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Research article

Dynamic spillover effects between oil prices and stock markets: New evidence from pre and during COVID-19 outbreak

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Abstract: In this study, we employ both the spillover index of Diebold and Yilmaz [1], and the wavelet coherence approaches to investigate the impacts of return spillovers and dynamic time-frequency linkages between crude oil prices and five developed stock markets in Europe (the United Kingdom, Spain, Italy, German, and France) in the pre and during Covid-19 outbreak periods. The results highlight that IBEX and CAC series are net recipients of risks, while the other assets are a net transmitter of shocks in the pre-Covid-19 period. In contrast to the results for the pre-Covid-19 period, LSE, CAC, and IBEX are the net recipients of return spillovers, reaching a maximum level of about 23% during the Covid-19 outbreak. Specifically, in comparison with the pre-Covid-19 period, the return transmission is more apparent during the Covid-19 crisis. More importantly, there exist significant dependent patterns about the information spillovers, and time-frequency linkages between crude oil and five major stock markets might provide urgent prominent implications for portfolio managers, investors, and government agencies.

Keywords: Covid-19; oil market; stock market; Europe; spillover index; wavelet coherence

1. Introduction

Highly contagious coronavirus (Covid-19) spread given rise to by severe acute respiratory syndrome worldwide has influenced 3.822.860 individuals and has taken the life of 265.076 persons by 7 May 2020. And the global economy is facing two severe shocks: the novel Covid-19 spread and the recent oil price slump. These drawbacks will have short and long-run economics, banking and insurance, financial markets, financing and costs of capital and governments and publics effects throughout the world [2]. Specifically, the combination of these issues would initiate a long-run economic downturn and drive the European countries into the next recession.

Variations in oil prices and stock markets during the Covid-19 outbreak pandemics represent a double challenge for policymakers because the interdependence in these markets can not only have important implications for production costs, corporate profits and employment growth rates but also result in deviations from macroeconomic policies to enhance development and social welfare. The Covid-19 outbreak is a source of systematic risk. Therefore, it is necessary to carry out further research on the financial impacts of Covid-19 spread. In this article, we provide novel insight into the oil-stock relationship by exploring the effect of the Covid-19 crisis on the time-frequency connectedness and return spillovers across crude oil and five major stock markets in Europe (the United Kingdom, Spain, Italy, German, and France).

The risk and return spillovers of crude oil and stock markets are heavily investigated in the literature. Variations in the oil price have created an unpredictable effect on the trajectory of world oil pricing and stock markets [3]. In addition, a large volume of studies developed on the connectedness between oil prices and real economic activity after the major oil price shocks of the 1970s [4–10]. Hamilton [11] uncovers that oil price shocks are a primary factor contributing to the recession in the US. Overall, these studies unveil that the economic activities of different countries are impacted by the oil-price fluctuations.

Recently, Wei et al. [12] reveal that the oil futures market has considerable influence on China stock market through both a direct and indirect way. Ni et al. [13] report that a sharp rise and fall of oil prices might cause stock market fluctuations because of investors' sentiments aroused. At the same time, the effect of negative oil price innovations on the stock exchanges is more substantial than of positive innovations and constituted the most significant source of variations in the stock exchanges in the Caspian Basin-Iran, Kazakhstan and Russia [14]. Similar findings are reported by Köse and Ünal [14], Shahrestani and Rafei [15] document that the oil price shocks have both positive and negative effects on the Tehran stock exchange. Zhu et al. [16] measure the risk of carbon market accurately by taking the European allowance futures price with maturity, suggest that the proposed multiscale VaR estimation can achieve a higher precision than conventional VaR estimation. In a similar fashion, Zhu et al. [17] study the risk spillover effects between carbon market and electricity market, and point out that the risks of high frequency modes are higher than those of intermediate and low frequency modes.

Xiao and Wang [18] suggest that there exist nonlinear bidirectional causal interactions and the corresponding information transfers between crude oil prices and stock markets. More importantly, the paper also finds that information flows are generally time-varying and more significantly and stronger between oil prices and stock indices during the period of the financial crisis. Another interesting paper, Hamma et al. [19] indicate that the Gumbel copula is the best model for modeling the conditional dependence structure of crude oil and stock markets. Based on the same method, Mokni and Youssef [20] report that the oil-GCC stock market interaction is significantly positive and experience various degrees of persistence. In the European country context, Bagirov and Mateus [21] uncover the persistence of the interrelatedness between oil and European stock markets.

None of these studies concentrates, however, on the new crisis generated by the Covid-19 outbreak. Therefore, the present paper is the first endeavor to capture how the Covid-19 crisis affects the co-movements between crude oil price and five major stock markets in Europe before and during the Covid-19 periods. By doing so, both the spillover index of Diebold and Yilmaz [1] and the wavelet coherence frameworks have been employed, which allow us to estimate the directional of spillover and lead-lag interplay among different variables in the pre and during Covid-19 period. Moreover, we use wavelet analysis to estimate the interconnection between crude oil and five major stock markets and within the various time-scales and frequency bands, which means that depending on differences in risk profiles, heterogeneous expectations and different perception of risk, international investors might react differently in their investment decision over investment horizons [22,23]. Specifically, the advance of the spillover index is that it estimates the dynamic magnitude of return and spillovers over time and sheds light on the direction of spillovers [24].

