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This paper contributes to Covid-19 outbreak impacts literature. We investigate the connectedness between stock market and oil prices under bullish and bearish economic conditions and uncertainty level at different investment horizons. We applied the wavelet framework on daily dataset cover the pre-COVID-19 and COVID-19 period. We find that the linkage between the economic and financial pairs is characterized by significant changes over the time during the sample period, where the huge co-movements has been identified during the pandemic period at the low scale. We show that due to lockdown policy and oil price shock, the stock return decline, the aggregate business conditions reached its lowest level and the uncertainty increase. The result indicates that the COVID-19 outbreak negatively affects the economy and the financial markets and support the sensitivity, especially between oil-stock and economic condition and uncertainty.

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stock market returns in the U.S. Most of papers concluded that oil price increase must have a negative impact on stock market returns in the U.S (Park and Ratti, 2008; Apergis and Miller, 2009; Sadorsky, 1999). Oil price volatility should also affect market indices and its impact may vary across sectors (Narayan and Sharma, 2014; Chiang et al., 2015; Phan et al., 2015a,b; Chiang and Hughen, 2017; Narayan et al., 2018; Van Eynden et al., 2019; Jia et al., 2021. For example, Narayan and Sharma (2011) used heterogeneous firm-level data to show that the returns of firms belonging to the energy and transportation sectors are positively affected by higher oil prices. The two-way causality between oil prices and stock returns can be illustrated through different channels. From a production cost perspective, higher oil prices will increase input costs and production costs, reducing firms’ profits and negatively impacting stock prices (Narayan and Sharma, 2011; Sadorsky, 1999; Xu, 2015). In addition, oil price volatility must affect firms’ cash flows as consumers will revise their saving-spending trade-off and expect unemployment. This type of behavior must reduce firms’ earnings and stock prices. Furthermore, from the perspective of firm investment, oil price volatility increases uncertainty and leads firms to reconsider their future investment strategy (Edelstein and Kilian, 2009). Overall, the effect of the oil prices on the stock markets is mixed, where, several investigations have concluded a negative impact of oil price volatility on stock returns (Park and Ratti, 2008; Sadorsky, 1999; Ciner, 2001; Abdollahi, 2020; Miljkovic and Goetz, 2020), and some authors have suggested that oil price volatility has a significant positive impact on stock returns (Zhu, Li, & Li, 2014; Lee, Yang, & Huang, 2012). In most of these studies, the authors argued that the nature of the link between oil price and stock returns depends on whether the country is an oil importer or exporter. In contrast, other studies show that the sign of the link between oil prices and stocks depends on the nature of oil shocks. Demand shocks have a positive impact on stock returns, but supply shocks that are due to oil availability are less likely to affect stock returns (Kilian and Park, 2009). Recently, related to the repercussions of the COVID-19 pandemic on the financial market and energy sector, some studies have revisiting and investigating the nexus between oil-markets. For instance, Youfisi et al. (2021a) explore that dynamic correlation between oil prices and S&P500 index during the end of the first quarter of 2020. Sharif et al. (2020) shows a strong dependency between oil and stock market where oil prices are leading the stock market. Sakurai and Kurosaki (2020) investigate the relationship between oil and the US stock market changed after the Covid-19 crisis and they indicate that both upside and downside correlations increased after the pandemic crisis. Salisu et al. (2020) exhibit that oil prices and stock markets may experience greater initial and prolonged effects of own and cross shocks during the COVID-19 pandemic period. Zhang and Hamori (2021) confirm the effect of the pandemic on the link between oil and stock markets.

The main contribution of this paper is to model the interdependence between oil and stock markets as well as the implied volatility of oil and U.S. business conditions before and during the COVID-19 era at different investment horizons. In fact, we focus on the effect of the pandemic during the first and second waves on the nexus between different assets. Although the literature has studied the co-movement between oil and stock markets even in the COVID-19 era, this paper is a pioneer in incorporating the business conditions as a proxy measure of economic growth when studying the co-movement between oil and stock markets, with the presence of uncertainty. We referred to the aggregate business conditions measure conducted by Aruoba et al. (2009). This index was designed to track the actual situation of firms at a high observation frequency. Its underlying economic indicators (seasonally adjusted) mix high and low frequency data, such as weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly real personal income minus transfer payments, monthly real sales of manufactured goods and trade, and quarterly real GDP.

