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Do Oil Price Shocks and COVID-19 Lead to Policy Uncertainty?

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ABSTRACT

This study examines the asymmetric effects of the structural oil price shocks and COVID-19 pandemic on four uncertainty indexes. The author used the SVAR approach for the period 31-Dec-2019 to 28-Jun-2020. The results indicate that the effects are asymmetric of oil price shocks. The author also finds that COVID-19 shocks lead to positive responses to the economic policy uncertainty index. In addition, oil prices (their shocks) have a negative impact on the four indicators of uncertainty. Consequently, governments should actively take effective measures to prevent crude oil prices from shocking and maintain stable economic policies.

1. Introduction

Since the emergence of the coronavirus (COVID-19) in China and its subsequent expansion to other continents, the uncertainty in the markets has increased markedly. The uncertainty index on US economic policy, compiled by the St. Louis Federal Reserve, shows its highest values since the financial crisis of 2008 when the United States was going through a recession.

Uncertainty is an elusive concept that receives various interpretations. The economist Knight [1] was one of the first to formally distinguish between the concepts of risk and uncertainty: while risk describes a known probability distribution for a set of events, uncertainty characterizes the inability to assess the probability of occurrence of certain cases.

Before the COVID-19 epidemic, the global economy was struggling to fully recover, following the effects it still felt, among other things, increased trade protectionism, trade disputes between major trading partners, lower commodity prices and economic uncertainty. According to the

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IMF's world economic outlook① for April 2020, economic activity slowed from 3.6% in 2018 to 2.9% in 2019. With the COVID-19 pandemic, the world economy is expected to regress sharply by 3% in 2020, a situation that is much worse than that of the 2008-2009 financial crisis. This downward revision mainly reflects the uncertainty of trade policy, geopolitical tensions, and idiosyncratic shocks in the main emerging market economies, given that these uncertainties continue to weigh on world economic activity, especially in manufacturing and commerce. The development of oil prices indicates that the price of oil collapsed into a negative position for the first time in history on April 20, 2020, trading under $ 0, due to increased supply and lower demand for crude oil caused by a coronavirus. In addition, oil price fluctuations have interesting effects on economic activity [2-11].

In this context, the economic literature has resorted to various ways of quantifying uncertainty, although in all of them the concepts of risk and uncertainty are mixed. Greater volatility in the prices of financial assets (stocks, bonds, or exchange rates) or in economic variables, both macro (GDP) and micro (sales of companies), is usually associated with greater difficulty in making forecasts and, for, Therefore, to greater uncertainty. Another measure - relatively simple - is the frequency with which words related to political or economic uncertainty appear in newspaper articles [12], in such a way that an increase in this index would reflect growth in uncertainty. As Bloom [13] emphasizes, the effects of increases in uncertainties such as those observed after the Cuban missile crisis, oil shocks in the 1970s, or terrorist attacks on September 11, 2001 increase the fluctuations of shocks affecting companies (i.e. increases in uncertainty) generate sharp falls in investment, employment, output, and productivity in the economy. Although they are followed by a rebound when volatility returns to its initial level. These falls in output are more pronounced than for other recessions, but also less persistent - depending on the duration of the underlying cause of increased uncertainty.

The COVID-19 pandemic shock had a greater impact on uncertainty than the impact of the 2008-2009 financial crisis and was more similar in magnitude with increased uncertainty during the Great Depression of 1929-1933 [14]. Although Bloom [15] complement this work and find that increases in uncertainty play an important role in economic cycles, both as an initial impulse or as an amplification mechanism for these cycles. The International Monetary Fund (IMF, 2020)② notes that, following the uncertainties related to the duration and intensity of the health shock of the COVID-19, the macroeconomic fallout of the latter, its disturbances on the financial markets and on the markets of commodities, also remain uncertain which can deteriorate. Indeed, as Albulescu [16,17] estimates, the COVID-19 pandemic is creating more fear and uncertainty, affecting the global economy and increasing volatility in the financial markets. According to Baker [14], analyzing the macroeconomic impact of COVID-19, 50% of the future contraction in US GDP would be explained by the effects of this pandemic, which pass through the uncertainties created by the said pandemic, captured by the following three indicators: stock market volatility, economic uncertainty linked to information produced in newspapers and subjective uncertainty in business expectation surveys [18].

However, studying the effects of the COVID-19 epidemic and oil price shocks on economic uncertainty is extremely important, given the effects of economic uncertainty on economic activity [14,19-21] and others. Specifically, researching the sources of economic uncertainty is of great importance as economic uncertainty affects business cycles through its impact on economic activity as explained by some literature such as Bloom, Caldara and Fernández [13,22-24], either through fixed investment decisions or family consumption decisions. That is to say, the greater the economic uncertainty, the lower the consumption of households and the greater the delay in capital investment.

However, none of this literature focuses on the latter situation resulting from the COVID-19 pandemic crisis. Therefore, we fill this gap and test the asymmetric effects of crude oil prices and the number of infected cases of COVID-19 pandemic cases globally on indicators of uncertainty. To our knowledge, this is the first paper to address the impact of the COVID-19 crisis on four indicators of uncertainty. Our study is distinguished by use of modern daily data.

The rest of the paper is organized as follows: The second section identifies the methodology. The third section concerns discussing the results. The fourth section presents the conclusion and recommendations.

2. Data and Methodology

Data

The data used in our study include the daily observations from 31-Dec-2019, to 28-Jun-2020, of four indicators of uncertainty: US economic policy uncertainty index (EPU), equity market-related economic uncertainty index (EMU), equity market volatility (EMV) and the Chicago stock exchange volatility index (VIX). In addition to two other indicators, West Texas Intermediate crude oil prices (WTI) a proxy for the oil price. Finally, an indicator, the

① IMF: https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020

② IMF: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 number of infected cases of COVID-19 pandemic cases globally as a proxy of COVID-19.