Our study derives several significant findings. First, we explore the dynamic associations between crude oil price and five major stock markets in Europe, namely, oil-stock relationships are low in the pre-Covid-19 period, but they are considerably increased during the Covid-19 outbreak. The variations in the pattern become more profound after decisive structural breaks occur after the WHO announcement in January 2020. Second, the directional spillovers between crude oil prices and stock markets are different and vary through time before and during the Covid-19 crisis. Third, we provide fresh insight into the difference between interconnection and contagion among assets and estimate their degree and direction at different time horizons. Finally, by comparing and contrasting the multiple influences between the pre-Covid-19 period and during the Covid-19 outbreak, we can offer vital implications for investors in connection with risk management across various regimes.

The rest of the paper is organized as follows. Section 2 introduces the econometric method. Section 3 depicts the data. Section 4 reports the empirical results. Section 5 concludes the paper.

2. Methodologies

2.1. Spillover index approach

Taking into consideration a covariance stationary Vector AutoRegression (VAR) model of order p and N variables, $x_i = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_i$, where $\varepsilon \sim (0, \Sigma)$ is a vector of independent and identically distributed distances. We can turn the VAR into a moving average (MA) representation, that is, $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ where $N \times N$ coefficient matrix A_i is obtained by the recursive substitution, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with $A_0 = I_n$, which is an identity matrix of order n, and $A_i = 0$ for $i < 0$. The MA presentation can be employed to forecast the future with the H-step-ahead.

The H-step-ahead generalized forecast-error variance decomposition can be written as:

$$\phi_{ij}^{g}(H) = \frac{\sigma_{ij} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \sum e_i \right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \sum A_h^{'} e_i \right)} \tag{1}$$

where $\sum$ is the variance matrix of the error vector, σ_{ii} is the standard deviation of the error term for the i[th] equation, and e_i is the selection vector with 1 as the i[th] elements, and 0 otherwise.

According to the properties of generalized VAR, we have $\sum_{j=1}^{N}\phi_{ij}^{g}(H)\neq 1$. Each entry of the variance decomposition matrix is normalized by the row sum as

$$\tilde{\theta}_{ij}^{g}=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{2}$$

where $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)=N$

Total volatility spillover index proposed by Diebold and Yilmaz [1] is defined as

$$S^{g}(H)=\frac{\sum_{i,j=1,j\neq i}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{3}$$

We can measure the directional volatility spillovers received by market i from all other markets j as:

$$S_{i.}^{g}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100 \tag{4}$$

Similarly, we can calculate the directional spillovers transmitted by market i to all other markets j as:

$$S_{i.}^{g}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\times 100 \tag{5}$$

We can also obtain the net volatility spillover for each market by calculating the difference between (5) and (4) as:

$$S_{i}^{g}(H)=S_{.i}^{g}(H)-S_{i.}^{g}(H) \tag{6}$$

The net volatility spillover is simply the difference between the gross volatility shocks transmitted to and those received from all other markets [1].

2.2. Wavelet coherence

A brief note on wavelet coherence is defined as follows:

$$R_n^2(S) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right).S(s^{-1}\left|W_n^Y(s)\right|^2} \tag{7}$$

where S is a smoothing operator. Smoothing is achieved by convolution in time and scale.

$$S(W) = S_{scale}\left(S_{time}\left(W_n(s)\right)\right) \tag{8}$$

where S_{scale} and S_{time} illustrate smoothing on the wavelet scale axis and in time, respectively. Smoothing operator we use in this study is the Morlet wavelet, so the more suitable definition is given by Torrence and Webster [25]:

$$S_{time}(W) = \left(W_n(s) * c_1^{\frac{-t^2}{2s^2}}\right)\Bigg|_s \text{ and } S_{time}(W)_s = \left(W_n(s) * c_2 \Pi\left(0.6s\right)\right)_s\Big|_n \tag{9}$$

where c_1 and c_2 are normalization constants and Π is the rectangle function, the scale decorrelation length for the Morlet wavelet is 0.6

The wavelet coherence coefficient measures the local linear correlation between two stationary time series at each scale and ranges $R_n^2(s) \in [0,1]$.

$W_n^{XY}(s)$ is the cross-wavelet power. It can be seen as the local covariance between the two-time series at each scale. Given time series $x(t)$ and $y(t)$, the cross-wavelet power can be written as

$$W_n^{XY}(s) = W_n^X(s)W_n^{*Y}(s) \tag{10}$$

where $W_n^X(s)$ and $W_n^{*Y}(s)$ are continuous wavelet transforms of two time series $x(t)$ and $y(t)$. The symbol * represents a complex conjugate.

The wavelet coherence phase is defined as

$$\phi_n^{XY}(s) = \tan^{-1}\left(\frac{I\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}{R\left\{S\left(s^{-1}W_n^{XY}(s)\right)\right\}}\right) \tag{11}$$

where I and R are the imaginary and real parts of smooth power spectrum.

3. Data

In this paper, the daily data of crude oil prices (WTI) and five major stock markets in Europe: LSE index (United Kingdom), CAC index (France), the DAX index (Germany), FTSEMID index (Italy) and IBEX index (Spain), is used to capture the rapidity and intensity of the oil-stock connectedness before and after WHO announces Covid-19 outbreak 30 January 2020 (Covid-19).

The data used spans from May 2018 to April 2020. The whole examination period is subdivided into two sub-periods: Pre-Covid-19 period: 4 May 2018 to 30 January 2020, the Covid-19 period: 31 January 2020 to 30 April 2020. The reason for selecting daily data is to estimate more the accurate information content of variations in oil prices and stock markets that doing weekly or monthly data [26,27]. All prices time series are collected from the Bloomberg database. Continuously compounded returns are calculated by taking the difference in the logarithm of two consecutive prices.