Moreover, the methodological debate is still ongoing, and several research methods have been used to study the link between oil prices and stock returns. Most papers use parametric econometric models. In this paper, we used an innovative wavelet approach to study and compare the interdependence between oil prices, implied oil volatility, stock returns, and U.S. business conditions during the pre-COVID-19 and COVID-19 periods. One of the advantages of the wavelet coherence approach, compared to the econometric approach, is its ability to allow for a variety of scale locations. Our results explore a strong relationships between the financial assets and the economic aggregate, where we confirm the effects of COVID-19 crisis on the linkage between each couple variables. We show that the general quarantine in the U.S. during the COVID-19 pandemic created a shock on the demand side of oil. As a result, stock returns were negatively affected, and overall business conditions reached their lowest levels, worse than during the last financial crisis in 2008, also increase the uncertainty levels. Overall, this study establish that the pandemic has a hard repercussion on the economic state and financial markets, as well as it increase the connectedness between the stock market, oil, implied volatility and business condition.

The rest of the paper is organized as follows: we describe the empirical methodology in Section 2. In Section 3, we describe the data and then discuss the empirical results in Section 4. Finally, we conclude the paper in Section 5.

2. Empirical methodology

To achieve the objective of the paper and to study the interdependence between oil, the stock market, and U.S. business conditions during the time of the COVID-19 outbreaks, we used the wavelet approach. The wavelet approach was originally developed by Grinsted et al. (2004). The empirical methodology aims to detect the co-movement between the U.S. market, the oil market, the oil implied volatility index, and U.S. business conditions before and then during the recent COVID-19 pandemic health crisis.

The main advantage of wavelet analysis over standard econometric time series modeling methods is its ability to capture slow and persistent co-movements, allowing for a more nuanced understanding of the interdependence between
two time series in the time and frequency domains. However, as Reboredo and Rivera-Castro (2013) report, standard methods only consider the time domain perspective rather than the time and frequency domains. The wavelet method uses a bivariate framework established on a continuous wavelet transform (Morlet set to 6). This allows for a variety of scaled localization (Rua & Nunes, 2009). To capture and interpret the co-movement between two time series in the time and frequency domains, we use wavelet coherence using both the cross-wavelet transform and the coherence approach.

2.1. The continuous wavelet transforms

The continuous wavelet transforms $N_a(p, q)$ shows the projection of a wavelet $\psi(\cdot)$ in contrast to the time sequence $a(t) \in K^2(\mathbb{R})$, i.e.

$$N_a(p, q) = \int_{-\infty}^{\infty} a(t) \frac{1}{\sqrt{q}} \psi\left(\frac{t - p}{M}\right) dt.$$ (1)

An essential feature of this technique is its potential to decompose consequently and seamlessly recreate a time series $a(t) \in K^2(\mathbb{R})$.

$$a(t) = \frac{1}{C_{\psi}} \int_{0}^{\infty} \left[ \int_{-\infty}^{\infty} N_a(p, q) \psi_{p,q}(t) du \right] dq M^2, M > 0.$$ (2)

Furthermore, this technique preserves the power of the observed time sequence as follows:

$$\|a\|^2 = \frac{1}{C_{\psi}} \int_{0}^{\infty} \left[ \int_{-\infty}^{\infty} |N_a(p, q)|^2 dp \right] dq M^2.$$ (3)

In this paper, we rely on the aforementioned flexible tactic in the form of wavelet coherence, which enumerates the successiveness between two time series in a bivariate model.

2.2. The wavelet coherence

The connectedness between the U.S. stock market, the oil market, the oil implied volatility index, and the U.S. business conditions can be analyzed across time scales by considering the widely implemented methodology independent of time series (i.e., wavelet consistency). In practice, the cross-wavelet power and the cross-wavelet transform are defined first. Torrence and Compo (1998) stated that the cross-wavelet transform can be clarified by a two-time sequence $a(t)$ and $b(t)$ as follows:

$$N_{ab}(p, q) = N_a(p, q) N_b^*(p, q)$$ (4)

where, $N_a(p, q)$ and $N_b(p, q)$ represent two continuous transforms of $a(t)$ and $b(t)$, separately, $p$ represents the location index and $q$ the measure, whereas composite conjugate is shown by ($^*$). The cross-wavelet transform can be used to calculate wavelet power by $|N_{ab}(p, q)|$. The cross-wavelet power spectra separate the section in which a high energy concentration is revealed (cumulus of restricted variance) in the time–frequency related domain from the time series under consideration. The wavelet coherence technique can determine the specific parts in the time–frequency domain where unexpected and major variations occur in the co-motion patterns of the observed time series. The equation for the adjusted wavelet coherence coefficient, as identified by Torrence and Webster (1999), is defined as follows:

$$W^2(p, q) = \frac{|M(M^{-1}N_{ab}(p, q))|^2}{M(M^{-1}|N_a(p, q)|^2) M^{-1}N_b(p, q)|^2}$$ (5)

