all the cases. Moreover, a high R-squared is good

Table 7
Short-run estimation results.

Variable	Model 1	Model 2	Model 3	Model 4
D(WTI(-1))		0.067**		0.057***
		[0.027]		[0.018]
D(L.EPU)	−0.101***	−0.100***	−0.102***	−0.104***
	[0.029]	[0.029]	[0.029]	[0.028]
D(L.EPU(-1))	−0.073***	−0.071***	−0.071***	−0.064***
	[0.024]	[0.024]	[0.024]	[0.023]
D(L.EPU(-2))	−0.045**	−0.044**	−0.044**	−0.038**
	[0.019]	[0.019]	[0.019]	[0.018]
D(L.EUI)	−0.168	−0.182	−0.176	
	[0.409]	[0.402]	[0.411]	
D(L.VIX)	−5.320***	−5.160***	−5.287***	−5.011***
	[1.339]	[1.321]	[1.394]	[1.408]
D(L.VIX(-1))	−0.216***	−0.289***	−0.240***	−0.261***
	[0.063]	[0.063]	[0.064]	[0.076]
D(L.USDT)				−39.825
				[27.728]
D(L.USDT(-1))				−5.644
				[26.661]
D(L.MSCI)	19.241***			17.846**
	[6.126]			[7.968]
D(L.MSCI(-1))	−2.864			−9.926
	[4.719]			[6.042]
D(L.MSCI(-2))	13.681***			−9.262
	[4.652]			[6.059]
D(L.FTSE)		21.681***		
		[6.417]		
D(L.FTSE(-1))		−3.266		
		[4.983]		
D(L.SP100)			18.585***	
			[6.469]	
D(L.SP100(-1))			−3.468	
			[4.909]	
D(L.SP100(-2))			14.523***	
			[4.867]	
D(SPREAD)	−1.022***	−1.023***	−1.019***	−1.015***
	[0.018]	[0.018]	[0.018]	[0.018]
D(SPREAD(-1))	−0.600***		−0.612***	
	[0.201]		[0.202]	
ECT(-1)	−0.179***	−0.182***	−0.172***	−0.175***
	[0.021]	[0.021]	[0.020]	[0.021]
DUMMY	−4.745***	−4.664***	−4.842***	−5.090***
	[0.618]	[0.613]	[0.629]	[0.668]
Constant	−33.222***	−36.328***	−27.936	−3.571
	[3.855]	[4.243]	[3.243]	[0.477]
Observations	145	145	145	144

	Model 5	Model 6	Model 7
D(WTI(-1))	0.061**		0.062**
	[0.028]		[0.028]
D(L.EPU)	−0.137**	0.102**	−0.093***
	[0.063]	[0.042]	[0.029]
D(L.EPU(-1))	−0.100	−0.106***	−0.073***
	[0.061]	[0.036]	[0.024]
D(L.EPU(-2))	−0.212***	−0.192**	−0.048**
	[0.063]	[0.078]	[0.019]
D(L.EUI)	−0.128	−0.121	−0.154
	[0.214]	[0.101]	[0.327]
D(L.EUI(-1))		0.012	
		[0.015]	
D(L.EUI(-2))		−0.313**	
		[0.156]	
D(L.VIX)	−6.140***	−6.577***	−6.874***
	[1.332]	[1.331]	[1.351]
D(L.VIX(-1))	−0.150***	−0.251**	−0.254***
	[0.603]	[0.106]	[0.086]
D(L.USDI)		−0.3861	
		[0.497]	
D(L.USDI(-1))		−0.146	

(*continued on next page*)

Table 7 (*continued*)

	Model 5	Model 6	Model 7
		[0.468]	
D(L.USDI(-2))		0.583	
		[0.593]	
D(L.USDI(-3))		−1.461***	
		[0.325]	
D(L.MSCI)	22.225**	15.928**	15.704**
	[7.780]	[6.193]	[6.269]
D(L.MSCI(-1))	0.210***	0.0754	0.753
	[0.514]	[4.724]	[4.778]
D(L.MSCI(-2))		12.845***	
		[4.659]	
D(L.MSCI(-3))			
D(L.TCASE)	−0.768***		
	[0.164]		
D(L.NDEATH)		−0.039***	
		[0.014]	
D(L.TDEATH)			−0.612**
			[0.302]
D(SPREAD)	−1.017***	−1.028***	−1.018***
	[0.018]	[0.018]	[0.018]
ECT(-1)	−0.166***	−0.150***	−0.161***
	[0.020]	[0.018]	[0.019]
DUMMY	−3.956***	−4.199***	−3.872***
	[0.555]	[0.583]	[0.551]
Constant	42.681***	27.768***	58.646***
	[5.207]	[3.404]	[7.231]
Observations	145	145	145

Table 7 presents the short-run estimation results for the WTI crude oil price as the dependent variable, based on the ARDL-ECM model. The independent variables include EPU, EUI, VIX, USDI, USDT, MSCI, FTSE, SP100, NCASE, TCASE, NDEATH, TDEATH, and SPREAD, which represent economic policy uncertainty, equity market–related economic uncertainty, financial stress and volatility, the US dollar index, the trade-weighted US dollar index, the global stock market index (the MSCI World Index, FTSE All-World Index, and S&P Global 100 Index), Covid-19 proxies (new/total infection cases, and new/total death cases), and speculation on the WTI (proxied by the price difference between BRENT crude and WTI crude), respectively. DUMMY is the dummy variable, which captures the impacts of the Russia–Saudi Arabia oil price war.