To measure uncertainty, we use daily indices constructed by Baker and his colleagues as described in Baker [12].

Specifically, first, we use the economic policy uncertainty index (EPU) which is based on US newspapers suggested by Baker [12]. Second, we use the equity market uncertainty index (EMU), which is based on an automated text-search process from access world news's news bank service news articles that contain terms related to uncertainty, economy, stock price and equity market. Third, we use the equity market volatility (infectious disease tracker). Fourth, the CBOE volatility index (VIX) is an indicator that measures volatility in the US stock market over the next 30 days. The VIX is seen as a sign of market sentiment - or pessimism - about expected fluctuations. Also known as the "Fear Gauge" or "Fear Index". The VIX is based on S&P 500 index and is the best-known volatility index in the markets. Specifically, an index projects the market's outlook for future volatility. All relevant time series data were collected as in Table 1.

Table 1. Definition of the variables.

Variable		Source
US Economic Policy Uncertainty	EPU	FRED ③
Equity market-related economic uncertainty.	EMU	FRED ④
Equity market volatility: infectious disease tracker.	EMV	FRED ⑤
CBOE volatility index (VIX)	VIX	Chicago Options Delayed Price ⑥. Currency/USD
Current West Texas Intermediate crude oil prices	WTI	FRED ⑦
Coronavirus Disease 2019	COVID-19	Our world in data database ⑧.

The partial impetus for choosing this period which starting from December 31, 2019, is the WHO ⑨ announcement regarding the outbreak of Coronavirus (COVID-19) disease that was first reported in Wuhan, China on December 31, 2019. In the series taken, there was some data lost due to holidays and other reasons; these missing values were filled in simply by predicting the use of linear interpolation. Moreover, all variables are expressed in the natural logarithm series.

Figure 1 shows that the economic policy uncertainty increased sharply as oil price volatility increased. However, when a shock occurs in oil prices (the oil price drops), the US economic policy uncertainty increases. We can observe the free fall of world oil prices, together with the dramatic increase in the number of infected cases by the COVID-19 pandemic in the world, which has greatly increased economic uncertainty over economic policy. These concerns are the driving force behind our study. It is the first endeavor to analyze the interaction and correlation between COVID-19, oil price, and uncertainty within a time-frequency approach. To achieve this goal, we resort to structural autoregression (SVAR) methods.

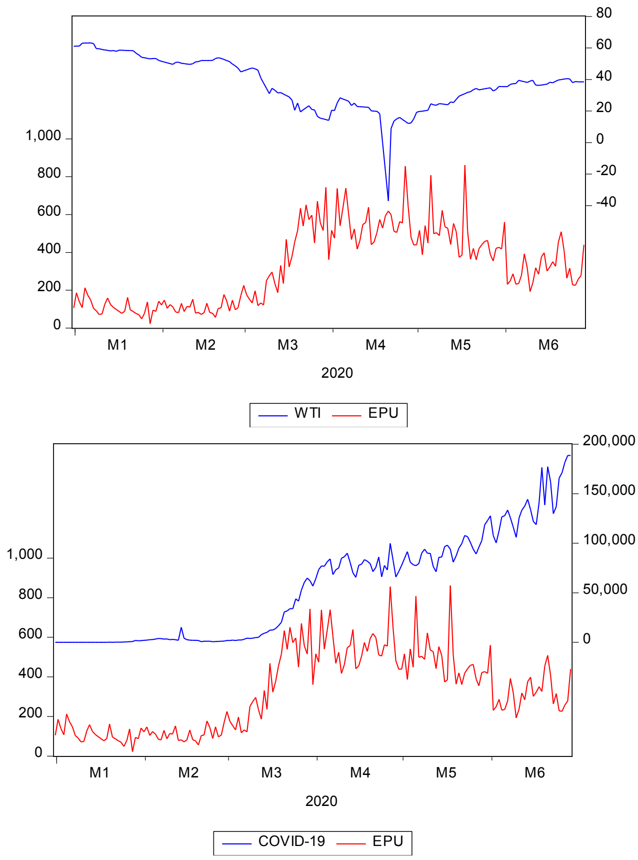

Figure 1. Trends in oil price (WTI), and COVID-19 and indices of US economic policy uncertainty (EPU).

Methodology of the structural VAR of Kilian and Park

Prior to the examination of the time-varying responses of the uncertainty indicators to COVID-19 shock and oil price shocks, we employ a structural vector autore-

③ FRED, Federal Reserve Bank of St. Louis database https://fred.stlouisfed.org/series/USEPUINDXD

④ https://fred.stlouisfed.org/series/WLEMUINDXD

⑤ https://fred.stlouisfed.org/series/INFECTDISEMVTRACKD

⑥ Formed by the Chicago Board Options Exchange (CBOE): https://finance.yahoo.com

⑦ https://fred.stlouisfed.org/series/DCOILWTICO

⑧ https://ourworldindata.org/grapher/daily-cases-covid-19?tab=table&time=..

⑨ https://www.who.int/

gressive (SVAR) model in order to explore the impact of COVID-19 shock and oil price shocks (oil price shock, positive and negative oil price shocks) on the respective four uncertainty indices, based on the full sample. The generic name of uncertainty series is UNCERT.

The structural representation of the VAR model of order p in a five variable setting is as Equation (1),

$$A_0 y_t = c_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \quad (1)$$

where, A_0 represents the [5×5] matrix that summarizes the contemporaneous relationship between the variables of the model, c_0 is a [5×1] vector of constants, A_i are [5×5] autoregressive coefficient matrices and ε_t is a [5×1] vector of error terms "structural shocks". Finally, y_t is a [5 × 1] vector of 5 endogenous variables and specifically, $y_t=(OILP_t,\ OILPP_t,\ OILPN_t,\ UNCERT_t,\ COVIDA19)$, where OILP is Crude oil prices, OILPP, OILPN are a shock of positive and negative oil prices, respectively, $UNCERT_t$ refers each time at one of the four uncertainty indicators that are considered in this study and COVID-19 expresses the number of people infected daily in the world due to the COVID-19.