With $M$ is the smoothing mechanism. The value of the wavelet squared coherence varies between zero and one ($0 \leq W^2(p, q) \leq 1$), this shows the range of squared wavelet coherence coefficient. Proximity to zero is an indication of no correlation (no co-movement), while proximity to one is an indication of high correlation (high co-movement) and can be considered as a scale-specific squared correlation between the series. The Monte Carlo method is used to examine the hypothetical allocation of wavelet coherence. The WC approach allows us to examine the lead/lag relationship between two series while avoiding the problem of squared coherence that cannot distinguish between the positive and negative relationship between two series.

3. Data and their proprieties

We are interested in studying the interaction and interdependence between the oil market, the U.S. stock market, and the U.S. business conditions before and during the COVID-19 outbreak. Therefore, we collected a sample of daily data describing the implied volatility of the oil market (OVX), the US stock market (S&P500) and the US business conditions index. The time horizon of our daily data covered the period from January 2018 to December 2020. Therefore, the data takes on an interesting feature by covering, not only the pre-COVID-19 period, but also the first and second wave of the
COVID–19 pandemic spread. Therefore, we will be able to detect any changes in the behavior of the oil-stock co-movement when the world entered the COVID–19 era.

We select for all series a total of 750 daily observations. The choice of the start and end date is justified by the main objective of the paper. Indeed, oil prices (in dollars per barrel) are measured by the prices of the benchmark crude oil WTI. The OVX measures the implied volatility index of oil. The CBOE Crude Oil Volatility Index measures the markets’ expectation of the 30-day volatility of crude oil prices by applying the VIX methodology to U.S Oil Fund, LP (Ticker-USO) options covering a wide range of strike prices. Higher OVX values represent significant uncertainty or fear in the oil market, while lower OVX values indicate less uncertainty in the oil market. For the U.S. stock market, we used the S&P500 index, which measures the stock performance of 500 large publicly traded companies.

The ADS index is the measure of US business condition. Aruoba et al. (2009) designed the ADS index to track real business conditions at a high observation frequency. Its underlying (seasonally adjusted) economic indicators combine high and low frequency data, such as weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly real personal income minus transfer payments, monthly real sales of manufactured goods and trade, and quarterly real GDP. The average value for the U.S. business conditions is zero. Progressively larger positive values indicate progressively better than average conditions, while progressively larger negative values indicate progressively worse than average conditions. This index can be used to compare business conditions at different time periods. Oil prices are available on the EIA website. The oil implied volatility data is derived from Yahoo Finance. The U.S. stock index (S&P500 stock prices) is available from the Federal Reserve Bank of St. Louis. The ADS index is obtained from the Philadelphia-fed website (www.philadelphiafed.org).

To further the descriptive analysis of the data, we have plotted the time series graphs of daily returns and prices below. Fig. 1 shows the dynamics of the time series graphs, we can see that the U.S. stock and oil markets experienced a significant decline during the rapid spread of the COVID–19 pandemic around the world. In addition, we can clearly see that the U.S. business conditions dropped to a negative value below −20 in March and April 2020. This indicates that business conditions are significantly worse than ever before, even during the 2008–2009 global recession, during which the ADS index never fell below −4. However, the Oil uncertainty (OVX) measure shows a sharp rise in prices at the same time. This means that higher OVX values represent more uncertainty or fear in the oil market during the COVID–19 outbreak. The plots of the return series illustrate the clustering of volatility (e.g., stylized factors for all stock prices) from the beginning of March to April 2020. We noted that this is primarily related to the COVID–19 outbreak.

After observing the daily returns and price trends, we calculated and presented the statistical properties of the daily data in Table 1. The descriptive statistics of S&P500, oil price, OVX and ADS confirmed the main conclusions drawn from the previous chart, presented in Fig. 1. The volatility and behavior of U.S. business conditions are influenced by the COVID–19 epidemic. The ADS is characterized by a higher standard deviation, about five times higher than the mean, indicating that the decline in business conditions was severe and more pronounced than its value during the 2008 global financial crisis.

To confirm the previous descriptive findings, we turn to objective analysis. We applied the wavelet transform and the coherence approach to detect the interdependencies and interactions between the oil price, the stock market, and the U.S. business conditions.