Table 1 reports the descriptive statistics of the data. Panel C shows that the London stock market return experience positive average daily returns, while the figure for the rest of the return series is negative over the period shown. Nevertheless, there are changes in the mean of returns before and during the Covid-19 outbreak. The unconditional volatility of the crude oil market, measured by standard deviations, is at least three times the volatility of stock markets, especially during the Covid-19 period. In addition, we can observe that all the selected variables are skewed and far from normally distributed. Jarque-Bera test statistics formally confirm this situation. Figure 1 depicts daily crude oil and stock prices under examination. We see that all the five developed stock markets follow similar movements over the research period, while the oil prices exhibit a downward trend.

Table 1. Descriptive statistics of daily returns.

	Mean	Max	Min	Std. Dev	Skew.	Kurt.	JB	Obs.
Panel A. Pre-Covid-19 outbreak								
WTI	−0.107858	24.53098	−14.98643	4.225058	0.102585	5.839915	147.9567*	438
LSE	0.135835	14.27012	−5.971921	1.524148	1.759149	20.65205	5912.512*	438
DAX	−0.017978	5.243612	−5.150632	1.121234	−0.402574	5.760438	150.8962*	438
CAC	0.021886	2.687831	−3.635481	0.843240	−0.559104	4.735468	77.78586*	438
FTSEMIB	0.012999	3.362118	−3.786893	1.050898	−0.327934	3.816614	20.02065*	438
IBEX	0.002589	2.485485	−2.806895	0.815433	−0.280774	3.644185	13.32814*	438
Panel B. Covid-19 outbreak								
WTI	−0.775447	34.88181	−26.44792	9.867031	0.432021	5.427927	17.43367*	63
LSE	−0.050898	9.890978	−10.16406	3.427994	−0.005279	4.231332	3.980260*	63
DAX	−0.323740	9.214956	−12.01539	3.577975	−0.848682	5.179627	20.03352*	63
CAC	−0.467330	8.056082	−13.09835	3.207518	−1.006618	6.382697	40.67637*	63
FTSEMIB	−0.547905	8.549457	−18.54114	3.558438	−2.299923	13.64382	352.9300*	63
IBEX	−0.648238	6.210298	−15.15118	2.873771	−2.460128	13.01439	326.8046*	63
Panel C. Full sample								
WTI	−0.191806	34.88181	−26.44792	5.265302	0.278230	10.18138	1083.034*	501
LSE	0.112354	14.27012	−10.16406	1.868505	0.742701	13.91330	2532.276*	501
DAX	−0.056427	9.214956	−12.01539	1.642101	−1.452690	16.15877	3790.782*	501
CAC	−0.039632	8.056082	−13.09835	1.386924	−2.217761	25.14910	10651.60*	501
FTSEMIB	−0.057534	8.549457	−18.54114	1.603134	−3.692986	45.24207	38387.99*	501
IBEX	−0.079251	6.210298	−15.15118	1.285251	−4.216625	47.02246	41939.89*	501

Note: * represents the null hypothesis of normality is rejected at the 1% level.

4. Empirical results

4.1. Directional spillover effects

Table 2 reports the total mean spillover index matrices of the pre-Covid-19 and during Covid-19 periods, respectively. We compute the interdependence table based on vector autoregressions and generalized variance decompositions of 10-week-ahead forecast errors. The total static spillover index between WTI and five major stock markets is calculated and decomposed by directional spillover transmitters ‘to other’ and receiver “from other” of mean spillovers. The net return spillover row provides the difference in total directional spillovers, and the total spillover index is approximately equal to the grand off-diagonal column sum (or row sum) regarding the grand column sum including diagonals, expressed in percentage points.

It is clear from the matrix that IBEX has highest return spillover received from other asset classes (26%) followed by CAC (16.8%) and WTI (14.7%) in the pre-Covid-19 period, while LSE is identified as the largest receiver of return spillover to other markets (61.9%) and IBEX becomes the lowest return spillover received from other markets during Covid-19 outbreak. The most contributing market to others is FTSEMIB (25.4%), followed by DAX (19.1) in the pre-Covid-19. By contrast, in the Covid-19 period, the contribution of DAX is highest, around 67.2 %, followed by the crude oil market, about 65.1%. However, CAC is the lowest contributor (7.4%) to other equities over the study period shown. Gross return spillover index reveals an average of 15.1% in the pre-Covid-19 period and 48.6% during the Covid-19 outbreak at the right-end corner of Table 2, which suggests that there is a bidirectional return spillover effect between crude oil prices and five major stock markets, especially during the Covid-19 pandemics. With regard to net return spillover, the FTSEMIB is the strongest net-transmitter of return spillovers, while the IBEX is the largest net-recipient of return spillovers in these markets in the pre-Covid-19 period. In the Covid-19 period, DAX has the highest value (19.4%), followed by WTI (11.7%) and become the strongest net-transmitter of return spillover. At the same time, LSE is the largest net-recipient of return spillovers in comparison with CAC and FTSEMIB.

Figure 2 demonstrates the time-varying return spillover index across equity markets under investigation, using 200-day rolling samples and 10-day-ahead forecast errors and estimating the total time dynamics of return for the selected stock prices and oil market. More precisely, all previous VAR analysis on the returns are developed on the assumption that spillover coefficients are invariant that the coefficients are constant through time. Apparently, the plot is somewhat uneventful, starting with a burst (25%) in 2018, the return spillover trend increases until the beginning of 2019 (28%). After that, it sharply declines in the middle of 2019, which corresponds to the European debt crisis. Most of the time, it fluctuates between 22% and 25% until the WHO announcement about the Covid-19 outbreak 30 January 2020. However, the spike of spillover index is triggered by the Covid-19 outbreak pandemics, suggesting the strong impact of the Covid-19 epidemic on return spillovers across oil-stock markets. Therefore, we conclude that such the Covid-19 outbreak crisis intensifies return spillovers across crude oil and five major stock markets. More importantly, after February 2020, the return spillover was decreasing due to the fall in the oil prices because of low demand in the Covid-19 outbreak pandemics.

