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Impact of COVID-19 pandemic on crude oil prices: Evidence from Econophysics approach

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A B S T R A C T

This paper provides an analysis of crude oil, diesel, and gasoline prices for the period from November 1, 2019 to December 31, 2020. We apply Log Periodic Power-Law Singularity (LPPLS) and Discrete Scale LPPLS bubble indicators to explore the dynamic bubbles of oil prices and predict their crash times. The results indicate that West Texas Light crude oil and North Sea Brent crude oil experienced a statistically significant negative financial bubble during the COVID-19 outbreak. In addition, gasoline and diesel prices are mainly driven by fundamentals. Our findings are expected to be useful to oil market investors, policymakers, and energy experts.

1. Introduction

Since the 1970s, oil prices have experienced complex fluctuations. These fluctuations are mostly related to historical events such as the first and second Gulf War, and the global financial crisis of 2008. The last decade was marked by a collapse of the oil market in 2014/2015 followed a few years later by the pandemic that caused an unprecedented fall in prices. Recently, on Monday, April 21, 2020, the price of U.S. crude oil turned negative for the first time in history, forcing producers to pay buyers to take the barrels that they could not store due to the oversupply of oil. This situation is a direct result of failed negotiations between Russia and the Organization of the Petroleum Exporting Countries (OPEC) to reduce daily barrel production and the drop in oil demand due to the COVID-19 outbreak. Energy consumption in general, and oil demand in particular, have decreased as offices shut and industrial activity slowed sharply with government travel and work restrictions to slow the spread of the coronavirus.

Despite the announced energy transition in many parts of the world, oil is one of the main sources of energy. Crude oil in particular is a major asset in the commodities market. The crude oil price has exhibited considerable fluctuations over the past decade (Perifanis and Dagoumas, 2019). In addition, the observed variations in oil prices have a significant impact on financial markets and the real economy of countries (Li et al., 2020). In this line, the debates surrounding the behavior of oil prices are of ongoing interest to academics, policymakers, and investors (Caspi et al., 2018). This interest is even more important when prices deviate from fundamental values and a price bubble phenomenon is observed. It is always important to question the detection of oil price bubbles; their underlying causes, and their lifetimes help inform financial authorities. Policy makers will then take care to prevent the formation of bubbles and to manage their eventual explosion through appropriate regulations.

Much of the literature questions the rationality of investors due to observed deviations of prices from their fundamentals (Zhang and Yao, 2016). This research attributes this phenomenon to the increasing speculative behavior of financial agents, linked to the financialization of commodity markets. Other research explains the existence of bubbles by sudden variations in supply and demand (Kilian and Murphy, 2014). We enrich this field of literature by detecting bubble episodes in the oil market during the Covid-19 pandemic. More specifically, this study attempts to understand whether the oil market behaved efficiently and rationally during the pandemic, or whether the shock of declining demand was associated with a negative financial bubble?

We contribute to the empirical literature related to oil price behavior in several ways. Firstly, we analyze the daily West Texas Light (WTI) and North Sea Brent (Brent) crude oil, diesel, and gasoline prices from

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November 1, 2019 to December 31, 2020. This studied period allows us not only to analyze the recent crash in the price of oil, but also to offer new, clarifying evidence for important previous shocks in oil prices, that of 2014–2015 for example, because this last decade was marked by an increase in the financialization of the markets. Furthermore, we explore the pricing behavior of two downstream products of crude oil, i.e., diesel and gasoline. Thus, we consider two reference prices of crude oil (United States, Europe) of the zones which were badly impacted by the pandemic. This makes it possible to assess whether the appearance of the bubble depends on where the oil is traded. In addition, we examine whether crude and refined products have similar movements. Secondly, we use multiple complementary techniques to test for financial bubbles. To begin with, we use the supremum augmented Dickey-Fuller (SADF) test, the generalized supremum augmented Dickey-Fuller (GSADF) test (Alola, 2020), and the explosive test strategy proposed by Phillips and Shi (2018) to focus on the detection and date stamping of mildly explosive periods. We also apply the LPPLS model for financial bubbles, an approach which was first developed by Sornette et al. (1999), Johansen et al. (1999), and Johansen et al. (1999). Then, we apply Sornette et al. (2015) DS LPPLS bubble indicators, i.e., the confidence and trust indicators, as effective warnings for identifying the negative bubble during the period of the COVID-19 outbreak.

In addition, all the techniques used, despite their methodological differences, lead to the same conclusion. The price of oil experienced a statistically significant negative financial bubble from March 6 to April 28, 2020. The beginning and termination of the COVID-19 bubble coincides with the news of COVID-19, i.e., “the Oil Price War between Saudi Arabia and Russia” and the OPEC agreement to cuts in crude oil production. Additionally, the DS LPPLS indicators based on the oil prices provide effective warnings for detecting the negative bubble during the period of the COVID-19 outbreak.

The remainder of the paper is organized as follows. In Section II, we discuss the related literature review. In Section III, we introduce the methods and data definitions. In Section IV, we present the empirical results and discussion. In Section V, we summarize the main findings and conclude.

2. Related literature review

The most widely recognized definition of a bubble considers that when the price of an asset deviates from the value given by fundamentals, a bubble exists (Stiglitz, 1990). According to the theory of rational expectations, the price of an asset increases when investors accept they will pay for an asset more than its fundamental value because they believe that they would be able to sell the asset for a higher price in the future. The rational bubble concept was first introduced by Blanchard and Watson (1982). Another characteristic of financial bubbles was given by Brunnermeier (2016) who explains that bubbles are typically associated with dramatic increases in asset prices followed by a collapse.