Before starting the empirical investigation by applying the wavelet approach, we tested the presence of unit root of the variables returns (see Table 2). We applied two unit root tests which are the ADF (1981) and the Phillips–Perron test. As described in Table 2, all variables become stationary in first difference. The volatility of the stock market index and the

| Table 1 | Statistical properties for daily data. |
|---------|-------------------------------------|
| Oil price | OVX | S&P500 | ADS |
| Mean | 53.96666 | 42.26936 | 2959.164 | −0.751522 |
| Median | 56.26000 | 33.73000 | 2888.320 | −0.089742 |
| Maximum | 77.41000 | 236.8000 | 3756.070 | 8.587538 |
| Minimum | 12.34000 | 21.20000 | 2237.400 | −27.99161 |
| Std. Dev. | 12.87109 | 28.49084 | 287.9699 | 5.545052 |
| Skewness | −0.775936 | 3.502017 | 0.732594 | −3.186255 |
| Kurtosis | 3.248745 | 16.81320 | 3.006887 | 15.07371 |
| Jarque–Bera | 77.29598 | 7505.652 | 67.17764 | 5832.247 |
| Probability | 0.000000 | 0.000000 | 0.000000 | 0.000000 |

Note: Std. dev: standard deviations. JB stats is the Jarque–Bera test with the null hypothesis of normality.

1 OVX measures the implied volatility of oil prices and is calculated using movements in the prices of financial options for WTI, the light, sweet crude oil priced at Cushing, Oklahoma. Crude oil volatility is typically higher than the S&P 500’s volatility, generally because OVX represents changes in one commodity and VIX represents changes across a diverse group of 500 companies.

2 The VIX Index measures the implied volatility of the S & P500 Index Options and represents the market’s expectation of stock market volatility over the next 30 days.
price of oil justify the presence of unit root in level. However, in the case of the business conditions index, this variable is stationary in level.

In addition, the descriptive correlations between the variables and the U.S. business conditions are calculated and presented in Table 3. We calculated the Pearson correlation and reported the coefficients with their $p$-value. Table 3 shows that the stock market index is positively correlated with the oil price but negatively correlated with the implied volatility of the oil price. The U.S. business conditions index is negatively correlated with the implied volatility of the oil price, which may point to the impact of the demand shock on the oil market. Finally, the stock market index is positively correlated with the U.S. business conditions but this correlation is not significant.

The presence of significant correlations between the variables representing the oil and stock markets and the U.S. business conditions will be tested and confirmed by the wavelet approach in the next section.

4. Empirical evidence and discussion

The empirical methodology presented in the previous section is applied to study the research question of this paper. The main contribution of this empirical study is twofold: (i) it considers the U.S. business conditions in the study of oil-stock co-movement. (ii) the change in the behavior of the time–frequency co-movement of oil and stocks when the world entered the COVID-19 era, through a long database from January 2018 to December 2020.

In order to capture and interpret the co-movement between two time series in both time and frequency domains, we employ wavelet coherence using both the cross-wavelet transform and the coherence approach. The wavelet analysis approach will capture the interdependencies between oil and stock markets with respect to U.S. business conditions during the COVID-19 pandemic. The empirical investigation is useful because we used daily data covering the pre- COVID-19 period as well as the first and second waves of the COVID-19 outbreak in the United States. The first step aims to transform the variables to observe their volatility movement with respect to the time horizon (short term vs. long term). The second
### Table 2
Unit root tests of daily data.

#### ADF test

|                | OIL  | OVX  | SP   | ADS  |
|----------------|------|------|------|------|
| **At level**   |      |      |      |      |
| With constant  | t-Statistic: -1.4463  | -2.4604 | -1.1216 | -4.3465  |
|                | Prob.: 0.5604            | 0.1258  | 0.7090  | 0.0004   |
| With constant & Trend | t-Statistic: -2.2037  | -2.5941 | -2.9363 | -4.3554  |
|                | Prob.: 0.4863            | 0.2832  | 0.1516  | 0.0027   |
| Without constant & Trend | t-Statistic: -0.6474  | -1.2391 | 0.7255  | -4.2843  |
|                | Prob.: 0.4368            | 0.1981  | 0.8713  | 0.0000   |
| **At first difference** |      |      |      |      |
| With constant  | t-Statistic: -27.9790  | -14.2512 | -7.9600 | -5.8386  |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |
| With constant & Trend | t-Statistic: -27.9606  | -14.2455 | -8.0140 | -5.8347  |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |
| Without constant & Trend | t-Statistic: -27.9929  | -14.2602 | -7.9179 | -5.8426  |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |

#### PP test

|                | OIL  | OVX  | SP   | ADS  |
|----------------|------|------|------|------|
| **At level**   |      |      |      |      |
| With constant  | t-Statistic: -1.5032  | -3.8213 | -1.0226 | -3.0331  |
|                | Prob.: 0.5316            | 0.0028  | 0.7468  | 0.0324   |
| With constant & Trend | t-Statistic: -2.3670  | -4.1904 | -2.7176 | -3.0352  |
|                | Prob.: 0.3966            | 0.0048  | 0.2297  | 0.1233   |
| Without constant & Trend | t-Statistic: -0.6482  | -1.7219 | 0.9063  | -3.0057  |
|                | Prob.: 0.4364            | 0.0807  | 0.9027  | 0.0026   |
| **At first difference** |      |      |      |      |
| With constant  | t-Statistic: -27.9825  | -33.7439 | -33.9087 | -18.3334 |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |
| With constant & Trend | t-Statistic: -27.9649  | -33.7436 | -33.9445 | -18.3288 |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |
| Without constant & Trend | t-Statistic: -27.9961  | -33.7653 | -33.8711 | -18.3385 |
|                | Prob.: 0.0000            | 0.0000  | 0.0000  | 0.0000   |

Notes:
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

The continuous wavelet transform (CWT) plots of all variables are shown in Fig. 2. The CWT describes the movement of each variable in the timescale and frequency bands. Indeed, the horizontal axis shows the time component, while the vertical axis shows the frequency component. The frequency component extends from the 0-day scale to the more than 256-day scale. The black contours in each graph indicate regions with a significance level of 5%. In Fig. 2, OIL, OVX, SP, and ADS represent the price of oil, the implied volatility of the price of oil, the S&P500 stock index, and the U.S. business conditions index, respectively.
Table 3
Pearson correlations between daily data.

|       | OIL     | OVX    | SP     | ADS     |
|-------|---------|--------|--------|---------|
| OIL   | 1.000   |        |        |         |
| P-value |        |        |        |         |
| OVX   | −0.5553 | 1.000  |        |         |
| P-value |        |        |        |         |
| SP    | 0.2810  | −0.3728| 1.000  |         |
| P-value |        |        |        |         |
| ADS   | 0.11441 | −0.0462| 0.0075 | 1.000   |
| P-value |        |        |        |         |

Note: Table 3 present the Pearson correlation between each couple variables.

If we look in detail at the price plots of oil, OVX, S&P500 and ADS, we can clearly observe that the CWT plots show different islands of high short- and long-term volatility (frequency bands of 0–256 days) during the COVID-19 period compared to the pre-COVID period.

This frequency band indicates an interesting interaction with the COVID-19 outbreak. Indeed, this volatility clustering coincides with the rapid spread of the COVID-19 pandemic around the world from March 2020 to mid-April 2020 (we can also see this dependence in Fig. 1). However, the U.S. business conditions plot reveals a different behavior of volatility. It shows, at the time of the COVID-19 pandemic, a higher volatility zone in the long term (frequency bands from 32 to 256 days) and small zones in the short term.

The plots of the U.S. stock, the oil markets, and the oil volatility index show numerous islands of higher volatility over frequency bands from the short term to the long term during the COVID-19 health crisis, in particular the U.S. market reveals a broad zone of higher volatility over frequency bands from 32 to 256 days. The oil market shows a significant zone of increased volatility at the long term between 2019 and 2020.

We noted that a particularly significant zone of volatility on both short- and long-term day frequency was observed during the COVID-19 pandemic rather than the pre-COVID period. Visual inspection shows that each series initially responded to COVID-19 information coming from around the world when the spread of COVID-19 worldwide was at its highest level (March 2020). Furthermore, after the global pandemic emergency and the declaration of the World Health Organization (WHO) that the COVID-19 epidemic is a global pandemic, the CWT shows that all variables were significantly impacted by the pandemic.

4.1.1. The wavelet coherence analysis

The second step is to apply wavelet coherence analysis to study and compare the interaction and interdependence between the volatility of the stock market, the oil market, and the overall U.S. business conditions during the pre-COVID-19 period and the COVID-19 pandemic. The mobilization of the U.S. business conditions as a proxy measure of economic growth represents the main contribution of this article to the previous literature. Indeed, the main concern of the previous literature is to study the correlation and interdependence between the stock market and oil prices. We add the measure of economic opportunity before and during the COVID-19 pandemic to further investigate the empirical relationship between the stock and oil markets.