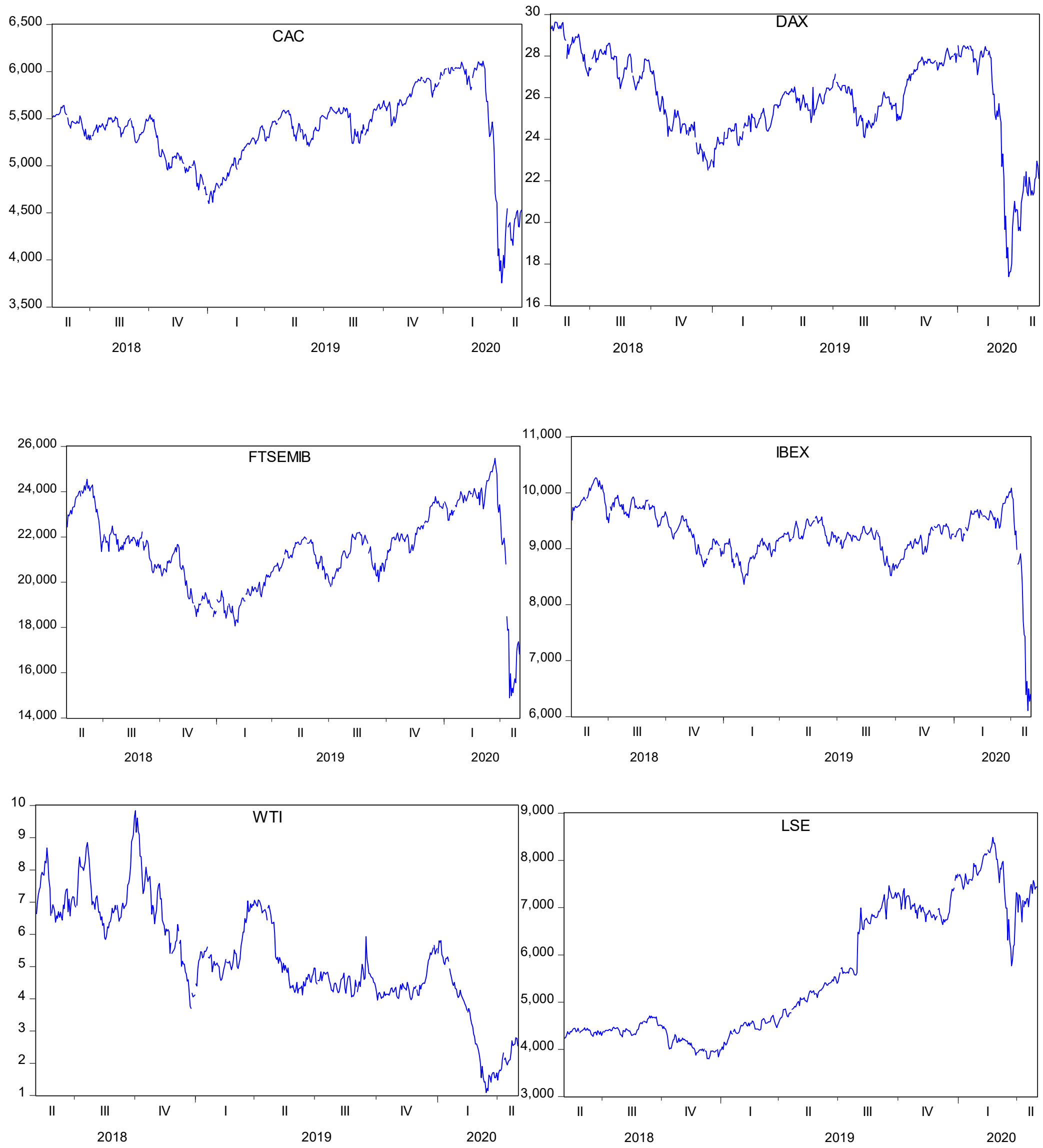


Figure 1. Daily WTI and stock prices.

To further investigate the dynamic behaviour of return spillover, we now take into account the net return spillover, which unveils features of directional return spillovers across crude oil price and five major stock markets. The dynamic net return spillover index is computed by subtracting directional 'to' spillover from directional 'from' spillover. Hence, we consider the different magnitude of return spillover according to positive or negative innovations. For example, positive (negative) values show a source (recipient) of volatility to (from) other equity markets. Figure 3 represents the sign of the net spillovers that allows us to distinguish proportion at which good and bad volatilities from individual assets propagate across markets and lead to positive and negative spillovers that materialize in the volatilities of the assets under examination. Throughout the visual inspection of these figures, we can observe that the net spillover varies over time. IBEX and CAC series are net recipients of risks, while the other assets are a net transmitter of shocks in the pre-Covid-19 period. In contrast to the results for the pre-Covid-19 period, LSE, CAC and IBEX are the recipients of return spillovers, reaching a maximum level of about 23% during the Covid-19 outbreak.