A large strand in the literature explains oil price bubbles created by market speculation. According to Sornette et al. (2009), the increase in oil price is mostly driven by the uncertainty created by speculation. Cifarelli and Paladino (2010) showed that increases in market speculation may lead to significant changes in the fundamental worth of prices. Thus, it is shown that speculation has a role in the volatility of oil price and the formation of bubbles. The results of Narayan et al. (2013) show that trading volume increases the frequency of stock price bubbles. Moreover, Elder et al. (2013) found that jumps in oil prices are driven by both oil-specific and non-oil-specific economic factors. More recently, Umar et al. (2021) defines bubble cycles as times of excessive activity, followed by the bursting of the asset bubble and a collapse. As a result, authorities must have strong analytical tools to detect the start of the bubble and whether or not to intervene throughout it. Ajmi et al. (2021) found that the primary contributors to this bubble behavior are political events, oil supply shocks, and global economic activity. Su et al. (2020) documented that the severe decrease in demand was directly driven by a drop-in consumer spending due to the economic crisis brought on by the development of the Coronavirus epidemic, as well as unsuccessful Russian-OPEC talks to cut regular oil supply.

The existence of financial market bubbles has been explored with many techniques. Markov regime switching (MRS) is one of the oldest techniques used by the scientific community (Hamilton, 1989; Van Norden, 1996; Lammerding et al., 2013). Moreover, the momentum threshold autoregressive (MTAR) model proposed by Engle and Granger (1987) has been widely applied to detect price bubbles. For instance, Bohl (2003) uses the MTAR model to examine the presence of periodically collapsing bubbles in the U.S. stock market. Payne and Waters (2007) use the same technique as well as the residual-ADF test to investigate periodically collapsing bubbles in the real estate investment trust market, and their results support periodically collapsing bubbles. Another approach to test for bubble was proposed by Phillips et al. (2011), and Phillips, Shi, and Yu (2015a, 2015b). It is based on SADF and GSADF tests. The authors reveal the existence of exuberance and date stamp its beginning and collapse. Gutterez (2011) analyzes the Nasdaq index and Case-Schiller’s house-price index to detect bubble characteristics with the bootstrap method which helps in computing the SADF technique. According to Tsvetanov et al. (2016), the GSADF technique shows conclusive evidence of bubbles starting in early 2004 for longer maturity contracts. Furthermore, Su et al. (2017) use the SADF and GSADF tests to detect the existence of multiple bubbles in WTI crude oil. According to their empirical findings, there were six oil price bubbles between 1986 and 2016, when the price of oil deviated from its inherent value based on market fundamentals. More recently, Gharib et al. (2021), employ the SADF, GSADF, and Phillips and Shi (2018) methodology, to crude oil from January 4, 2010, to May 4, 2020. The authors conclude that the COVID-19 outbreak has significantly perturbed the price dynamics of crude oil and gold. Likewise, Umar et al. (2021) detect multiple bubbles in the oil market using monthly data from 2000M01 to 2020M12 and use a variety of advanced econometric tools such as breakpoint unit root tests, probability-based bubble detection mechanism, SADF, GSADF approaches based on Monte Carlo and bootstrap critical values. Based on the probability-based method, the authors identified eight instances of bubbles, three of which occur in 2020, when the globe was confronting the COVID-19 crisis.

In comparison, the LPPLS technique was proposed by Sornette et al. (1999) to quantify the dynamic process of asset bubbles and to forecast crash times. According to Zhang and Yao (2016), the LPPLS model recognizes asset bubbles by analyzing super-exponential growth in market values along with log-periodic oscillations. Wosnitza and Denz (2013) employ the log-periodic power law to examine the 2000 financial crisis. Filimonov and Sornette (2013) use the LPPLS model to diagnose and forecast bubbles in the Shanghai Composite Index. Fantazzini (2016) uses the log-periodic power law to examine the bubble in oil prices in 2014–2015. The author finds the existence of a negative financial bubble which brought down oil prices beyond the level required by economists. Cheng et al. (2018) propose an improved LPPLS forecasting model based on multi-population genetic algorithms to predict turning points in international oil prices. The findings show that the LPPLS outperforms three statistical approaches and provides great potential for forecasting future turning points. In addition, they also determine that the WTI spot price variation in March 2017 was an alert of a significant turning point that turned out to be incorrect. This enhanced LPPL has the potential to be an important tool in predicting future turning points. Moreover, the LPPLS model has been used extensively to provide the dynamic movement of price bubbles in stock markets (Breie and Joseph, 2013; Wosnitza and Leker, 2014; Li, 2017), and numerous scholars demonstrate its powerful ability to identify bubbles and forecast their crash times.

The DS LPPLS indicators were introduced by Sornette et al. (2015). These two indicators have been briefly discussed to present the ex-ante forecast of the Chinese bubble and the burst that started in June 2015.
The DS LPPLS indicators are used by Zhang and Wang (2015) and Zhang et al. (2016) to identify positive and negative bubbles over two centuries of the S&P 500 index. The DS LPPLS successfully diagnoses positive and negative bubbles, constructs efficient end-of-bubble signals for all of the well-documented bubbles, and obtains for the first time new statistical evidence of bubbles for other events. Demirer et al. (2019) introduce the multi-scale LPPLS confidence indicator based on the LPPLS-based bubble indicators in the S&P 500 index. The bubble indicator DS LPPLS, which makes it possible to identify positive and negative bubbles, presents a valuable opening, allowing us to examine the predictability patterns of market booms and crashes separately. With crypto currency, Gerlach et al. (2019) apply LPPLS multiscale confidence indicators to detect Bitcoin long and short bubbles. Shi and Zhu (2020) propose an adaptive multilevel time series detection methodology based on the DS LPPLS confidence indicator and a finer (than daily) timescale for the Bitcoin price.