We apply wavelet coherence between the U.S. and oil market, implied oil volatility and U.S. business conditions, and OVX to study the interdependence between them. We present the wavelet coherence plots for each pair of variables in Fig. 3. The plots show the estimated wavelet coherence approach and the relative phasing of two series represented by arrows. The time period is represented by the horizontal axis from January 2018 to December 2020 and the frequency is represented by the vertical axis.

On the estimated WC plots, the black outline indicates the 5% significance level, the warmer red color corresponds to the area with higher co-movements, while the cooler blue color represents the area with low co-movements. Arrows indicate the direction of interdependence and causality relationships (Torrence and Webster, 1999; Tiwari, 2013; Yang et al., 2017; Pal and Mitra, 2019; Jiang and Yoon, 2020). If the arrows point to the right, this should indicate that the two series are positively correlated. On the other hand, when the arrows are turned to the left, it should indicate that the two variables are negatively correlated. Arrows facing up-right and down-left \( \nearrow \searrow \) mean that the first variable drives the second, while arrows facing down-right and up-left \( \nwarrow \nearrow \) indicate that there is a countercyclical effect where the second variable drives the first. In contrast, the right up \( \uparrow \) and down \( \downarrow \) arrows imply that the variable is leading and lagging, respectively.

We identify several significant high degree co-movements between each pair, we detect the existence of many small islands that indicate strong dependence at the beginning, middle, and end of the sample period on both the short- and long-term (0–256 days) day frequency bands. The oil market and the oil implied volatility pair show particularly significant co-movement throughout the sample period, but the large region of highest degree of co-movement is in the COVID-19 health crisis era. The direction of the arrows is mainly facing down-left \( \searrow \) which means that the Oil market and their implied volatility are negatively correlated, and that OVX leads the oil market. In addition, Oil and stock market also show
many upper and positive coherence areas during the sample period, as the direction of the arrows is mainly towards the down-right \( \searrow \), meaning that there is a countercyclical effect between the Oil market and the U.S. stock market. For the implied volatility of Oil and the U.S. stock market, we detect many regions of high and negative co-movement between them throughout the sample period. The direction of the arrows pointing up-left \( \nearrow \) suggests that there is a countercyclical effect between OVX and the S&P500 stock. During the COVID-19 pandemic, we can see that the direction of the arrows on the long-term frequency of 128 to 256 days is pointing down-left, indicating that the correlation between them remains negative while the OVX is leading the U.S. stock market.

Finally, we identify from the plots many small islands representing a high degree of co-movement between the U.S. business conditions and the remains financial assets over the short term. Particularly significant and huge coherences over the long-term time frequency bands are observed during the COVID-19 period, compared to the pre-COVID-19 pandemic. The direction of the arrows for the ADS and OIL pairs is turned up-right, indicating that the correlation between them is
positive, with the U.S. business conditions driving the oil market. While for the coherence area between ADS and OVX, the direction of the arrows changes in the coherence region (↙ and ↘) during the sample period. In the first year of the sample period (2018), the arrows are turned to the bottom-right, indicating that ADS is positively correlated with OVX and that there is a countercyclical effect between them. While during 2019 and COVID-19, the arrows are turned to the down-left and up-left, indicating that the correlation between ADS and OVX is negative where the U.S. business conditions lead and lag the oil volatility index, respectively. Based on the direction of the arrows (down-right/ up-right), we noted that the correlation between the U.S. business conditions and the U.S. stock market is positive, there is a countercyclical effect between them between the frequency bands of 32–128 days, where the US stock market leads the ADS. In addition, the U.S. business conditions lead the U.S. market on the 128–256 day's frequency during the COVID-19 period.

The high degree of co-movements, particularly during the COVID-19 health crisis, provides strong evidence of the contagion effect of the COVID-19 pandemic on the connectivity between each couple variables during the implementation of containment in the United States. During the COVID-19 crisis, U.S. demand for oil reached lower levels that negatively affected business activity, industry, and the U.S. economy. The spread COVID-19 infections and the rise deaths in the U.S. has been associated with a decline in the oil prices, the S&P500 stock market, and U.S. business conditions in the short and medium term. This was expected because U.S. governments, like many countries, have imposed social distancing, border closures, travel restrictions and general quarantine in countries that make up the world’s largest economies. While uncertainty or fear in the oil market has reached high levels. Our conclusion implies that the COVID-19 epidemic has strengthened the co-movement between our couple of variables, where oil plays the main role in supporting this interconnection.