Specifically, WTI, DAX and FTSEMIB continue net transmitters of return spillovers during the Covid-19 outbreak. It tallies with the results in Table 2. It seems that the net return spillovers are bidirectional across crude oil price and five major stock markets in Europe because the given graphs for each series perform a magnitude of negative and positive values through time.

Table 2. Total directional return spillovers.

	WTI	LSE	DAX	CAC	FTSEMIB	IBEX	From others
Panel A: Pre-Covid-19 period							
WTI	85.31	2.29	9.21	1.53	0.73	0.93	14.7
LSE	2.39	89.42	3.87	2.52	1.30	0.50	10.6
DAX	9.35	0.98	88.03	0.12	1.00	0.52	12.0
CAC	2.26	7.69	3.80	83.21	2.07	0.96	16.8
FTSEMIB	0.91	1.75	1.15	0.73	89.34	6.12	10.7
IBEX	0.50	1.67	1.03	2.54	20.25	74.02	26.0
Contribution to others	15.4	14.4	19.1	7.4	25.4	9.0	90.7
Contribution including own	100.7	103.8	107.1	90.6	114.7	83.0	15.1%
Net spillovers	0.7	3.8	7.1	-9.4	14.7	−17	
Panel B: Covid-19 period							
WTI	46.57	8.19	21.30	11.52	7.51	4.91	53.4
LSE	13.71	38.12	22.16	6.47	12.90	6.63	61.9
DAX	23.91	4.90	52.21	6.28	7.62	5.07	47.8
CAC	10.35	7.00	12.60	59.03	3.75	7.27	41.0
FTSEMIB	8.42	13.74	9.52	3.56	48.30	16.45	51.7
IBEX	8.75	4.10	1.66	6.32	15.00	64.17	35.8
Contribution to others	65.1	37.9	67.2	34.2	46.8	40.3	291.6
Contribution including own	111.7	76.1	119.4	93.2	95.1	104.5	48.6%
Net spillovers	11.7	−23.9	19.4	−6.8	−4.9	4.5	

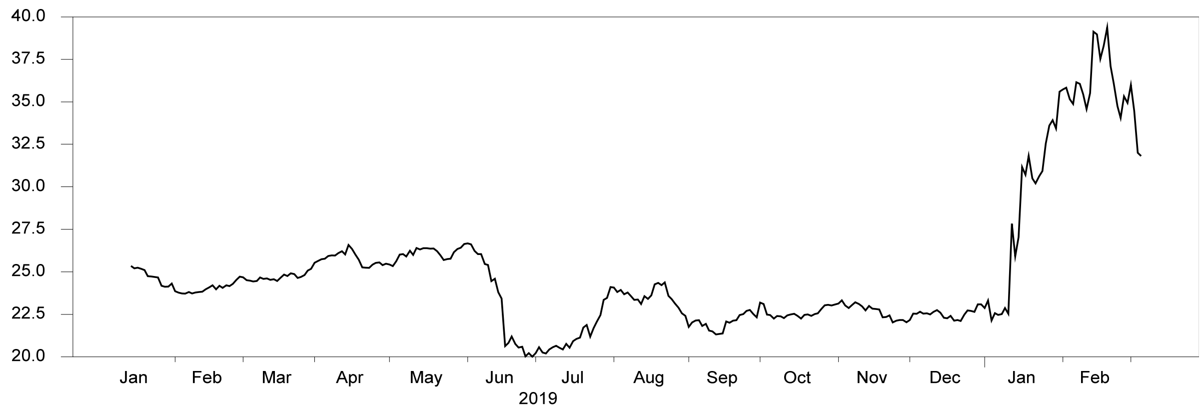


Figure 2. Dynamic return spillover indices across WTI and five major stock markets.

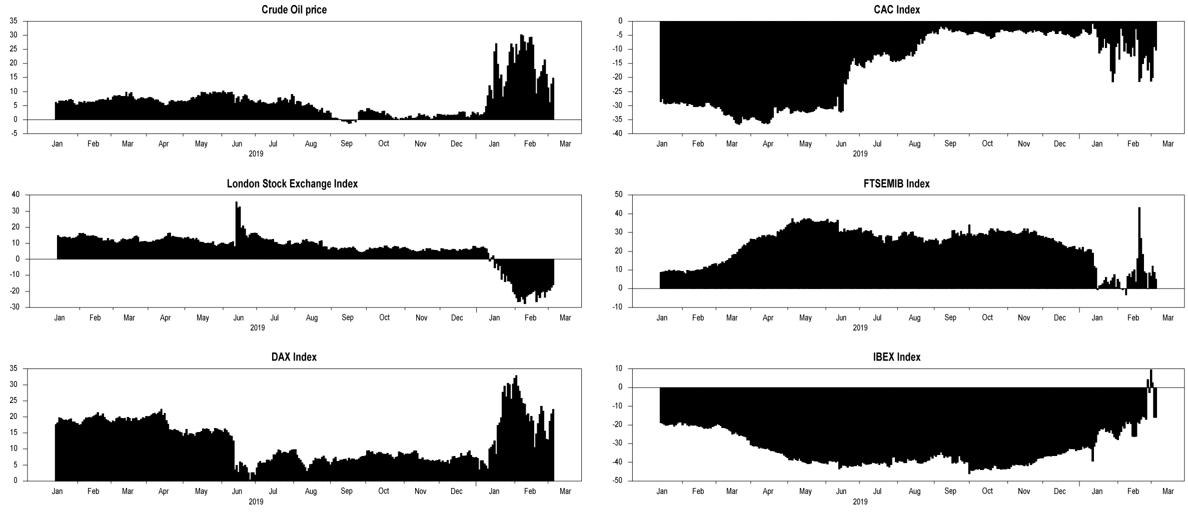


Figure 3. Net return spillovers, six asset classes.