The model attributes fluctuations in the price of oil to positive oil price shocks (OILPP) and positive oil price shocks (OILPN) measured by Mork [26].

To determine two auxiliary variables by separating the positive and negative changes from each other, The daily change in $lnoilp_t$ during the period from (t-1) to day (t), as in Equations (2) and (3):

$$\Delta lnoilp_t^{+} = \max(0, \Delta lnoilp_t) \quad (2)$$

$$\Delta lnoilp_t^{-} = \min(0, \Delta lnoilp_t) \quad (3)$$

$\Delta lnoilp_t$ represents the logarithm of crude oil price in day t.

In this context, we need to impose appropriate constraints on the short term to obtain structural shocks as in Equation (4).

$$\begin{bmatrix} e_t^{\Delta OILP} \\ e_t^{OILPP} \\ e_t^{OILPN} \\ e_t^{\text{UNCERT}} \\ e_t^{\text{COVID\_19}} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\Delta OILP} \\ \varepsilon_t^{\text{OILPP}} \\ \varepsilon_t^{\text{OILPN}} \\ \varepsilon_t^{\text{UNCERT}} \\ \varepsilon_t^{\text{COVID\_19}} \end{bmatrix} \quad (4)$$

in which $\varepsilon_t^{\Delta OILP}$ reflects the oil price shocks, $\varepsilon_t^{\Delta OILPP}$ captures the positive oil prices shocks, ε_t^{OILPN} denotes the negative oil price shock, ε_t^{UNCERT} measures the economic policy uncertainty shocks, and $\varepsilon_t^{\text{COVID\_19}}$ is the number of infected cases of COVID-19 pandemic cases globally shocks.

Although we have five indicators of uncertainty, we use five separate SVAR models. However, we should highlight that the short-term restrictions which are necessary in the context of SVAR models are based on Kilian & Park [25].

3. Empirical Findings

As is customary when using time series, we will start with the stationarity test of time series for the variables included in the analysis using by Dickey & Fuller [27], Phillips & Perron [28] and Kwiatkowski et al. [29].

In this regard, after calculating the number of lags based on the smallest value that the coefficient Akcaike takes, the results of stationarity tests showed the non-stationarity of these chains at all levels of variables used at the 5% significance level, which led us to conduct a test at the first differences. The results of this test are as shown in Table 2. By comparing the statistic t values with the criti-

Table 2. Unit root tests.

		Unit Root Test (ADF)		***Unit Root Test (PP)***		***Unit Root Test (KPSS)***	
		$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
lnWTI	C	–1.965	–8.208[a]	–2.998[b]	–16.093[a]	0.626[b]	0.168
	C&T	–1.813	–8.232[a]	–3.175[a]	–17.646[a]	0.291[a]	0.112
lnEPU	C	–1.443	–4.625[a]	–3.213[b]	–28.726[a]	1.136[a]	0.112
	C&T	–0.942	–4.737[a]	–3.934[b]	–28.816[a]	0.310[a]	0.092
lnEMU	C	–1.920	–6.265[a]	–6.248[a]	–31.952[a]	0.589[b]	0.058
	C&T	–1.641	–6.314[a]	–6.900[a]	–31.746[a]	0.298[a]	0.054
lnEMV	C	–2.261	–4.011[a]	–2.833[a]	–32.260[a]	1.012[a]	0.206
	C&T	–1.896	–4.191[a]	–3.916[b]	–35.727[a]	0.356[a]	0.155[b]
lnVIX	C	–1.393	–14.119[a]	–1.448	–14.123[a]	0.721[b]	0.166
	C&T	–1.297	–14.112[a]	–1.390	–14.112[a]	0.331[a]	0.115
lnCOVID_19	C	–4.587[a]	–3.387[b]	–1.465	–21.783[a]	1.357[a]	0.106
	C&T	–4.354[a]	–4.217[a]	–1.712	–22.665[a]	0.288[a]	0.045

Note: The optimum lag is chosen based on Akaike information criterion (AIC). [a], [b] and [c] denotes the rejection of the null hypothesis at the 1%, 5% and 10% level of significance, respectively. The numbers in parentheses ( ) denote the number of lags. C and T denote intercept and trend, respectively.

cal values, it is clear that the $I(1)$ for each of the variables are stationarity time series, in that the absolute values for t-statistic exceed that critical for all levels of statistical significance for the ADF and PP tests, and vice versa for the KPSS test. Although all the variables involved are stable, we now turn to co-integration tests with Johansen [30] and Johansen & Juselius [31] amongst the concerned time series as in Table 3.

Table 3 shows that λ_{trace} is smaller than the critical values at the 5% level of significance. Therefore, we accept the null hypothesis (H_0), the existence of a relationship of synchronous integration, where the number of synchronous integration vectors is $r=2$ at the level of significance 5%. This indicates the presence of long-term equilibrium relationships between variables, that is, they do not move away from each other in the long term so that they exhibit similar behavior. We now turn to determine the number of slowdowns or lags in the three models (VAR for three variables), as the results of this test came as shown in Table 3. Through the tests of the stationarity of the variance, it is clear that the estimated model fulfills the conditions of stationarity, as all transactions are smaller than one, all the roots fall within the unit circle, which means that the model does not have a problem in the association of errors or lack of contrast stationarity.

3.1 Dynamic Structural Impulse-Response Functions

In this step, we present the results of the impulse response functions based on the SVAR for the four systems of each uncertainty series to one standard deviation structural shocks, as shown in Figure 2. Considering the US economic policy uncertainty index (Model 1), the equity market-related economic uncertainty index (Model 2), the equity market volatility: infectious disease tracker (Model 3) and the volatility index (VIX) (Model 4).