Different from previous studies, our study adds to the literature on a broad variety of research topics, including bubble periods and contagion effects in worldwide oil, particularly during the COVID-19 epidemic. Our research uses the LPPLS detection method based on the DS LPPLS confidence indicators that can diagnose both positive and negative bubbles matched to well-known historical events using forward prediction, showing its exceptional ability to forecast bubbles in advance. The LPPLS model combines mathematical and statistical physics of bifurcation and transition phases, economic theory of a rational expectation, and behavioral funding of traders’ herding in a process of untenable faster-than-exponential growth (or decrease) that leads to an unlimited return in the short term, with a corrective response (Shu et al., 2021). Given that asset prices may be destabilized by collective behaviors of the noise traders via mass flooding and imitation transactions, the LPPLS model diagnoses financial bubbles by capturing two distinct characteristics of the price trajectories often seen in bubble regimes. Additionally, the DS LPPLS indicators used in this study, based on the oil prices, provide effective warnings for detecting the negative bubble during the period of the COVID-19 outbreak.

3. Data and methodology

3.1. Data

The dataset includes the daily West Texas Light crude oil and North Sea Brent crude, diesel, and gasoline prices over the period from November 1, 2019, to December 31, 2020. The nominal prices are the spot prices as provided by the U.S. Energy Information Administration (EIA). This sample is useful to analyze oil price volatility during the COVID-19 pandemic.

3.2. Empirical models

To explore the dynamic bubbles of oil prices, two categories of tests are used. The first one is based on the right-tailed ADF using rolling recursive windows where the alternative hypothesis is of a mildly explosive process. The right-tailed ADF tests allow us to identify periods of statistically significant explosive price behavior and date-stamp their occurrence. The tests consider that the formation of a bubble is a prerequisite for a price crash. The second category of tests is based on the Johansen-Ledoit-Sornette (2000) LPPLS model. This model does not require the formation of a bubble as a prerequisite for a price crash. We also use Sornette et al. (2015) DS LPPLS bubble indicators. These bubble indicators successfully distinguish between positive and negative bubbles in contrast to Phillips’s methodology.

3.2.1. The right-tailed ADF tests for bubble detection

3.2.1.1. Testing for a single periodically collapsing bubble. The procedure suggested by Phillips et al. (2011) allows us to detect and date-stamp multiple bubble episodes. It is based on recursive implementation of the ADF regression using a rolling window procedure. The empirical specification used is the following ADF regression, for a rolling interval beginning:

\[ y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{p} \theta_i y_{t-i} + \epsilon_t \]  

where \( y_t \) denotes the time series, and \( \mu, \delta, \) and \( \theta \) are parameters estimated using OLS. \( p \) is the maximum number of lags.

In the approach proposed by Phillips et al. (2011), the right-tailed ADF statistics are calculated in multiple recursive regressions on different subsamples. The starting fraction \( r_1 \) and the ending fraction \( r_2 \) of the total number of observations are such that \( 0 < r_1 < r_2 < 1 \). \( w_r \) is the size of the window defined by \( w_r = r_2 - r_1 \). It varies from the fixed initial window \( r_0 \) to the total sample. The Phillips et al. (2011) test involves implementation of the ADF test on a forward expanding sample sequence. The SADF statistic is defined as follows:

\[ SADF(r_0) = \sup_{r_0 < r < 1} ADF(r_0) \]  

According to Umar et al. (2021) the use of SADF statistics for unit root assessment is warranted because asset price bubbles are usually common. The conventional unit root tests have very little capacity for identifying such bubbles whereas the sup ADF testing technique provides a fairly efficient bubble detection approach in the face of one or two boom cycles of bubble phases. This approach may also include nonlinear structural breaks when analyzing the occurrence of numerous bubbles. The SADF technique utilizes an expanding forward window to compute explosive trends sequentially, while its extension, the GSADF, evaluates bubbles using all possible subsamples of a time series provided with a user-specified minimum window size.

3.2.1.2. Testing for multiple periodically collapsing bubbles. Phillips, Shi, and Yu (2015a, 2015b) extend the SADF test to the GSADF test. This procedure is based on ADF-type regressions using rolling estimation windows of different sizes. According to Li et al. (2020), the GSADF approach can identify the existence of multiple bubbles, and the simulations demonstrate that the test considerably improves the discriminatory power when multiple bubbles occur. Furthermore, the GSADF approach is regarded as a formal statistical test for detecting the presence of an asset bubble, whereas traditional alternative methods such as the fundamental model and cluster analysis approaches rely primarily on subject-based judgments of market fundamentals or moderate conditions. In addition, the GSADF test can identify explosive activity at any data frequency. As a result, in terms of performance, it is more helpful for monitoring bubbles than other methods (Khan et al., 2021).