Although some research efforts have been devoted to studying the co-movement of Oil and stock markets, our study is one of the first to incorporate business conditions into the study of the co-movement of oil and stock market. In this study, we analyze the time–frequency connectivity between the recent COVID-19 outbreak, oil prices, global activity, and the stock market in the United States, using the wavelet framework, which enable to investigate the dependence at different investment horizons. We use the aggregate business conditions and the business conditions index incorporated in our modeling as a proxy measure of U.S economic growth. We show that the lockdown in the United States during the COVID-19 pandemic created an oil shock. Our investigation shows that because of the oil shock, stock returns are low, and overall business conditions have bottomed out.

5. Conclusion and policy implications

The lockdown and confinement policy in many countries to mitigate the spread of the COVID-19 virus rapidly transformed to an economic and financial crisis. This health crisis affects the behavior of stock markets, especially energy sectors (Dutta et al., 2020). Revisiting the oil–stock co-movement has important implications for investors and energy policy makers, especially during the COVID-19 crisis. The oil–stock nexus has been extensively studied in the energy and finance literature through several empirical methods. This paper contributes to the energy finance literature by including the bullish and bearish U.S. business conditions when we check the interdependence between oil prices and stock returns. Moreover, we consider an interesting dataset cover the pre-COVID-19 period and the first and the second waves of the COVID-19 outbreak (i.e., January 2018 to December 2020), the paper detects the impact of the COVID-19 pandemic on the behavior of the oil–stock dependence. We use the continuous wavelet transformation and wavelet coherence approach to investigate response of stock returns, oil price, oil volatility and U.S. business conditions to the pandemic and their effects on the associations between them.

Our findings implies that the pandemic enforced the dependence between the most couple variables. This expected because the COVID-19 and their economic-financial costs increase the systematic risk in the markets (Yousfi et al., 2021a; Zhang et al., 2020). Moreover, we show that the oil market reached the lowest prices, the same case is observed on the average of the U.S business conditions and the U.S equity market has experienced a significant dropped, this related to contagion effect and high dependence during the pandemic. We find also that the implied volatility is negatively correlated to the remains variables. Actually, the rise of uncertainty has a negative repercussion on the economic condition and the stock market (Sharif et al., 2020; Yousfi et al., 2021b). In fact, the oil shock generated by the lockdown play a principal role on the degradation in the U.S economy as well as the financial market.

Our results have important new policy and practical implications. For policymakers, our results are very useful because they show that in any pandemic situation where the economy may face a negative shock to oil prices, the stock market will react downward. At the same time, in the event of a rise in oil prices, the stock market may react positively. This sensitivity of the stock market is detrimental to sustainable economic growth. Therefore, our policy recommendations are to reduce stock market volatility. Policymakers can achieve this objective by strengthening the coordination of monetary and fiscal policies. Other measures would be needed to reduce policy instability. Policy coherence can reduce the impact of the pandemic on the economy and society. In addition, there is much uncertainty about the end of the COVID-19 pandemic, a consistent policy framework to stabilize stock markets would improve the confidence of individual and institutional investors and, therefore, make stock markets more resilient to external oil price shocks.

Our study also has implications for the international governance. The COVID-19 pandemic has revealed many flaws in the regulatory environment of many countries. Dependence on fossil fuels should be reduced to avoid economic crisis, stock market crashes and herd behavior of individual investors. Given the uncertainties regarding the end of the COVID-19
crises, there could be a new oil demand shock. Our analysis is important not only for companies involved in the fossil fuel sector, but also for other companies in the hospitality and transportation sector. In addition, our results are a guide for investors to diversify their portfolios as our results show a significant negative impact of COVID-19 on the stock markets. Our results of poor stock market performance and general business conditions suggest that investors are more likely to withdraw capital from financial markets during future pandemics, particularly from sectors directly related to fossil fuels. These results are consistent with studies conducted during the global financial crises of 2007–09, when investors lost capital and exhibited extreme herding behavior.
References

Abdollahi, H., 2020. A novel hybrid model for forecasting crude oil price based on time series decomposition. Appl. Energy 267, 115035.

Apergis, N., Miller, S.M., 2009. Do structural oil-market shocks affect stock prices? Energy Econ. 31 (4), 569–575.

Aruoba, S.B., Diebold, F.X., Scotti, C., 2009. Real-time measurement of business conditions. J. Bus. Econom. Statist. 27 (4), 417–427.

Chang, C.L., McAlerie, M., Wang, Y.A., 2020. Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19. Renew. Sustain. Energy Rev. 134, 110349.

Chiang, I.H.E., Hughen, W.K., 2017. Do oil futures prices predict stock returns? J. Bank. Financ. 79, 129–141.

Chiang, I.H.E., Hughen, W.K., Sagi, J.S., 2015. Estimating oil risk factors using information from equity and derivatives markets. J. Finance 70 (2), 765–804.