In the empirical analysis, our study concentrates on four mutually orthogonal shocks: the oil price shock, shock of the increase and decrease in oil prices and the COVID-19 shock.

Table 3. Johansen Co-integration Results

Hypothesis	Eigenvalue	Trace Statistic	Critical Value (5%)	Max-Eigen Statistic	Critical Value (5%)
Model (1)					
None *	0.237	108.959***	69.819	47.625***	33.877
At most 1 *	0.191	61.334***	47.856	37.371***	27.584
At most 2	0.087	23.963	29.797	15.925	21.132
At most 3	0.033	8.038	15.495	5.995	14.265
At most 4	0.012	2.043	3.841	2.043	3.841
Model (2)					
None *	0.266	119.170***	69.819	54.409***	33.877
At most 1 *	0.199	64.761***	47.856	38.987***	27.584
At most 2	0.092	25.774	29.797	16.941	21.132
At most 3	0.031	8.833	15.495	5.602	14.265
At most 3	0.018	3.231	3.841	3.231	3.841
Model (3)					
None *	0.260	108.439***	69.819	52.958***	33.877
At most 1 *	0.188	55.481***	47.856	36.685***	27.584
At most 2	0.062	18.796	29.797	11.183	21.132
At most 3	0.024	7.614	15.495	4.320	14.265
At most 4	0.019	3.294	3.841	3.294	3.841
Model (4)					
None *	0.284	122.113***	69.819	58.898***	33.877
At most 1 *	0.208	63.215***	47.856	40.998***	27.584
At most 2	0.066	22.217	29.797	11.931	21.132
At most 3	0.037	10.285	15.495	6.603	14.265
At most 4	0.021	3.682	3.841	3.682	3.841

Notes: model (1) at Lag=4, model (2) at Lag=4, model (3) at Lag=4. Trace test indicates two co-integrating eqn(s) at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level. **MacKinnon,Haug,Michelis[32] p-values. *** indicates a significant level at 1%.

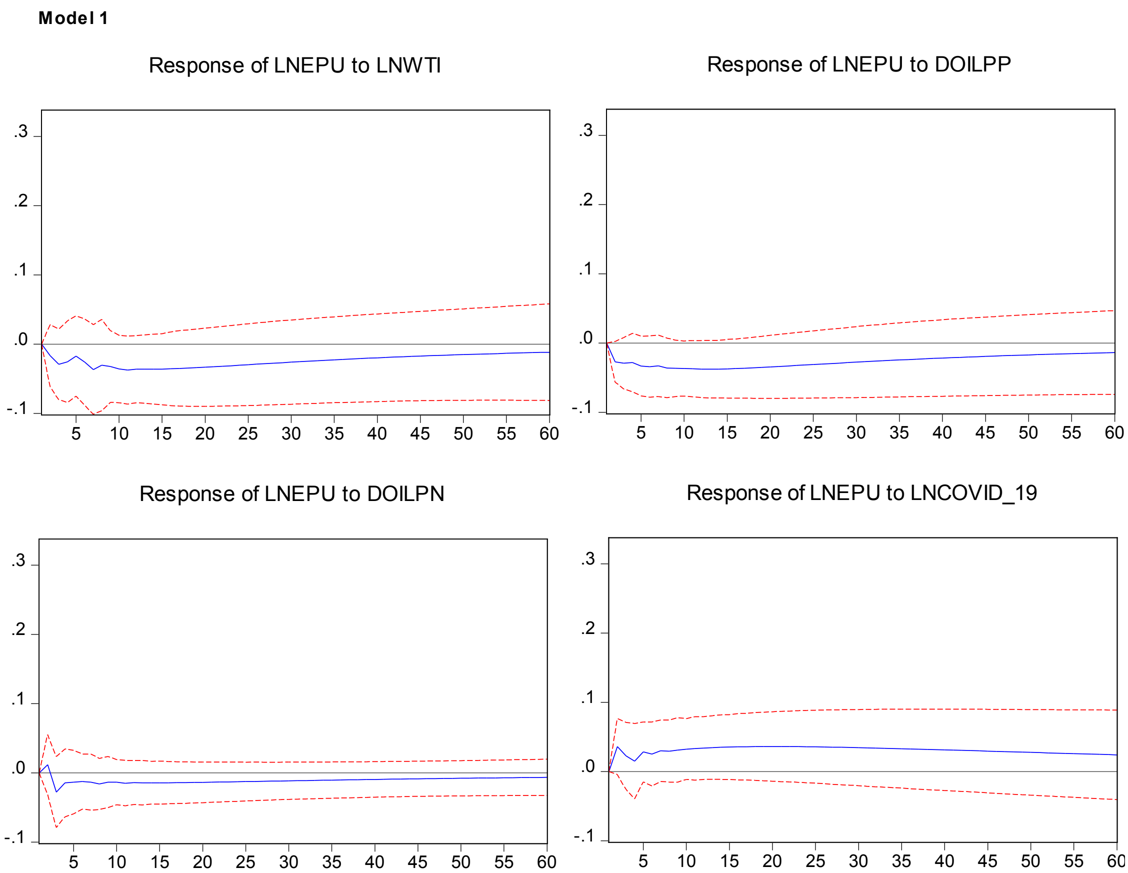

Figure 2. Responses of US economic policy uncertainty components to one-standard deviation structural shock.

Focusing on the first model of Figure 2, US economic policy uncertainty shock response to oil price shock, we find the negative responses from the index of US economic policy uncertainty have the asymmetrical effects from oil shocks (oil prices and its positive and negative shock). The impacts of oil price shock are statistically significant. According to Kilian [33], the main reason behind the negative relationship between the oil price and the uncertainty in economic policy is an increase in aggregate demand, rather than supply shocks. While we find that COVID-19 shocks lead to positive responses showing a one standard deviation shock of the economic policy uncertainty index, reaching 3.6% within 20 days following the shock occurred.