This technique allows us to identify and date-stamp multiple bubble episodes even in small sample sizes. The GSADF test then is constructed by implementing the SADF test repeatedly for each \( r_2 \in [r_0, 1] \). The GSADF test is as follows:

\[ GSADF(r_0) = \sup_{r_0 < r < 1} SADF(r_0) \]  

3.2.1.3. Testing for date stamping of multiple bubbles. We use Phillips and Shi (2018) bootstrap technique, which combines the two procedures of Harvey et al. (2016) and Phillips, Shi, and Yu (2015a, 2015b) procedures. According to Phillips and Shi (2018), the procedure for the combined techniques based on the recursive rolling window, i.e., the evolving Phillips, Shi, and Yu (2015a, 2015b) procedures, can be described as follows:

Step 1: Under the null hypotheses of \( \rho = 0 \), we estimate the following equation:

\[ \Delta y_t = \mu + \rho y_{t-1} + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \epsilon_t \]  

where \( \epsilon_t \) is the error term.
where $\rho$ is the estimate coefficient, $\mu$ is the intercept, and $\gamma_t$ is the regression error.

Step 2: We run a bootstrap sample expressed by the function:

$$\Delta y^b_t = \sum_{i=t}^{T} \hat{\beta}_i \Delta y_{t+i} + \epsilon^b_t$$  \hspace{1cm} (5)

where $\hat{\beta}_i$ is the coefficient obtained in the fitted regression from Step 1 with the Ordinary Least Square (OLS) method, and $\epsilon^b_t$ are the residuals.

Step 3: We calculate the PSY test statistic sequence with the bootstrapped series. The maximum value of the recursive evolving (Phillips, Shi, and Yu) test statistic is expressed as follows:

$$M^b_\tau = \max_{\tau \in [1, T-\tau-1]} (PSY^b_\tau)$$  \hspace{1cm} (6)

where $T$ is the fraction of the total sample, and $rb$ is the number of observations in the frame over which the dimension is to be controlled.

Step 4: For $B = 1, \ldots, 499$, we repeat Steps 2 to 3.

Step 5: The Phillips and Shi (2018) process is provided by the 95% percentile of the $\{M^b_\tau\}_{b=1}^B$ process.

3.2.2. Econophysics techniques for detecting bubbles

Different from the standard approach proposed by Phillips, Shi, and Yu (2015a, 2015b) and Phillips and Shi (2018), we use Filimonov and Sornette (2013) LPPLS model to detect financial bubbles in oil markets. The LPPL model does not require the formation of a bubble as a prerequisite for a price crash (Fantazzini, 2016). Additionally, one of the main advantages of the LPPL model is the powerful ability to make an exact prediction for the crash time of potential bubbles, hence the end of a sample period should be before the crash time, but no specific date is required. (Zhang et Yao, 2016). Also, the DS LPPLS methodology can provide real-time detection of bubbles and advanced forecast of crashes, as mentioned by Shu et al. (2021), Shu et Zhu (2020).

The LPPLS model is an extension of the Sornette et al. (1999), Johansen et al. (1999), and Johansen et al. (1999) LPPL model:

$$\ln(p(t)) = A + B(t_c - t)^\beta + C_1(t_c - t)^\beta \cos(\omega t) + C_2(t_c - t)^\beta \sin(\omega t)$$  \hspace{1cm} (7)

where $\beta$ quantifies the power-law acceleration of prices, $\omega$ represents the frequency of the price oscillations during the bubble, and $t_c$ is the so-called “critical time” that corresponds to the end of the bubble; see Sornette et al. (2015) for more details of the model and its estimation.1 The solutions of the LPPLS should be filtered under the conditions in Table 1.

Furthermore, we employ the DS LPPLS bubble indicators of Sornette et al. (2015). The DS LPPLS confidence and trust indicators are useful to evaluate the performance of the real-time prediction of bubbles based on shrinking window techniques.

The DS LPPLS confidence indicator measures the sensitivity of the observed bubble pattern to the time scale $[t_1, t_2]$ which satisfies

$$\text{Filtering condition 1: } \beta < 1, \quad \hat{B} < 0$$

$$\text{Filtering condition 2: } 0 < \beta < 1, \quad \hat{B} > 0$$

Table 1

| Filtering conditions | Notation | Search space | Filtering condition 1 | Filtering condition 2 |
|----------------------|----------|-------------|-----------------------|----------------------|
| 3 nonlinear parameters | $\rho$ | $[0.2]$ | $[0.01, 1.2]$ | $[0.01, 0.99]$ |
| $\omega$ | $[1, 5]$ | $[6, 13]$ | $[6, 13]$ |
| $\gamma_t$ | $[t_2 - 0.2, t_2 + 0.2]$ | $[t_2 - 0.05, t_2 + 0.1]$ | $[t_2 - 0.05, t_2 + 0.1]$ |
| Number of oscillations | $\omega C_1 C_2 | \beta | \omega^2 | [0.8, +\infty] | [1, +\infty] |
| Damping parameter | $\beta$ | $[\beta | \omega - \beta]$ | -- | -- |
| Relative error | $\beta | \sqrt{C_1 C_2}$ | $[0.05]$ | $[0.02]$ |
| Sample size | $d \beta^2 t_c - 1$ | -- | -- | -- |

Notes: Source Sornette et al. (2015).

Fantazzini (2016) and Sornette et al. (2015) filtering condition 1 in Table 1. In contrast, the DS LPPLS trust indicator measures the sensitivity of the bubble development to the LPPLS which satisfies Fantazzini (2016) and Sornette et al. (2015) filtering condition 2 in Table 1.