because it indicates that the model can fit and explain the data well.[6]

Furthermore, the variance inflation factor (VIF) was performed, indicating that all the VIF estimated coefficients had values less than 10. This implies the absence of multicollinearity among the explanatory variables of the models (Hair et al., 1998).[7]

5. Concluding remarks

Over the first several months in 2020, the oil market experienced an unprecedentedly challenging period as demand for the commodity continued to stall, bringing oil production to a standstill. The impact was aggravated by the oversupply of crude oil, particularly due to the initial disagreements among OPEC + countries. In this study, we examined the factors underlying the historic oil price fluctuation occurring during the Covid-19 pandemic. We applied the ARDL bounds testing approach to daily data series spanning 17 January to 14 September 2020. Thus, this is the first study on oil prices that covers two waves of the pandemic. We found that high US economic policy uncertainty, expected stock market volatility, and speculation on WTI crude seemed to reduce the WTI crude oil price, whereas the decrease in the global stock markets appears to have had significant negative impacts. Furthermore, we showed that the Russia–Saudi Arabia oil price war is a critical factor leading to the collapse of the oil markets. The results are consistent with our expectations.

Although low oil prices could benefit consumers and some businesses in the short run, it might not be the case in the medium run as the prices could spike. In addition, although the oil industry is expected to remain an essential part of the functioning of the global economy, the stability of this industry is threatened by low oil prices (International Energy Agency, 2020). Low oil prices lead to reductions in financial resources for the oil industry, weakening the ability to develop some of the technologies required for transitions to green energy around the globe (International Energy Agency, 2020). Thus, to address this historic oil price fluctuation we recommend several policy implications.

The stock market is regarded as an indicator of future economic activity, which represents the demand side for oil. The present

[6] The post-estimation diagnostic checks included the Jarque-Bera normality test (H0: the data were normally distributed), the Breusch-Godfrey LM test for serial correlation (H0: there was no serial correlation of any order up to two lags), and ARCH effects for conditional heteroscedasticity (with two lags) (H0: a series of residuals (rt) exhibited no conditional heteroscedasticity (ARCH effects)); Ramsey and CUSUM tests were used to check the stability. The results are not presented to conserve length of Table 7 but they are available upon request.

[7] The VIF results are not presented here to conserve space, but they are available upon request.

results confirmed that demand was the main cause of this unprecedented fall in oil prices. It also represents the solution to this problem. In other words, policy measures and actions taken to accelerate the economic recovery would contribute to alleviating the decrease in oil demand and thus, its price in the short run and the long run. For the economy to recover from the crisis, timely assistance should be provided to people and businesses that really need it, especially for workers who have lost their jobs due to the blockade policy. Social welfare services are vital to ensure that people still have the level of income necessary for daily life during this period. Moreover, support for small and medium enterprises is extremely important so that when the economies reopen, businesses can operate immediately without significant interruptions. Liquidity must be injected into the system to ensure that businesses that were performing well before the Covid-19 pandemic do not go bankrupt because of a sudden lack of liquidity.

We also identified oil production as an important factor contributing to the decrease in the oil price. In addition to extraordinary low demand, overproduction made oil markets experience physical stress due to the limitation in storage capacity. Thus, to prevent such a scenario, while waiting for the global oil demand to pick up, OPEC members and other big oil producers might need to scale up their supply-cut agreement. On 9 April 2020, the OPEC + alliance including Russia agreed to reduce global oil production by 9.7 million barrels a day, which would take effect starting 1 May 2020.[8] Although the largest oil production cut in history, the deal was not immediately able to offset the negative impacts of the Covid-19 pandemic on the demand side to rebalance the oil markets. Furthermore, we showed that an increase in the VIX, reflecting fear in the financial markets, seems to have had a significantly negative relation to the crude oil price. We witnessed a sharp rise in the VIX as the Covid-19 pandemic swept across the globe. This was not surprising as the VIX tends to increase during financial and economic crises. We also found that the increase in economic policy uncertainty significantly negative influenced the current oil prices. In this context, governments could improve the situation by focusing on certain policy measures while avoiding or limiting associated uncertainty over policy responses to the pandemic.

Overall, the recommended policy actions might help alleviate the sharp fall in the oil price to some extent. It is reasonable to assume that stronger support for the oil market is the pick-up in the global oil demand, which happens only when governments can lift lockdowns and restart their economies. The oil crisis will be solved when nations around the world have controlled the Covid-19 pandemic. Note that in this study, we also found strong impacts of the Covid-19 pandemic on oil prices in the long run. In this regard, as the Covid-19 pandemic led to the current oil price crash, oil markets are able to return to normal (or to the "new normal," as the effects are shown to be long-lasting) only once the coronavirus is defeated.

Author statement

Thai-Ha Le: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing.

Anh-Tu Le: Conceptualization, Resources, Writing- Reviewing and Editing.

Ha-Chi Le: Data curation, Software, Formal analysis, Writing- Original draft preparation, Writing- Reviewing and Editing.

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[8] For two months or so, then smaller cuts thereafter for a total period of two years.

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