The impact of the unexpectedly positive oil price shock leads to a decrease in US economic policy uncertainty, which is more evident. The fact that economic uncertainty responds negatively to positive changes in oil prices is not self-evident. The bizarre advantage of these results may be hiding by the overall measure of oil price shocks. In other words, we emphasize that the classification of oil price shocks can provide a clearer picture of impulse response functions. It should be noted here that the response to the economic policy uncertainty of the positive oil price shock and the negative oil shock is asymmetrical in the absolute size of the response to the shock. Instead of a positive price shock of the same magnitude, a negative price shock has a relatively lesser effect on economic policy uncertainty than a positive price shock; on the other hand, there is not much difference in the continuation of the effect between the two.

We also note from Figure 3 of the model (2) that a negative effect within 25 days after any of the three shocks occurred (oil price shock and positive and negative oil price shock) of one standard deviation shock of the equity market related economic uncertainty. Oil price shocks seem to have symmetrical effects on the equity market related economic uncertainty. In addition, the negative responses to the equity market related economic uncertainty on oil price shocks innovations appear to be immediate and disappear quickly within a few months. This indicates that the relationship between oil prices and the equity market related economic uncertainty does not lag long. In addition, the decreasing positive impact of the COVID-19 shock on the economic uncertainty related to the stock market.

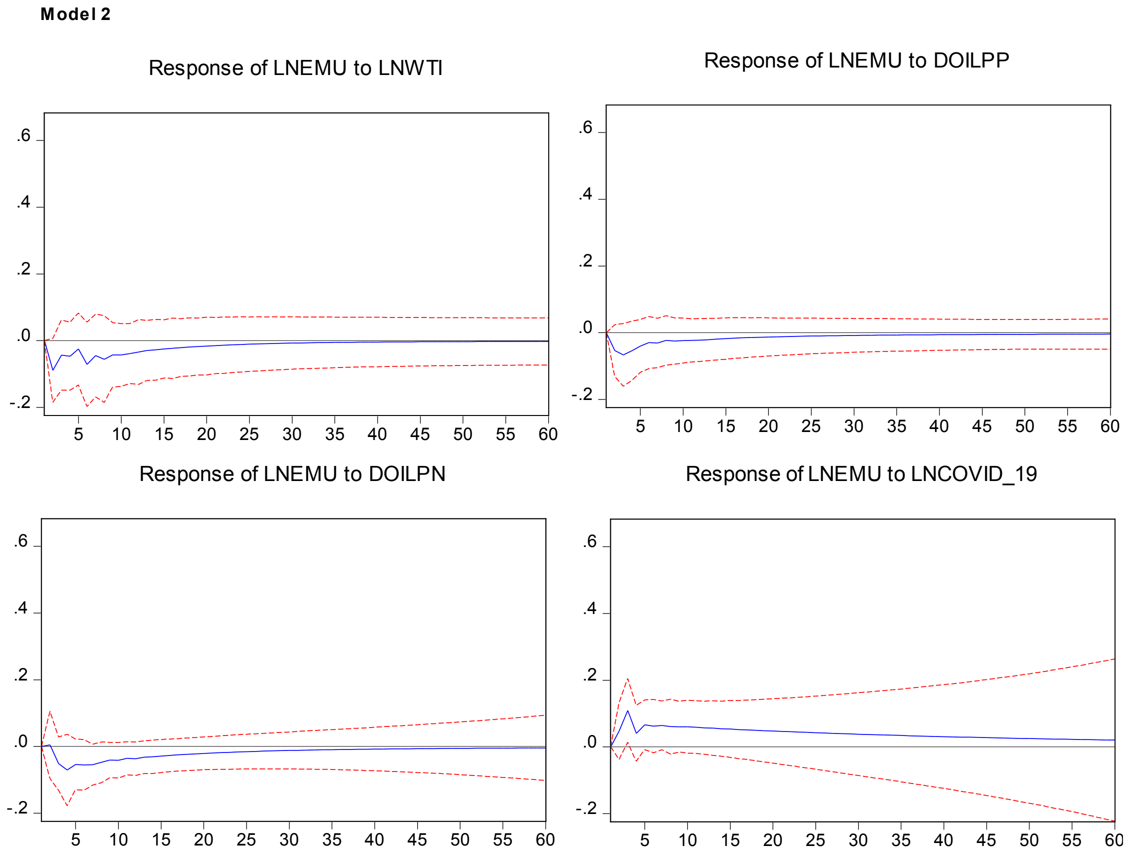

Figure 3. Responses of equity market-related economic uncertainty components to one-standard deviation structural shock.

Figure 4 shows impulsivity response functions of the standard deviation of equity market volatility (infectious disease tracker). The unexpected shock of oil prices (oil price shock and positive and negative shock) leads to a temporary negative impact in the time frame between one to 25 days of these three shocks, but its effect will disappear until the end of the period. While a positive impact of the COVID-19 shock occurred on the uncertainty of the stock market fluctuations, but at an increasing rate during the thirty days following the shock occurred. This finding is consistent with the results of Bloom et al. [34] and Baker et al. [14,35,36], as they found evidence that the developments of COVID-19 led to a rise in volatility and stock market crash during the period from February 19 to March 31, 2020.

However, the situation differs for model 4 in Figure 5, as there is an asymmetric negative impact of the oil price shock on the uncertainty of the volatility index during the first 15 days following the shock occurred, after which the effect turns into positive but this effect decreases in the long-run. Similarly, with regard to the shock of positive oil prices and the shock of COVID-19, these two shocks had no effect at the beginning of the period, and after 10 days of the shock, a positive impact of this shock will occur on the volatility uncertainty index (VIX) and up to 60 days following the shock. By contrast, no negative oil price shock responses to the volatility uncertainty index (VIX) for the entire period were observed. Consequently, we can conclude that previous results indicate that oil price shocks and the COVID-19 shock are expected to lead to greater uncertainties that do not persist throughout the study period but rather the responses are variable over time. The effects of the oil shock and the COVID-19 shock were statistically significant for all of the models involved. Similar results have been reported by Antonakakis [37] based on the index proposed by Diebold and Yilmaz [38] they found that the shocks of the uncertainty in economic policy respond negatively to the oil price shocks and vice versa.