Fantazzini (2016)2 filtering conditions are reported in the following:

For a positive bubble: $0 < \beta < 1, \quad \hat{B} < 0$, the hazard rate $\hat{B} \equiv -B \beta - C(\sqrt{\beta^2 + \omega^2} \geq 0$ and the LPPLS residuals are stationary at the 5% level (using the KPSS test statistic).

For a negative bubble: $0 < \beta < 1, \quad \hat{B} > 0$ and $\hat{B} \equiv -B \beta - C(\sqrt{\beta^2 + \omega^2} \leq 0$ and the LPPLS residuals are stationary at the 5% level (using the KPSS test statistic).

4. Results and discussion

4.1. Preliminary analysis

We analyze the daily WTI and Brent crude oil, diesel, and gasoline prices from November 1, 2019, to December 31, 2020. As Fig. 1 shows, there is the first indication of the presence of bubbles in oil markets which indicates a period of decrease in early 2020. The descriptive statistics in Table 2 also show that all oil price series are not stationary and reject the normal distribution.

We observe that the price of Brent the highest average price ($45.15$), followed by the WTI price ($41.80$). In contrast, the prices of Brent and diesel are the lowest average price ($32.10$), followed by the WTI price ($30.80$). The price of crude oil is pushed down from an average of $45.15$ per barrel in April of the same year. Brent that raised at an average of $52.52$ per barrel in March, slipped to $9.12$ per barrel on April 21, 2020. The price of gasoline raised from $1.738$ per barrel on December 1, 2019 to $2.621$ per barrel on April 28, 2020.
31, 2019, and fell to $0.43 per barrel on March 26, 2020.

4.2. Econometric tests for explosive behavior

We conduct a real-time monitoring strategy for bubbles and crises in oil markets with the recursive right-sided unit root testing procedures (Phillips et al., 2011; Phillips, Shi, and Yu (2015a, 2015b)). Table 3 reports the SADF and GSADF statistics with their critical values obtained with a minimum estimation window \( r_0 = 0.01 + \frac{1.8}{\sqrt{T}} \) and \( T \) is the sample size. An investigation reveals the presence of multiple explosive behaviors in all oil prices.

Fig. 1. Evolution of oil markets.

### Table 2
Summary statistics.

|        | Brent | WTI   | Diesel | Gasoline |
|--------|-------|-------|--------|----------|
| Min.   | 9.12  | -36.98| 0.602  | 0.434    |
| Max.   | 70.25 | 62.37 | 2.054  | 1.796    |
| Mean   | 45.15 | 41.80 | 1.342  | 1.250    |
| St. dev.| 13.89 | 12.65 | 0.356  | 0.341    |
| Kurtosis| -0.441| -0.295| -0.684 | -0.573   |
| Skewness| -0.147| -1.090| -0.551 | -0.711   |
| Jarque-Bera| 20.71**| 288.2**| 20.4** | 9.879**  |
| ADF    | -1.270| -1.331| -1.703 | -1.581   |
| KPSS   | 1.435**| 1.060**| 2.068**| 1.088    |

**Notes:** Summary statistics for daily Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019 to December 31, 2020. Jarque-Bera statistic tests for the null hypothesis of Gaussian distribution. ADF denotes the statistics of the augmented Dickey-Fuller test. KPSS denotes the statistics of the KPSS test. ***, **, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

### Table 3
Explosive behavior detection.

|        | SADF      | CV_{SADF,95%} | GSADF    | CV_{GSADF,95%} |
|--------|-----------|---------------|----------|----------------|
| Brent  | 3.430**   | 2.217         | 3.452**  | 2.235          |
| Diesel | 2.149**   | 1.140         | 2.647**  | 1.488          |
| Gasoline | 3.614**  | 1.496         | 3.646**  | 1.560          |
| WTI    | 3.394**   | 1.608         | 3.394**  | 1.608          |

**Notes:** Explosive behavior detection of daily Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019 to December 31, 2020. ***, **, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively. SADF and GSADF are the Phillips et al. (2011) and Phillips, Shi, and Yu (2015a, 2015b) statistics, respectively. CV_{SADF,95%} and CV_{GSADF,95%} are 95% right-tail critical values for SADF and GSADF, respectively.

Brent: 90% and 99% right-tail critical values for SADF are 1.031 and 2.880, respectively. 90% and 99% right-tail critical values for GSADF are 1.069 and 2.927, respectively.

Diesel: 90% and 99% right-tail critical values for SADF are 0.884 and 2.033, respectively. 90% and 99% right-tail critical values for GSADF are 0.995 and 2.142, respectively.

Gasoline: 90% and 99% right-tail critical values for SADF are 0.050 and 3.111, respectively. 90% and 99% right-tail critical values for GSADF are 0.617 and 3.121, respectively.

WTI: 90% and 99% right-tail critical values for SADF are 0.318 and 2.522, respectively. 90% and 99% right-tail critical values for GSADF are 0.825 and 2.522, respectively.

phenomenon are reported in Table 4. The results identify that a common bubble episode exists in each oil price series we tested. Appendix A illustrates robustness test results with weekly datasets to support the results.

We detect a common bubble in oil markets during March and April 2020, i.e., during the first wave of the COVID-19 outbreak. We identify a period of explosive behavior in Brent crude oil prices between March 6
and April 2, 2020, but two short periods of explosive behavior in WTI crude oil prices between March 30, 2020 and April 21, 2020. Brent and WTI oil prices fell by 85 percent between January 2020 and April 21, 2020 before recovering in May 2020. We also identify two short periods of explosive behavior in diesel prices between March 16–30, and between April 27–28, 2020, and in gasoline prices between March 11–30, 2020.