4.2. Wavelet coherence analysis

In this study, the wavelet coherence method is employed to analyze the associations between crude oil prices and five major stock markets under consideration because wavelet frameworks are powerful specifications that allow us to capture the co-movements and lead-lag correlation structures between the selected variables quickly. More precisely, wavelet coherence can explore how much two-time series co-vary and estimate the comparative phase of different time sequences in present time-frequency spaces [28,29]. Figure 4 illustrates the wavelet coherence plots for each couple of variables corresponding to pre-and during Covid-19 periods.

The horizon axis denotes the time components and frequency components are shown on the vertical axis. The horizontal axis covers the pre-Covid-19 period from May 2018 to January 2020, corresponding to 50 and 400, and the Covid-19 period between February 2020 to April 2020, corresponding to 10 and 60. By contrast, the frequency bands on the vertical axis are based on daily units spanning from 4-to 128-day scales for the pre-Covid-19 period and from 4-to 16-day scales for the Covid-19 period. The colour code measures the degree of interdependence between the pair of series. Areas with significant interrelatedness are represented by warmer colours (yellow), while cooler colours (blue) regions illustrate the two series are less dependent. Cool areas beyond the significant regions indicate frequencies and time with no relationship in the variables. Both zones over time and scales where the pairs of relevant indices co-move together significantly can be determined or otherwise, corresponding to the local correlation spanning from 0 to 1.

Wavelet coherence sheds light on the interconnectedness in index pairs, while the dynamic linkages of series are identified by observing lead-lag structure through various investment horizons. An arrow in the wavelet coherence plots describes the direction of intercorrelation and cause-effect interactions. A phase difference of zero explains that the two variables move together on a particular scale. Arrows point to the right, and the left suggests that the two series are in-phase and out-phase, respectively. An in-phase wavelet phase difference shows that the return series move in the same direction (positive relationship), while they move in the opposite direction when two variables are in out of phase (negative correlation).

We detect the persistence of small regions of strong interconnection at the beginning, the mid and the end of the sample period. Overall, the plots pair of wavelet coherence indicates that crude oil and five major stock markets experience significant relationships over time and frequency domain. In the pre-Covid-19 period, the associations between WTI and DAX, LSE exhibit high coherence, which exits at the medium and long run; nevertheless, the highest level of associations was recorded at scales ranging from 64-to128-day scales, and the arrows are mostly pointed to the left where crude oil prices are leading. On the other hand, co-movements between WTI and CAC, IBEX, FTSEMIB reveal a weak relationship, there are some regions with significant wavelet coherence in 64-and-128-day scales corresponding to the periods December 2019 and January 2020 when Chinese authorities announced the novel coronavirus incurred in Wuhan.

The contagion during the Covid-19 outbreak, six markets under research seem to react to bad news coming from Wuhan city, Chinese authorities announced the novel virus that causes the fatal human on 31 December 2019. Furthermore, another high coherence regions are determined on mid-February corresponding to several Covid-19 pandemics bad news; namely, the first patient death in the US was reported on 28 February as well as the number of international rose to 87.000 with the high-level warning announced by the US authorities. More specifically, the WHO declared that cases by country across Europe had doubled in the middle of March 2020, which means that numerous infected cases were identified in European countries. We also find the last significant coherence at the end of the sample period. This situation might be due to the combined impact of the dramatic drop in oil prices and Covid-19 fears.