In general, the effect of total oil prices (and their shocks) has a negative impact on the four indicators of uncertainty. This is partly in line with Antonakakis [39] who found a negative impact of oil price shocks on the dynamic correlation of stock market returns, implicit volatility, and uncertainty in economic policy.

Model 3

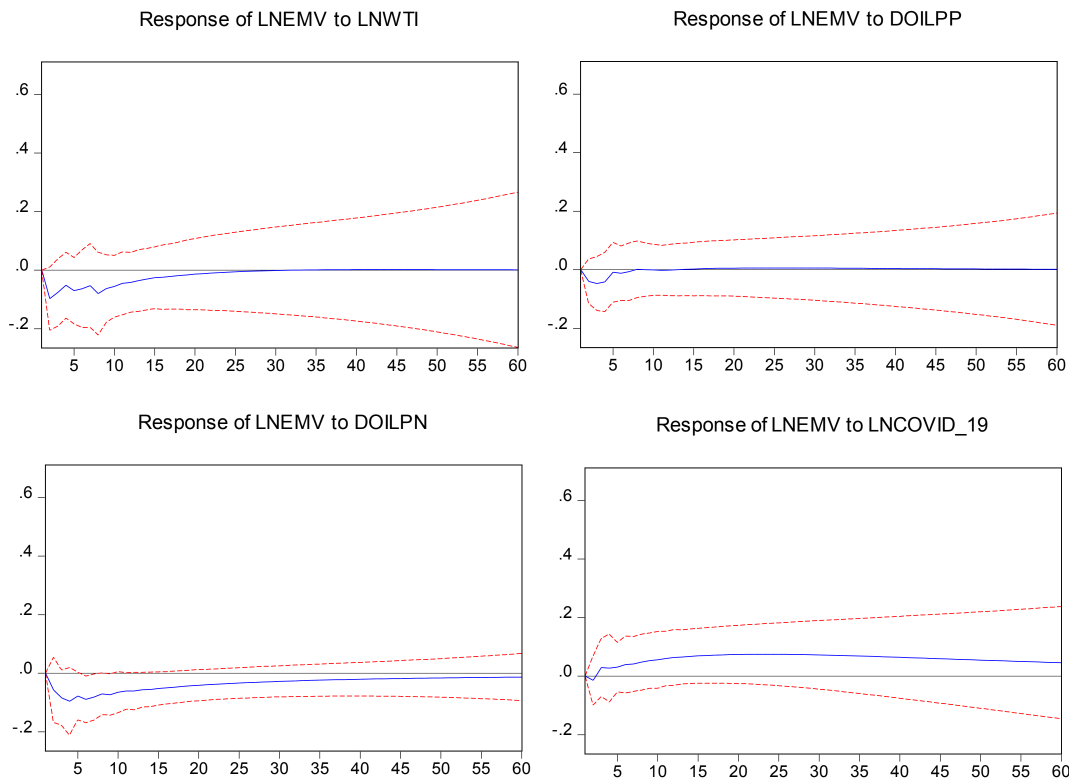

Figure 4. Responses of equity market volatility components to one-standard deviation structural shock.

Model 4

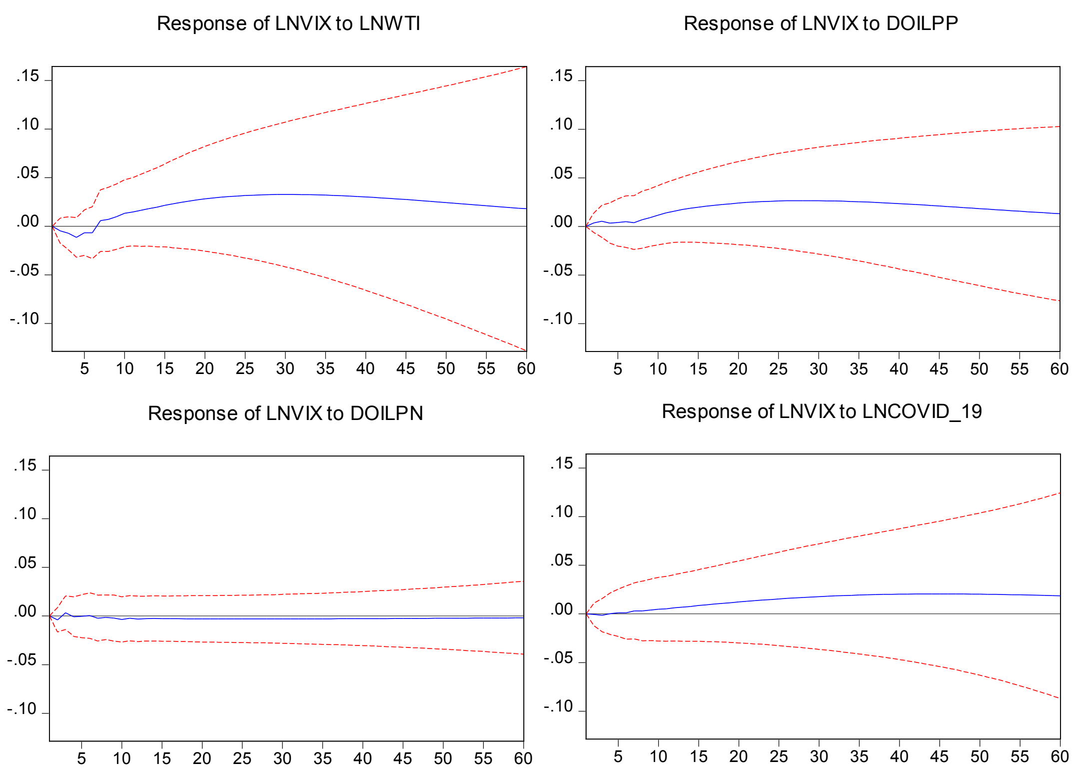

Figure 5. Responses of CBOE volatility index (VIX) components to one-standard deviation structural shock.