The reason behind the oil price bubble could be explained a priori by the oil supply and demand imbalance (Adedeji et al., 2021). The COVID-19 pandemic generates a decrease in global industrial production causing lower oil consumption which decreases the barrel price. Previous episodes of significant oil price declines have often been associated with a weak global economy. Furthermore, the Russia–Saudi Arabia oil price war is the second reason that can explain the oil price drop (Ali et al., 2020). In March 2020, Saudi Arabia and Russia fail to reach an agreement on production cuts: Russia refuses to reduce oil production to keep oil prices at moderate levels. This disagreement exacerbates the crisis. Our findings confirm those of Bourghelle et al. (2021), Adedeji et al. (2021), Alqahtani et al. (2021), Albulescu (2020), Abdulkabir et al. (2021), Ozili and Arun (2020), Bakas and Triantafyllou (2020). Similarly, Hassan and Riveros Gavilanes (2021) state that the oil price drop cannot be solely explained by the Coronavirus-related induced reduction in global demand, the “Oil Price War” between Saudi Arabia and Russia is also a significant cause. Indeed, in the beginning of May 2020, oil prices (WTI and Brent) began to rebound as nations emerged from lockdown and OPEC agreed to significant cuts in crude oil production. In addition, refinery gasoline yields reverted back to levels similar to historical yields as the recent shift toward gasoline demand has supported increased gasoline production. Although diesel demand decreased less than gasoline demand during the initial stages of COVID-19-related restrictions, gasoline demand has recently begun to increase more than diesel.

### 4.3. The LPPLS approach for detecting financial bubbles

In this section, we estimate Filimonov and Sornette (2013) LPPLS model with Geraskin and Fantazzini’s (2013) method. According to Zhang and Yao (2016) the log-periodic power law (LPPL) model for negative bubbles as super-exponential decline with log-periodic oscillations. The results shown in Table 5 suggest that the crash rate is negative, indicating the presence of a negative bubble in the oil markets from January 1, 2020 to April 30, 2020.

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### Table 4

| Number | Exuberance Date   | Collapse Date   | Duration |
|--------|-------------------|-----------------|----------|
| Brent  |                   |                 |          |
| 1      | March 02, 2020    | April 02, 2020  | 2        |
| 2      | March 09, 2020    | February 04, 2020| 25       |
| 3      | 04/21/2020        | 04/21/2020      | 1        |
| Diesel |                   |                 |          |
| 1      | 01/24/2020        | 01/27/2020      | 4        |
| 2      | 01/30/2020        | April 02, 2020  | 6        |
| 3      | September 03, 2020| September 03, 2020| 1       |
| 4      | December 03, 2020 | December 03, 2020| 1       |
| 5      | 03/16/2020        | 03/20/2020      | 5        |
| 6      | April 27, 2020    | April 28, 2020  | 2        |
| Gasoline|                 |                 |          |
| 1      | September 03, 2020| September 03, 2020| 1       |
| 2      | March 11, 2020    | January 04, 2020| 21       |
| WTI    |                   |                 |          |
| 1      | September 03, 2020| September 03, 2020| 1       |
| 2      | 03/16/2020        | 03/31/2020      | 16       |
| 3      | 04/20/2020        | 04/20/2020      | 1        |

Notes: Following to Phillips et al. (2011), we consider explosive bubbles only if the duration of explosive behavior is more than 5 days (log(T)). T is equal to 395, the number of observations for the daily Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019 to December 31, 2020.

3. https://www.investopedia.com/articles/investing/100615/will-oil-prices-go-2017.asp.
4. U.S. Energy Information Administration, “Short-Term Energy Outlook (STEO),” https://www.eia.gov/outlooks/steo/archives/jun20.pdf (accessed June 22, 2020).
Specifically, according to Table 5, the condition of the relative error $\frac{|\hat{p} - p|}{\hat{p}} < 0.05$ is rejected by gasoline and diesel prices, and in contrast, is satisfied by WTI and Brent crude oil prices. In addition, the LPPLS parameters $\hat{\beta}$, $\hat{\omega}$, and $B$ satisfy the conditions for a negative financial bubble during the COVID-19 outbreak only for WTI and Brent prices.

The visualization of the LPPLS fitted series for daily data are illustrated in Figure B of Appendix B to support our results. The findings show that the LPPLS model has excellent goodness of fit only for the WTI and Brent price series. Consequently, there is no significant negative bubble in gasoline and diesel prices during this sub-sample period. Their prices are less impacted by the COVID shock and we do not detect a significant negative bubble. They have their own distinctive pricing mechanisms and market characteristics, which bring about different bubble processes (Zhang and Yao (2016)). Instead, the main driver of the decline in gasoline and diesel prices during COVID turmoil, are fundamentals, i.e., supply and demand in the market.

Additionally, our empirical results in Table 5 reveal that the predicted critical time for the Brent and WTI crude oil price bubbles are May 5, 2020, and May 8, 2020, respectively. The front-month futures price for Brent crude oil settles at $20.40 per barrel on May 4, 2020, an increase from $9.12 on April 21, 2020. The front-month futures price for WTI crude oil increases from $-39.00 during the same period, settling at $24.02 on May 11, 2020 and oil prices rose in May 2020. Thus, it can be seen that the crash time predicted by the LPPLS model in this paper is close to the EIA statistics.