Ciner, C., 2001. Energy shocks and financial markets: nonlinear linkages. Stud. Nonlinear Dyn. Econom. 5 (3), 2003–2012.

Dutta, A., Das, D., Jana, R.K., Vo, X.V., 2020. COVID-19 and oil market crash: Revisiting the safe haven property of gold and bitcoin. Resour. Policy 69, 101816.

Edelstein, P., Kilian, L., 2009. How sensitive are consumer expenditures to retail energy prices? J. Monetary Econ. 56 (6), 766–779.

Jammazi, R., Ferrer, R., Jareño, F., Shalzad, S.J.H., 2017. Time-varying causality between crude oil and stock markets: What can we learn from a multiscale perspective? Int. Rev. Econ. Finance 49, 453–483.

Jia, Z., Wen, S., Lin, B., 2021. The effects and re-acts of COVID-19 pandemic and international oil price on energy, economy, and environment in China. Appl. Energy 32 (15), 117612.

Jiang, Z., Yoon, S.M., 2020. Dynamic co-motion between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. Energy Econ. 90, 104835.

Kilian, L., Park, C., 2009. The impact of oil price shocks on the US stock market. Internat. Econom. Rev. 50 (4), 1267–1287.

Miljkovic, D., Goetz, C., 2020. The effects of futures markets on oil spot price volatility in regional US markets. Appl. Energy 273, 115288.

Narayan, P.K., Sharma, S.S., 2011. New evidence on oil price and firm returns. J. Bank. Financ. 35 (12), 3253–3262.

Narayan, P.K., Sharma, S.S., 2014. Firm return volatility and economic gains: the role of oil prices. Econ. Model. 38, 142–151.

Pal, D., Mitra, S.K., 2019. Oil price and automobile stock return co-movement: A wavelet coherence analysis. Econ. Model. 76, 172–181.

Park, J., Ratti, R.A., 2008. Oil price shocks and stock markets in the US and 13 European countries. Energy Econ. 30 (5), 2587–2608.

Phan, D.H.B., Sharma, S.S., Narayan, P.K., 2015a. Oil price and stock returns of consumers and producers of crude oil. J. Int. Financ. Mark. Inst. Money 34, 245–262.

Phan, D.H.B., Sharma, S.S., Narayan, P.K., 2015b. Stock return forecasting: Some new evidence. Int. Rev. Financ. Anal. 40, 38–51.

Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Econ. 21 (5), 449–469.

Sakurai, Y., Kurokaki, T., 2020. How has the relationship between oil and the US stock market changed after the Covid-19 crisis? Finance Res. Lett. 37, 101773.

Salisu, A.A., Ebuh, G.U., Usman, N., 2020. Revisiting oil-stock nexus during COVID-19 pandemic: Some preliminary results. Int. Rev. Econ. Finance 69, 280–294.

Sharif, A., Aloui, C., Varovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal. 70, 101496.

Tiwari, A.K., 2013. Oil prices and the macroeconomy reconsideration for Germany: Using continuous wavelet. Econ. Model. 30, 636–642.

Torrence, C., Compo, G.P., 1998. A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. 79 (1), 61–78.

Torrence, C., Webster, P.J., 1999. Interdecadal changes in the ENSO–monsoon system. J. Clim. 12 (8), 2679–2690.

Van Eyden, R., Difeto, M., Gupta, R., Wohar, M.E., 2019. Oil price volatility and economic growth: Evidence from advanced economies using more than a century’s data. Appl. Energy 233, 612–621.

Xu, B., 2015. Oil prices and UK industry-level stock returns. Appl. Econ. 47 (25), 2608–2627.

Yang, L., Cai, X.J., Hamori, S., 2017. Does the crude oil price influence the exchange rates of oil-importing and oil-exporting countries differently? A wavelet coherence analysis. Int. Rev. Econ. Finance 48, 536–547.

Yousfi, M., Daouai, A., Bouzgarrou, H., 2021a. Risk spillover during the COVID-19 global pandemic and portfolio management. J. Risk Financ. Manage. 14 (5), 222.

Yousfi, M., Zayed, Y.B., Cheikh, N.B., Lahouel, B.B., Bouzgarrou, H., 2021b. Effects of the COVID-19 pandemic on the US stock market and uncertainty: A comparative assessment between the first and second waves. Technol. Forecast. Soc. Change 167, 120710.

Zhang, W., Hamori, S., 2021. Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany. Int. Rev. Financ. Anal. 74, 101702.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 36, 101528.