3.2 Variance Decomposition

This section describes the results of the variance decomposition of the forecast error 60 steps forward. The results indicate the proportion of the variance of the forecast error of the system variables that is explained by each structural shock in the residual vector.

Table 4 shows the results of the variance decomposition for the four systems. The numbers reported in columns (a, b, c, d) indicate in the model (1) the percentage of error expected in each variable that can be attributed to innovations in other variables in 60 different horizons: 1 to 60 days (short to long term). Specifically, under column (a) on the third day, 88% of the variability in US economic policy uncertainty changes is explained by oil price shock innovations. Two months later, nearly 10% of the variance was explained by the innovations of the overall oil price shock. As shown in column (b), US economic policy uncertainty is generally affected by positive oil price changes at the lowest possible level. On the first day, approximately 1.2% of US economic policy uncertainty fluctuations were explained by the positive oil price shock. The highest volatility of 12% in the second month is explained by the positive oil price shock. Likewise in the event of a negative oil price shock, as shown in column (c), US economic policy uncertainty is generally affected by changes in negative oil prices at the lowest possible level on the first day, approximately 0.71% of the fluctuations the highest volatility of 2.16% in the second month is explained by the negative shock of oil prices. In the short and long term, negative oil price shocks have little impact on economic policy uncertainty. We also note that the impact of the positive oil price shock on the US economic policy uncertainty is relatively greater than the impact of the negative shock of oil prices. For the COVID-19 indicator presented in column (d), 1.4% of the US economic policy uncertainty changes were attributable to COVID-19 changes on the first day. After two months, the US economic policy uncertainty represents about 15.8% of the error difference in COVID-19 projections. In the long run, COVID-19 shocks have greater the US economic policy uncertainty than oil price shocks.

Table 4. Variance decomposition of uncertainty.

Percentage change in uncertainty due to oil price or COVID-19 (60-day horizon)				
SVAR model	a	b	c	d
Model(1)	Due to *lnoilp*	Due to *lnoilpp*	Due to *lnoilpn*	Due to *lnCOVID*
3	0.876	1.226	0.705	1.415
12	4.612	5.736	1.219	4.404
24	8.312	9.516	1.705	8.719
60	10.322	11.953	2.162	15.866
Model(2)	Due to *lnoilp*	Due to *lnoilpp*	Due to *lnoilpn*	Due to *lnCOVID*
3	2.092	1.545	0.564	3.015
12	4.121	2.315	3.508	6.481
24	4.328	2.424	4.046	9.574
60	4.213	2.471	4.159	13.117
Model(3)	Due to *lnoilp*	Due to *lnoilpp*	Due to *lnoilpn*	Due to *lnCOVID*
3	2.656	0.663	1.792	0.187
12	4.692	0.581	6.216	2.204
24	4.268	0.498	7.143	6.940
60	3.631	0.467	7.212	15.617
Model(4)	Due to *lnoilp*	Due to *lnoilpp*	Due to *lnoilpn*	Due to *lnCOVID*
3	0.774	0.201	0.100	0.008
12	1.332	0.959	0.077	0.154
24	5.983	4.499	0.104	1.092
60	15.189	9.866	0.163	6.157

Notes: ***, ** and *, denote statistical significance at the 1%, 5%, 10% levels, respectively.

In the model (2), on the first day, approximately 2.09% of equity market-related economic uncertainty in volatility were explained by the oil price shock. The highest volatility of uncertainty at 8.33% within 24 days is explained by oil price shock innovations, but volatility decreases from the end of the second month. As shown in the two columns (a, b), equity market-related economic uncertainty is generally affected by positive and negative oil price changes at the lowest possible level 1.55% and 0.56%, respectively on the first day, approximately 4.16% and 2.47% of fluctuations of uncertainty were interpreted by the oil price shock positive and negative, respectively. As shown in column (c), equity market-related economic uncertainty is generally affected by COVID-19 changes at the lowest possible level 3.02% on the first day; approximately 13.12% of fluctuations of uncertainty were interpreted by the COVID-19 in the second month. It should be noted that in the medium and long term, COVID-19 shocks have relatively greater effects than oil price shocks on equity market-related economic uncertainty.

In the event of equity market volatility uncertainty as shown in the model (3) in column (a, b, c, d). Given in column (a) equity market volatility is affected by the shock of oil prices at the lowest level of 2.66% at the first day, approximately 3.63% of the equity market volatility uncertainty by the oil price shock in the second month. In the short and long term, a simple (almost negligible) explanation for the change in equity market volatility uncertainty is through the innovations of the positive oil price shock, where the ratio ranges between 0.66 to 0.46%. While the negative oil price shock as in column (c), equity market volatility uncertainty is generally influenced by negative oil price changes at the lowest possible level in the first day, approximately 1.79% of the uncertainty was explained by the positive oil price shock. The highest volatility of 7.21% in the second month is explained by the positive oil price shock. While the COVID-19 shock as in column (c), the equity market volatility uncertainty in stock market fluctuation is generally affected by changes in COVID-19 at the lowest possible level on the first day, about 0.19% of the uncertainty was explained by the COVID-19 shock. The highest volatility of 15.62% in the second month explains the COVID-19 shock.