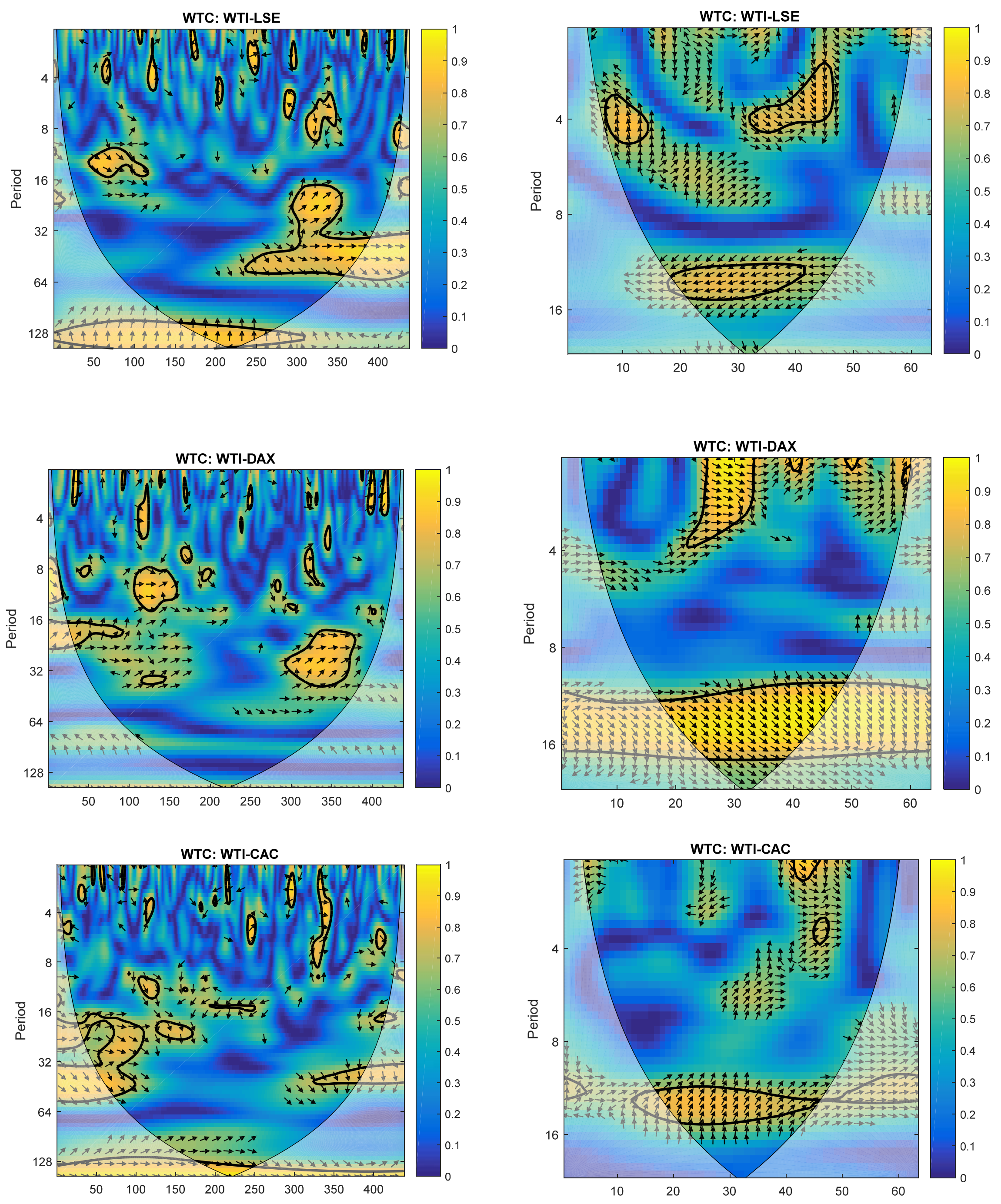
Looking as the case of WTI-LSE, WTI-DAX, WTI-CAC, WTI-IBEX, wavelet coherence plot also demonstrates the persistence of strong coherence regions at the onset of the novel coronavirus and by the end of April 2020 corresponding to a constant rise of the infected counts in Europe and the free fall of oil prices. The arrows are predominantly pointed up and to the right showing that crude oil prices are leading, implying that oil prices are positively correlated with the five major stock markets. These findings are apparently impacted by several episodes of the Covid-19 outbreak. In the significant islands, we note the phase-related information, as indicated by arrows.

We find some net information flows change their directions during the Covid-19 outbreak, LSE, DAX, CAC, and IBEX especially, creating the role of WTI more balanced during the Covid-19 outbreak pandemics. This scenario suggests that the importance of fluctuations in crude oil prices and its fundamental role in the stock market. Several past studies also examined the co-movements between crude oil prices and stock markets before and after previous financial turmoil. For example,

Our results provide several significant implications. The Covid-19 pandemic is causing the widespread disruption, in particular, the unprecedented response of the stock market as crude oil and stock markets are found to be strongly correlated under the Covid-19 outbreak. The Covid-19 crisis can further impact oil prices because of the travel limitations across the world during the pandemic, whereas the oil volatility shocks would be sensed due to a transitory risk depressed through the OPEC+ deals. This phenomenon is crucial for oil companies as well as companies in the transportation and hospitality industries. More importantly, investors need to employ risk management strategies to protect against considerable fluctuations in the stock sensitive to oil prices. From an asset management perspective, the findings of this study uncover the significant short- term influence of Covid-19 on the five major stock markets in Europe and crude oil markets. We would believe the contingency of the further government interventions, once the European financial markets will be able to recover in the long run. Furthermore, asset managers and individual investors should know how to grasp market variation and systematic risk in connection with Covid-19 outbreak.