We also use the DS LPPLS confidence indicators as a diagnostic tool for identifying bubbles using the daily data on oil prices during the sub-sample period. Figs. 3 and 4 show the DS LPPLS bubble indicators (confidence and trust) for positive bubbles in green, and negative bubbles in orange, along with the oil prices in blue. As shown in Figs. 3 and 4, in diesel and gasoline prices, we detect two little negative bubbles from March to April 2020.

In contrast, the negative bubble during the COVID-19 outbreak is associated with downwardly accelerating price decreases in the WTI and Brent crude oil prices. This result largely confirms the findings of the previous studies of Musa et al. (2020), Ali et al. (2020), Shu et al. (2021). Weng et al. (2021) find that COVID-19 related news affects the price of crude oil futures, which has a certain explanatory power for the volatility of crude oil futures. Similarly, Ari et al. (2021), find that COVID-19 deaths and panic have negative effects on crude oil price. Likewise, by examining the international crude price and the currency Chinese exchange rate from January 23 to February 8, 2020, Majiama’a et al. (2020) conclude that the crude oil price is significantly and negatively related to the coronavirus infection cases. In addition, COVID-19 creates fear and stress on financial markets causing increases in stock prices and then shocks in oil prices. Also, a cluster of bubble patterns are detected from September to November 2020 indicating a positive bubble due to the recent good news about COVID-19 vaccines, which prompted a new upswing in oil prices as suggested by Bourghelle et al. (2021). The DS LPPLS bubble indicators at different time horizons are illustrated in Figures C and D in Appendix D and support our results.

All checks confirmed that WTI and Brent prices experienced a statistically significant negative financial bubble during the COVID outbreak. Therefore, the improved LPPLS model can not only help investors assess their investment opportunities, but also has some implications on the stock price in the energy sector of the financial market, since the fluctuations in oil price will inevitably lead to volatility in equity holdings of oil companies Cheng et al. (2018).

5. Conclusion and policy implications

This paper sets to study explosive behavior and bubbles in oil price (WTI, Brent, gasoline, and diesel) during the period from November 1, 2019 to December 31, 2020 using SADF, GSADF, and LPPLS techniques. These methods not only test for the existence of episodes of explosive behavior, but also identify the beginning and the end of each of these episodes. The findings show that the LPPLS model has excellent goodness of fit for the WTI and Brent price series with super exponential growth. The WTI and Brent crude oil prices during the COVID-19 pandemic are significantly driven by bubbles. The WTI and Brent crude oil price dynamics present super-exponential decay decorated by obvious log-periodic oscillations, which indicate self-reinforced behaviors and similar behaviors among traders during the COVID-19 pandemic. In contrast, gasoline and diesel prices are mainly driven by fundamentals during the same period. We conclude that the DS LPPLS confidence and trust indicators based on oil prices provide effective warnings for detecting the negative bubble during the period of the COVID-19 outbreak. Overall, the differences in detection methods lead to the same conclusion.

We believe our analysis of the oil price dynamics through the COVID-19 outbreak provides an essential way to study the economic impact of the pandemic on the prices of important resources, which are crucial for the overall stability of the worldwide financial system and the global economy. Adverse movements in oil prices cannot only have important consequences for production costs and corporate profits, but also lead to deviations from macroeconomic policies to enhance growth and give boost to employment growth rates and then social welfare. Our results are likely to be valuable for oil market players, policy makers (e.g., the Federal Energy Regulatory Commission), and energy analysts. First, detecting the accurate time of bubbles by SADF, GSADF, and LPPLS identifies the contagion effect of bubbles in oil to other markets, such as stock markets or other commodity markets. Second, identification of explosive behavior and bubbles is of further importance in light of the links between energy prices and the overall economic activity. Moreover, our findings are also important given the common agreement that the most recent financial crisis originated from a bubble burst (Wang and Wong, 2015; Kunieda and Shibata, 2016; Baur and Heaney, 2017; Acharya and Naqvi, 2019, Su et al., 2017). Therefore, policy makers should pay attention to (negative and positive) bubbles in the oil markets. This concerns monetary policy decisions in particular, because there is a link between the U.S. dollar and oil prices. Bubbles in the oil market have an impact on exchange rate stability. Timely identification of bubbles will give policy makers the opportunity to act. Third, bubbles in oil markets are systemic, and they result from geopolitical crises or pandemics (Qin et al., 2020). These kinds of events are very difficult to anticipate. Consequently, policy makers should develop appropriate strategies in order to lessen the impact of oil price uncertainty. As such, they could invest in alternative sources of energy, especially renewable energy. Investing in other sources of energy could reduce the bubble tendency and minimize the dependency on the crude oil market.
(a) WTI

(b) Brent

Fig. 3. DS LPPLS confidence for positive and negative bubbles.
(c) Diesel

Fig. 3. (continued).

(d) Gasoline

Fig. 3. (continued).
Fig. 4. DS LPPLS trust for positive and negative bubbles.
(c) Diesel

(d) Gasoline

Fig. 4. (continued).
Alternatively, policies towards increasing the availability of finances to the renewable energy sector represent an important step for promoting technological development in this sector. Also, to increase the usage of alternative energies and then to reduce the use of crude oil, governments can choose to tax fossil fuel usage (Sadorsky, 2012). Finally, in a context of great uncertainty, these results show that regulation is insufficient to ensure the efficiency of the oil market. In extreme crisis situations during which (positive and negative) bubbles are significant, regulation should make it possible to limit speculative transactions (Cosgrove, 2009).