Finally, regarding the volatility index uncertainty (VIX), and considering the two columns (a, b and c) in the model (4). The volatility index uncertainty is affected by the shock of the overall positive, negative, oil prices at the lowest level of (0.77%, 0.20% and 0.10%), respectively on the first day, and the uncertainty of the volatility index due to the shock of oil prices (overall, positive, negative) in the second month is affected by rates (15.19%, 9.87 and 0.16%), respectively. In the medium and long term, COVID-19 shocks have minimal effects on the volatility index uncertainty (VIX).

In sum, the contribution of the impact of the total oil price shock on the equity market-related economic uncertainty is similar to the effect on the equity market volatility (infectious disease tracker). In this context, the largest contribution of the impact of the oil price shock on equity market volatility (infectious disease tracker) in the short term, although in the long-run, it was the largest contribution from the volatility index (VIX) uncertainty by 15%. With regard to the contribution of positive and negative oil price shocks in the case of the two indicators, US economic policy uncertainty and volatility index (VIX) uncertainty, the contribution of positive shock is relatively greater than the contribution of negative shock in the short and long run. On the contrary, in the case of the two indicators of equity market-related economic uncertainty and equity market volatility (infectious disease tracker), the contribution of the negative oil price shock is relatively greater than the contribution of the positive shock of these two indicators. In addition, the largest contribution to the shock of the COVID-19 at the US economic policy uncertainty at 8.15%, and at the equity market volatility (infectious disease tracker) index at 6.15%.

4. Conclusions

The COVID-19 pandemic and the measures taken to limit its spread provoke a large-scale recessive shock that has not been seen in recent history. The response to the health crisis by confining the population in many countries greatly reduces economic activity, which weighs on employment, income and the financial situation of businesses, certain sectors being particularly affected. The shock started in the real economy, but it is transmitted to the financial markets, affected by the uncertainty linked to the health crisis and by the slowdown in global economic activity.

For this purpose, this study examines the asymmetric effects of the structural oil price shocks and COVID-19 pandemic on four uncertainty indexes. To achieve this goal, we use a structural vector autoregressive (SVAR) approach based on a daily period from 31-Dec-2019 to 28-Jun-2020. We also used the US economic policy uncertainty index (Model 1), the equity market-related economic uncertainty index (Model 2), the equity market volatility "infectious disease tracker" (Model 3) and the volatility index (VIX) (Model 4). Specifically, our study concentrates on four mutually orthogonal shocks: the oil price shock, shock of the increase and decrease in oil prices and the COVID-19 shock based on the SVAR for the four systems of each uncertainty series to one standard deviation structural shocks. Our approach is characterized by many advantages compared to the models used in the existing literature to model the relationship between the oil price and the COVID-19 epidemic and indicators of uncertainty. First, unlike previous literature that studies the relationship between oil prices and economic policy uncertainty, instead, our study uses the relationship between oil price shocks, the COVID-19 epidemic on the one hand, and uncertainty on the other. Second, we allow the evolution of the asymmetric effects of oil price shocks and the COVID-19 epidemic on the uncertainty of four indicators. Third, we estimate the trend functions for each uncertainty index to assess patterns of individual trend functions versus the trend function for each of the four indicators of uncertainty.

In particular, Johansen and Juselius [40] is applied to reveal the long-term equilibrium relationship between the variables involved. The results of this test confirm a long-term equilibrium relationship between all the variables involved. Additionally, the results of the IRFs showed the negative responses from the index of US economic policy uncertainty have the asymmetrical effects from oil shocks (oil prices and its positive and negative shock). While we find that COVID-19 shocks lead to positive responses of the economic policy uncertainty index. Furthermore, the impact of the unexpectedly positive oil price shock leads to a decrease in US economic policy uncertainty, which is more evident. The fact that economic uncertainty responds negatively to positive changes in oil prices is not self-evident. The bizarre advantage of these results may be hiding by the overall measure of oil price shocks. It should be noted here that the response to the economic policy uncertainty of the positive oil price shock and the negative oil shock is asymmetrical in the absolute size of the response to the shock. In addition, a negative price shock has a relatively lesser effect on economic policy uncertainty than a positive price shock; on the other hand, there is not much difference in the continuation of the effect between the two. Oil price shocks seem to have effects symmetric on the equity market related economic uncertainty. In addition, the decreasing positive impact of the COVID-19 shock on the economic uncertainty related to the stock market.

The unexpected shock of oil prices (oil price shock and positive and negative shock) leads to a temporary negative impact in the time frame between one to 25 days of these three shocks, but its effect will disappear until the end of the period. While a positive impact of the COVID-19 shock occurred on the uncertainty of the stock market fluctuations, but at an increasing rate during the thirty days after the shock occurred. In this aspect, there is an asymmetric negative impact of the oil price shock on the uncertainty of the volatility index during the first 15 days following the shock occurred, after which the effect turns into positive but this effect decreases in the long run. Moreover, with regard to the shock of positive oil prices and the shock of COVID-19, they have no effect at the beginning of the period, and after 10 days of the shock, a positive impact of this shock will occur on the volatility uncertainty index (VIX) and up to 60 days following the shock. By contrast, no negative oil shock responses to the volatility uncertainty index (VIX) for the entire period were observed. Consequently, we can conclude that previous results indicate that oil price shocks and the COVID-19 shock are expected to lead to greater uncertainties that do not persist throughout the study period but rather the responses are variable over time. Similar results have been reported by Antonakakis et al. [37] based on the index proposed by Diebold and Yilmaz [38], they found that the shocks of the uncertainty in economic policy respond negatively to the oil price shocks and vice versa.

In general, the effect of total oil prices (and their shocks) has a negative impact on the four indicators of uncertainty. This is partly in line with Antonakakis et al. [39] who found a negative impact of oil price shocks on the dynamic correlation of stock market returns, implicit volatility, and uncertainty in economic policy. We, therefore, underline an amplification of COVID-19 risk to the financial and real economy, generated by an increased, US policy-induced economic uncertainty.

Conflict of Interest

Author declares no conflict of interests.

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