Pre-Covid-19 period

Covid-19 outbreak



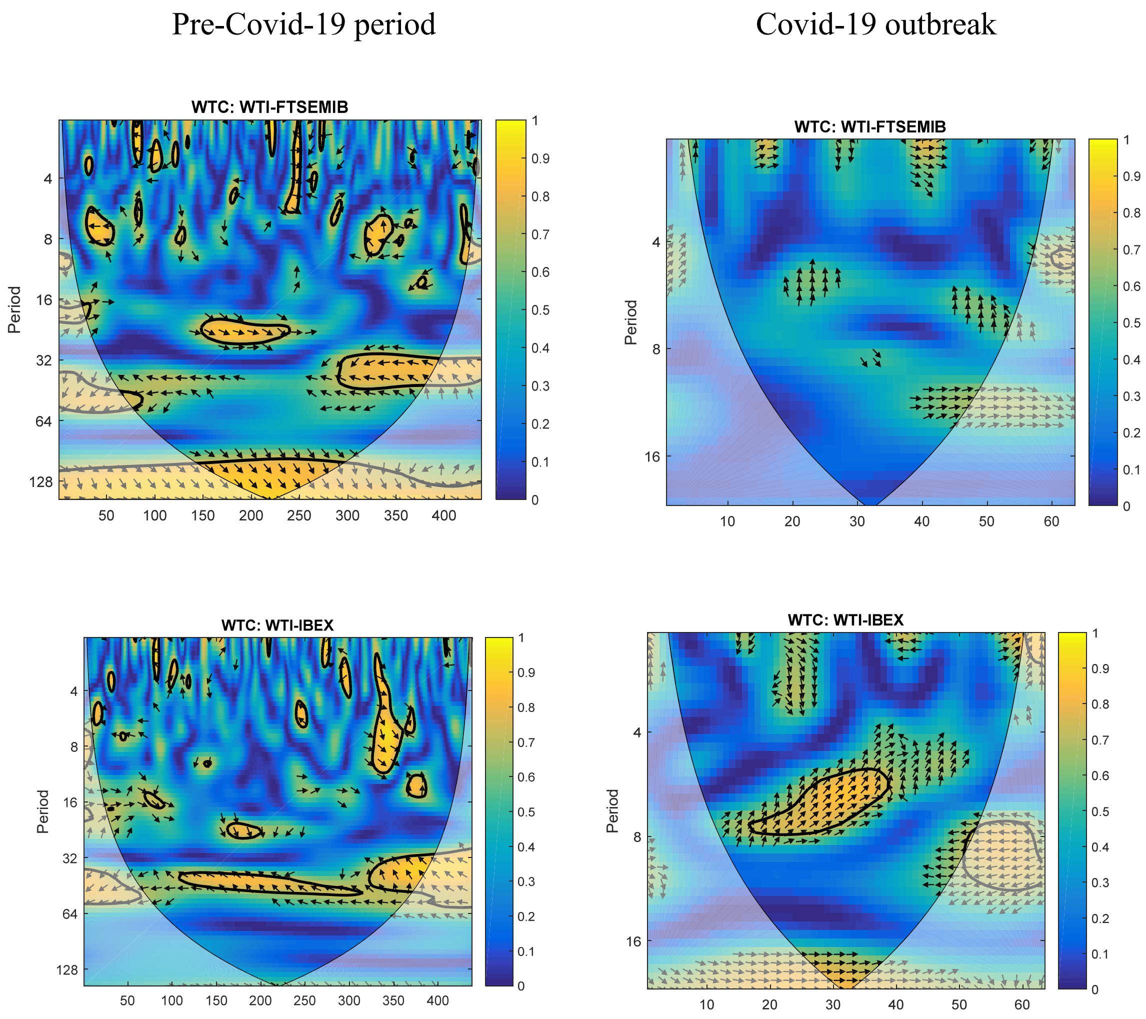


Figure 4. Wavelet Coherence plots, pairwise estimates.

5. Conclusions

The novel coronavirus (Covid-19) has been spread rapidly throughout the world already. Nevertheless, how deep and long the crisis may depend on the practical solutions taken to stop the spread of the Covid-19 outbreak, the effects of government policies would play a prominent role in alleviating the present turbulence. The economic and social costs of the Covid-19 pandemics involve in society, policymakers, market participants, and investors. To examine the impacts of return spillovers and dynamic time-frequency linkages between crude oil prices and five primary stock markets in Europe (the United Kingdom, Spain, Italy, German, and France), we employ both the spillover index of Diebold and Yilmaz [1] and the wavelet coherence. The sampling period is from 2018 to 2020. The first period covers the pre-Covid-19 period from 4 May 2018 to 30 January 2020. The second period is the Covid-19 period from 31 January 2020 to 30 April 2020, which was characterized by widespread Covid-19. More importantly, we assess whether the time-varying dynamic return spillover index exhibited the intensity and direction of transmission during the Covid-19 outbreak.

This study is one of the pioneer papers that takes into account the influences of the Covid-19 pandemic on the fluctuation of crude oil prices and five major stock markets in Europe. Therefore, the findings of this article provide some significant pieces of evidence.

The results highlight that IBEX and CAC series are net recipients of risks, while the other assets are a net transmitter of shocks in the pre-Covid-19 period. In contrast to the results for the pre-Covid-19 period, LSE, CAC, and IBEX are the net recipients of return spillovers, reaching a maximum level of about 23% during the Covid-19 outbreak. Specifically, WTI, DAX, and FTSEMIB continue net transmitters of return spillovers during the Covid-19 outbreak. Wavelet coherence plot also demonstrates the persistence of strong coherence regions in the case of WTI-LSE, WTI-DAX, WTI-CAC, WTI-IBEX at the onset of the novel coronavirus and by the end of April 2020 corresponding to a constant rise of the infected counts in Europe and the free fall of oil prices.

Overall, the current results shed light on that in comparison with the pre-Covid-19 period, and the return transmission is more apparent during the Covid-19 crisis. More importantly, there exist significant dependent patterns about the information spillovers, and time-frequency linkages between crude oil and five major stock markets might provide urgent prominent implications for portfolio managers, investors, and government agencies.

Our findings have significant implications for policymakers and investors. The adverse impact of a large number of confirmed Covid-19 cases could show its dark side on financial markets and energy. Therefore, policymakers should take into consideration the variations in global oil prices associated with the dynamics of the stock markets in European countries. International investors are interested in understanding how the oil market shocks remarkably influence stock prices and whether this impact has similar strength in the short or medium compared to long investment horizons. More importantly, investors can work according to various time horizons since the spillover mechanism of oil shocks to stock markets could carry on a period, so they should perceive that oil-stock nexus would differ from different time horizons and under different market situations and pay more attention to portfolio design and risk management (Hung, 2020c). Further, they can apply this study to construct the optimal oil-stock portfolios and estimate a more precise forecast of price spillovers patterns in building their hedging strategies.

There are some potential limitations in the design of the current examination in connection with the sample. We acknowledge that our results should be taken with caution, given the small size of the sample and statistical inference from the used methods. However, they prepare for many research questions about the short and long-run impacts of the Covid-19 outbreak on the output, financial stability, monetary policy, and other macroeconomic indicators employing a large sample.

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Conflict of interest

The author declares no conflict of interest in this paper.

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