Negative and positive bubbles in oil markets have strong economic consequences. In view of the impact of the oil market on the world economy and the exceptional situation of COVID-19, the study of bubbles in the financial oil market is a research field that must continue to be explored. It would be also interesting, as a future research avenue, to explore in more details the specific reasons underlying each bubble.

Appendix. Robustness checks

We wanted to verify that our results also hold with different methods and different time periods. To verify our results, we employ a) tests with lower frequency data, b) the visualization of the fits and the original data c) the diagnostic tests based on the LPPL fitting residuals and finally d) robustness checks with a different time period: the oil price crash in 2014/2015.

A. Tests with weekly data

We now test the robustness of our results using weekly data to examine whether they are sensitive to data frequencies (Narayan et al., 2013). SADF, GSADF, and Phillips and Shi (2018) results of the weekly are illustrated in Table A, Table B, and Figure A. We find that for weekly data, as for the daily data, the central results are not significantly affected. We validate the presence of multiple explosive processes in our dataset as showed in Table A. Also, Figure A illustrates the multiple bubble in oil markets. We detect a common bubble in oil markets during March and April 2020, i.e., during the period of the COVID-19 outbreak for weekly data as illustrated in Table B. This validates the results of bubble detection for daily datasets indicating that the oil market is gravely affected by the COVID-19 pandemic.

### Table A

Explosive Behavior Detection

|          | SADF  | CV_SADF_95% | GSADF | CV_GSADF_95% |
|----------|-------|-------------|-------|--------------|
| Brent    | 2.633*** | 1.995       | 2.645*** | 1.003        |
| Diesel   | 1.405*** | 0.992       | 1.405*** | 0.994        |
| Gasoline | 1.373*** | 0.819       | 2.746*** | 1.165        |
| WTI      | 3.358*** | 2.557       | 3.358*** | 2.529        |

**Notes:** Explosive behavior detection of weekly Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019, to December 31, 2020. ***, **, and * indicate statistical significance at the 10%, 5%, and 1% levels, respectively. SADF and GSADF, and the Phillips et al. (2011) and Phillips, Shi, and Yu (2015a, 2015b) statistics, respectively. CV_SADF_95% and CV_GSADF_95% are 95% right-tail critical values for SADF and GSADF, respectively.

Brent:
- 90% and 99% right-tail critical values for SADF are 1.120 and 2.633, respectively.
- 90% and 99% right-tail critical values for GSADF are 1.120 and 2.645, respectively.

Diesel:
- 90% and 99% right-tail critical values for SADF are 0.711 and 1.405, respectively.
- 90% and 99% right-tail critical values for GSADF are 0.738 and 1.405, respectively.

Gasoline:
- 90% and 99% right-tail critical values for SADF are 0.186 and 1.373, respectively.
- 90% and 99% right-tail critical values for GSADF are 0.514 and 2.764, respectively.

WTI:
- 90% and 99% right-tail critical values for SADF are 1.238 and 3.358, respectively.
- 90% and 99% right-tail critical values for GSADF are 1.238 and 3.358, respectively.

### Table B

Bubbles and Crisis Detection

|          | Exuberance Date | Collapse Date  | Duration |
|----------|-----------------|----------------|----------|
| Brent    | 03/13/2020      | October 04, 2020 | 5        |
| Diesel   | 04/24/2020      | 04/30/2020     | 1        |
| Gasoline | 03/20/2020      | 03/27/2020     | 1        |
| WTI      | 03/13/2020      | March 04, 2020 | 3        |
|          | 04/24/2020      | 04/30/2020     | 1        |

**Notes:** Following Phillips, Wu, and Yu (2011), we consider explosive bubbles only if the duration of explosive behavior is more than 4 weeks (log(T)). T is equal to 61, the number of observations for the weekly Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019 to December 31, 2020.
Fig. A. Bubble and Crisis Periods in Oil Markets

Note: The solid line is the price and the shaded areas in green are the periods when the Phillips, Shi, and Yu statistic exceeds its 95% bootstrapped critical value. Following Phillips et al. (2011), we consider explosive bubbles only if the duration of explosive behavior is more than 4 weeks (log(T)). T is equal to 61, the number of observations for the weekly Brent and WTI crude oil, Diesel, and Gasoline prices from November 1, 2019, to December 31, 2020.

B. Visualization of the LPPL fitted series for daily data

Sornette et al. (2015) argue that the quality of the fits with the JLS model is furthermore checked by the visualization of the fits and the original data as showed in Figure B. The findings show that the LPPLS model has excellent goodness of fit for the WTI and Brent price series. As seen in Figure B, the LPPLS fitted series are close to the original data. Contrarily to diesel and gasoline, the LPPLS fitted series are distant from the original data. This demonstrates the results of goodness of fit of the LPPLS model with WTI and Brent in contrast to diesel and gasoline during the period of the COVID-19 outbreak.
C. The oil price crash in 2014/2015

To verify our results, we employ the WTI spot oil price from November 1, 2014 to February 28, 2015 and the results are shown in Figures C and D. This demonstrates a statistically significant negative financial bubble from the end of 2014 until the beginning of 2015. This oil crash is driven by low demand and the rising supply of shale oil. Similarly, OPEC increases the supply of crude oil by removing the cap and authorizing member states to make their own crude decisions (Khan et al., 2021). The findings agree with some previous studies, including Su et al. (2017), Fantazzini (2016), Zhao et al. (2020), Figuerola-Ferretti et al. (2020), Ajmi et al. (2021).
Fig. C. DS LPPLS Confidence for WTI in 2014/2015

Fig. D. DS LPPLS Trust for WTI in 2014/2015
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